Escaping to nature during a pandemic: A natural experiment in Asian cities during the COVID-19 pandemic with big social media data

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HIGHLIGHTS

- Mass social media data enabled an extensive investigation into greenspace use patterns.
- Urban greenspace use increased in four Asian cities during the COVID-19 outbreak.
- During the COVID-19 outbreak, residents preferred large nature parks close to city centers.

GRAPHICAL ABSTRACT
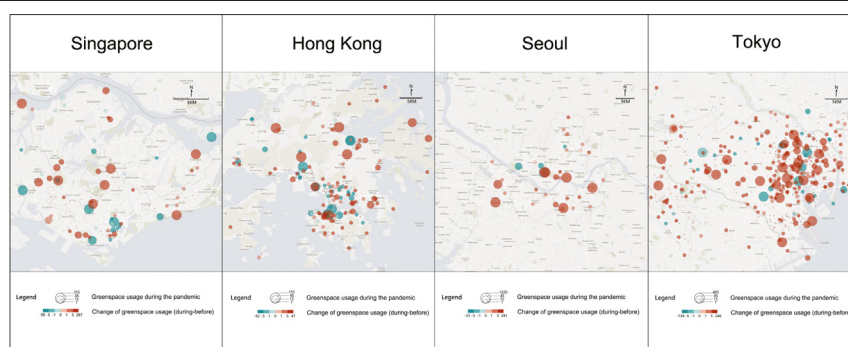
ABSTRACT

As global communities respond to the spread of coronavirus disease 2019 (COVID-19), urban residents worldwide have reduced their mobility, which may have incidentally kept people away from greenspaces. Surprisingly, anecdotal evidence suggests greenspace use surged in Asian cities. In this study, we used the COVID-19 pandemic as a natural experiment to investigate individuals' behavioral changes in greenspace use before and during the pandemic. We created a longitudinal panel dataset comprising Instagram posts from 100,232 users relating to 1185 greenspaces in four Asian cities: Hong Kong, Singapore, Tokyo, and Seoul. We found a 5.3% increase in the odds of people using greenspaces for every 100-case increase in weekly new cases. The models also revealed that people prefer nature parks that are large and close to city centers. In summary, because of the established physical and mental health benefits of greenspaces, people have been escaping to nature to cope with the pandemic in Asian cities.

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1. Introduction

The World Health Organization (WHO) declared the coronavirus disease 2019 (COVID-19) outbreak a public health emergency on January 30, 2020, and a global pandemic on March 11, 2020. By September 15, 2020, there were 29.1 million infected cases and 925,965 deaths worldwide, with both cases and deaths increasing every day (WHO, 2020).

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The COVID-19 pandemic has impacted our lives and society profoundly. Cities worldwide have implemented various social distancing measures, which remain the most effective way to control the spread of the virus (Gu et al., 2020; Tian et al., 2020; Wilder-Smith and Freedman, 2020). However, social distancing measures may keep people away from nature.

Based on Google COVID-19 Community Mobility Reports, one study showed that greenspace use decreased in European and North American cities (Samuelsson et al., 2020). In contrast, news reports indicate a surge in greenspace use in Asian cities, for example in Hong Kong, Tokyo, Seoul, and Singapore (Appendix 1), where social distancing measures were lenient (Chang, 2020; Jiji, 2020; Sun et al., 2020). Escaping to nature is a human instinct to avoid harsh environments and disease outbreaks (Tuan, 1998). Therefore, greenspace use may be a way for residents of Asian cities to cope with the COVID-19 pandemic.

Modern urban greenspace facilities can be partially viewed as the planning outcome of cities' response to previous crises and pandemics. Urban planning was shaped by the deteriorated living environment and the frequent pandemic outbreaks in European cities in the 19th century (Johnson, 2006). The 1853 cholera pandemic claimed over 10,000 deaths in London, primarily due to the dense living conditions and poor sanitation. In response, London created the first public park—Victoria Park—to improve public health after this cholera outbreak (Waller, 2000). The same planning motivation underlies the creation of Central Park in New York City, Emerald Necklace in Boston, and the tree-lined boulevards in Paris (Savitch, 2014). These greenspaces have become an integral component of the urban environment.

Urban greenspaces have well-established physical and mental health benefits (Hartig et al., 2014; Triguero-Mas et al., 2015; van den Bosch and Ode Sang, 2017). Exposure to urban greenspaces during a pandemic may have health benefits via the following five pathways (Fig. 1):

- Maintaining physical activity: Because of social distancing measures, many people are forced to adopt a sedentary lifestyle, leading to a sharp decline in their physical activity levels (Sallis et al., 2020). Urban greenspaces serve as a suitable setting for people to maintain their active lifestyles (Hunter et al., 2015).
- Reducing electronic device use: With many employers implementing work from home policies, people rely on electronic devices to communicate and complete their work. Prolonged electronic device use may increase the risk of depression and feelings of loneliness (WHO, 2015). Visiting greenspaces can provide a break from electronic device use (Jiang et al., 2019).
- Reducing stress: People experience stress during a pandemic, especially when they are confined to indoor environments (Stieger et al., 2020). The biophilia hypothesis, stress reduction theory, and attention

restoration theory all posit that greenspaces facilitate recovery from mental fatigue, stress, and negative moods because people have an inherent affinity for nature (Kaplan, 1995; Ulrich, 1993; Ulrich et al., 1991; Wilson, 1984). Visiting greenspaces during a pandemic is likely to provide opportunities to make contact with nature and thus reduce stress.
- Avoiding home stressors: Because of prolonged stays at home, people are exposed and susceptible to potentially harmful interpersonal and environmental stimuli, including domestic violence and abuse, deteriorating family relationships, noise, temperature, air pollution, and crowding (Douglas et al., 2020). Visiting urban greenspaces can reduce exposure to such adverse stressors.
- Increasing social cohesion: In greenspaces, social contact can be maintained while complying with social distancing measures. For instance, Hong Kong allowed for gatherings of small groups in public places, even during the worst stage of the COVID-19 pandemic. When verbal communication with strangers is not feasible, visual contact can nevertheless be beneficial. Neuroscience and cognition studies have found that social gaze is hardwired in the brain and that it is a foundational component of communication and social interaction (Emery, 2000; Senju and Johnson, 2009). Therefore, seeing other people in greenspaces may stimulate a sense of social cohesion (Fone et al., 2014; Y. Liu et al., 2020).

The evidence during non-pandemic periods supports that four major types of factors may affects park use: intrapersonal, interpersonal, structural, and weather-related factors (H. Liu et al., 2017). Intrapersonal factors include a person's socioeconomic status (SES), free time, and personal attitudes and perceptions to parks, e.g., the desire to gain physical activity, and perceived safety (H. Liu et al., 2017; Sreetheran, 2017). Interpersonal factor is mainly the existence of companions, e.g., family members or friends, or programs in parks, e.g., jogging club or public square dancing. Structural factors include physical characteristics of the parks and the city, for example park accessibility, proximity to public transit, urban density, park type and size, and park facilities and maintenance (Rossi et al., 2015). Last, weather suitability influences people's park visitation (Mak and Jim, 2019; Sreetheran, 2017; D. Wang et al., 2015). People prefer mild and dry weathers. On the other hand, extreme hot or cold temperature, precipitation, and strong wind have negative effect towards park visitation (Mak and Jim, 2019).

Empirical research findings on how people are using greenspaces during the COVID-19 pandemic are inconclusive. There are also strong regional disparities in greenspace preferences and usage. Urban residents in China and Italy have an increased demand and usage in small nearby urban greenspaces, e.g., pocket gardens, tree-lined streets (Ugolini et al., 2020; Xie et al., 2020; Zhu and Xu, 2021). Whereas people
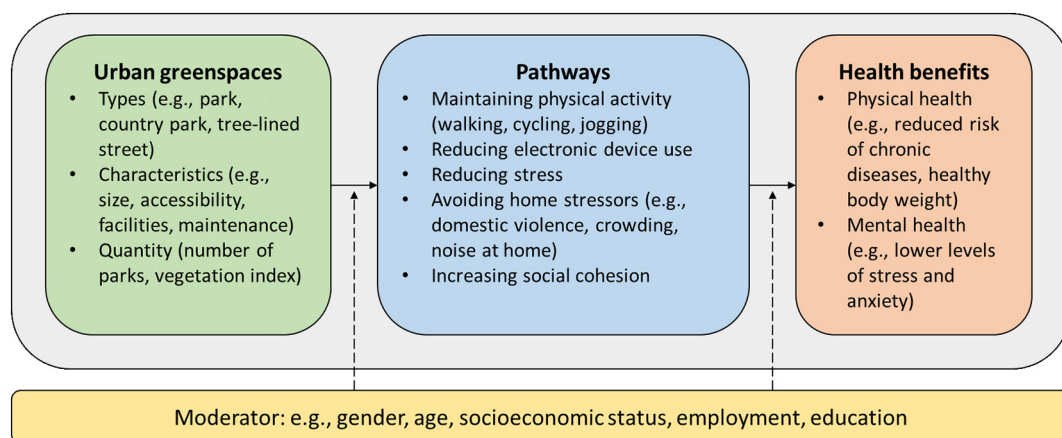

Fig. 1. Five pathways through which urban greenspaces can contribute to health. Note. During the COVID-19 pandemic, exposure to urban greenspaces can affect both physical and mental health via these pathways.

in Spain and Israel prefer nearby nature parks (Ugolini et al., 2020; Xie et al., 2020). However, one study based on Google mobility data from 111 counties in the U.S. found that changes in park visit patterns were mainly due to seasonality, not the pandemic (Rice and Pan, 2020). These inconsistent results can be attributed to data aggregation: many studies analyzed data aggregated at either the county level or the greenspace level, an approach through which pandemic response at the individual level cannot be inferred.

Nevertheless, the aforementioned studies have strengths associated with their use of big data. Because of the large volume, wide variety, and high velocity of data, the big data approach provides vast datasets to assess the relationships among urban greenspace, their use, and health outcomes during the pandemic (Ilieva and McPhearson, 2018; Laney, 2001). Recent studies assessing eye-level street greenery using large street view imageries have associated greenery with health outcomes in Hong Kong (Lu, 2019; R. Wang et al., 2019). A study of 717,527 people whose physical activity data were retrieved from smartphones with built-in accelerometer revealed physical activity inequality around the world (Althoff et al., 2017). Researchers have even used geotagged social media data, including data from Twitter, Flickr, and Instagram, to understand the patterns and potential drivers of park use (Chen et al., 2018a; Donahue et al., 2018; Hamstead et al., 2018). The foregoing studies were all made possible because of the wide availability of online data.

In this study, we extracted geotagged social media data from different time points to form longitudinal panel datasets. Specifically, we identified the individual greenspace visiting behaviors of 100,232 Instagram users in Singapore, Hong Kong, Tokyo, and Seoul before and during the different stages of the COVID-19 pandemic. Using these longitudinal panel data, we investigated how people modified their greenspace visiting patterns in response to the pandemic and how greenspace characteristics influence greenspace use patterns.

Our study contributes to academia and society in three aspects. First, because of the use of longitudinal panel data, our results are more rigorous than those of previous cross-sectional studies (Craig et al., 2017; Frees, 2004; Leatherdale, 2018). In particular, we used a natural experiment research design, with the COVID-19 outbreak as the intervention. Individual-level park visiting behaviors were collected both before and during the pandemic. Unlike previous studies using survey or social media platform to collect self-reported preferences and use of greenspaces (Rice and Pan, 2020; Ugolini et al., 2020; Xie et al., 2020), park use behaviors were objectively assessed based on geolocated social media data, which are more reliable than self-reported data. Second, as little is known about the relationships among pandemic status, park characteristics, and park visiting behaviors, we addressed the following two questions: do people visit urban greenspaces more often during a pandemic than usual? What types of greenspaces have become more popular during the pandemic? Third, we expanded upon the current understanding of greenspace use in high-density Asian cities. Greenspace use patterns in Singapore, Hong Kong, Tokyo, and Seoul during the COVID-19 pandemic have been largely under-investigated, despite their relative success in controlling the spread of the virus.

2. Methods

2.1. Research design

With the COVID-19 outbreak as the intervention, we evaluated the effect of the outbreak on park visit behaviors in Singapore, Hong Kong, Seoul, and Tokyo. We selected these four Asian cities as they are densely populated metropolises with lenient social distancing measures that had successfully controlled the pandemic at the time of the analysis (March 2020). The social distancing measures of these four Asian cities were collected in Appendix 2. In this longitudinal study, we used Instagram data to compare people's greenspace visiting behaviors before and during the pandemic.

This study comprises two analyses. Analysis 1 examined how people used greenspaces before and during the pandemic. Analysis 2 examined which type of parks received more visits. No control group was present in this study because the outbreak occurred in nearly all cities around the world.

We divided the pandemic timeline into three stages on the basis of announcements from the WHO, as listed below. The timeline was aggregated at the weekly level to optimize both computational power and interpretability.

- Stage 0 is the pre-COVID-19 stage, which covers seven weeks from December 16, 2019, to February 2, 2020, the week in which the WHO declared COVID-19 a "public health emergency of international concern" (on January 30).
- Stage 1 is the pre-pandemic stage, which covers the five weeks from February 3 to March 8, 2020, the week in which the WHO declared COVID-19 a pandemic (on March 11, 2020).
- Stage 2 is the post-pandemic stage, which covers the subsequent three weeks from March 9 to March 29, 2020. The ending date was when we ceased data collection and started the analysis.

2.2. Instagram data

Instagram has 1158 million active users in 2020 and is one of the most popular social platforms worldwide (Statista, 2020b). In Singapore and Hong Kong, Instagram users account for more than 60% of all internet users (AsiaPac, 2020; Statista, 2019). In Korea and Japan, Instagram is the third most popular social media platform (city-level data in Seoul and Tokyo were unavailable) (Herald, 2020; Statista, 2020a). Hence, the Instagram data in all these cities are highly representative. There is also an increased use of Instagram data in recent research studies (Chen et al., 2018b; Hassanpour et al., 2019).

We retrieved park visit-related Instagram posts published in the four cities between December 16, 2019, and March 29, 2020, using *instaloader*, an open-source API for Instagram (Graf and Koch-Kramer, 2019). We also collected data on the weather, new COVID-19 cases, greenspace characteristics (size, distance to city center, and type), and three covariates (weekly average temperature, outdoor-suitable days in a week, and holidays and weekends in a week).

First, we collected a list of greenspaces in each of the four cities from the relevant government websites (Lands Department of Hong Kong, 2014; Tokyo Metropolitan Government Bureau of Construction, 2018; Urban greening Department of Seoul, 2019; Urban Redevelopment Authority, 2017), following which we retrieved the Instagram unique numeric *location ID* for each greenspace using the API. Thereafter, we extracted all Instagram posts with these *location IDs*. Each Instagram post includes a unique *user ID*, the date and time of posting, and a *location ID*. We removed all Instagram posts with duplicated metadata, that is, posts with the same *location ID* and *user ID* published on the same date.

Instagram posts were aggregated at the weekly level into two datasets, one of each based on Instagram users and greenspaces. The first dataset, for Analysis 1 (user-based), contains the longitudinal data of 100,232 users who posted on Instagram during the study period. Because each *user ID* is unique to a user, we can analyze a specific individual's greenspace visiting behaviors during the study period (Fig. 2). Greenspace visit behaviors were converted to a binary outcome because most users posted only once during the study period. The second dataset, for Analysis 2 (greenspace-based), contains the data of 1185 greenspaces in the four cities (Fig. 3).

2.3. Pandemic severity and greenspace characteristics

Because COVID-19 acts as a natural intervention to people's greenspace-visiting behaviors in this study, the number of daily new COVID-19 cases during the study period acts as a proxy for the severity
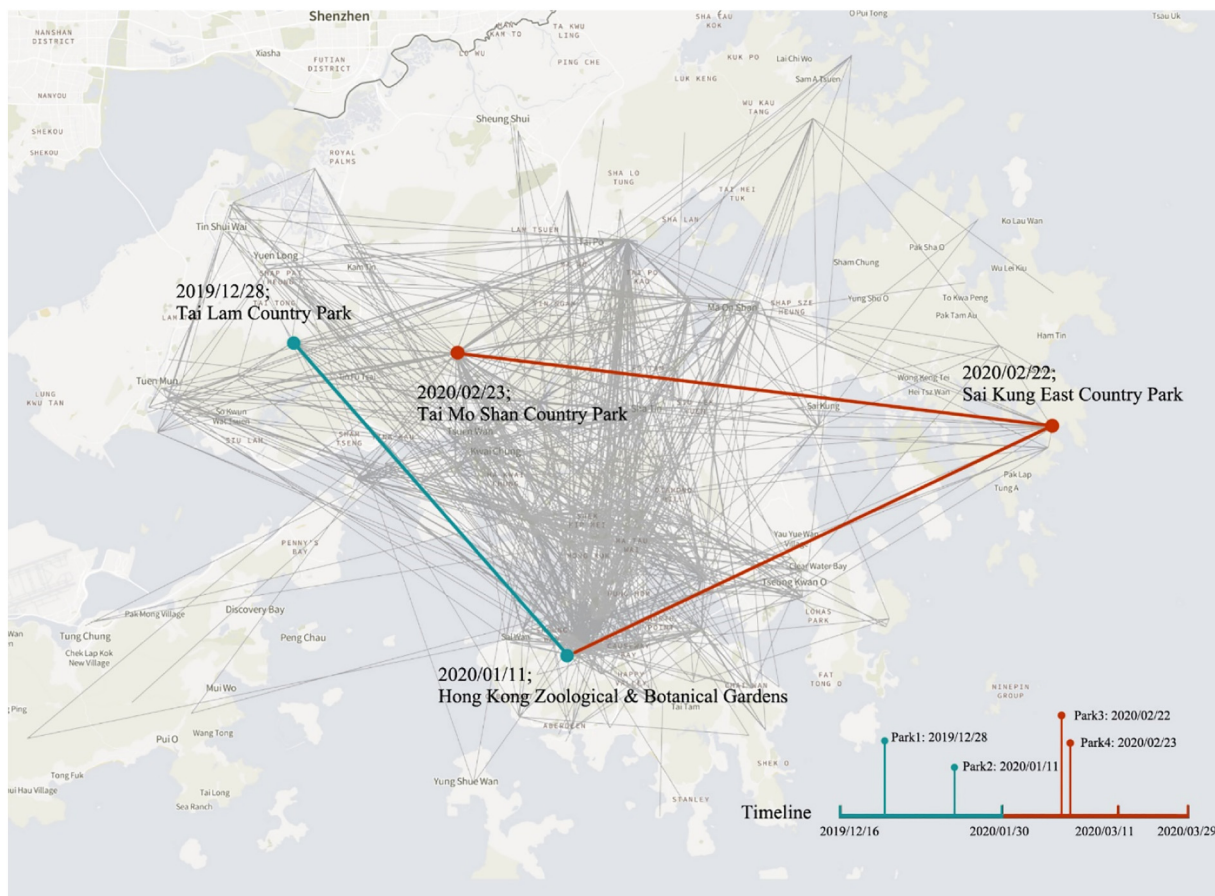
Fig. 2. A Hong Kong Instagram user's greenspace use before (blue dots) and during (orange dots) the coronavirus outbreak.

of the pandemic and is thus crucial to our study. Daily new case data were collected from each city's government portal (Appendix 3) and aggregated as weekly new cases, in units of 100 cases.

Guided by previous evidence (H. Liu et al., 2017), we assessed a few important structural factors including park type, size, and location, as well as weather, and the presence of public holiday in each city. Park types are categorized into two major types only (urban park and nature park), due to the inconsistent standard to classify parks and greenspaces in different cities. Due to data unavailability, we cannot collect interpersonal and intrapersonal factors, such as gender, SES, residential location, companions or other personal information.

The collected greenspace characteristics include size, distance to city center, and greenspace type. Greenspaces were classified as urban parks and nature parks (Appendix 4). Their sizes were obtained from the cities' official websites, and their distances from the city-center were calculated as the Euclidean distance. The coordinates of each greenspace were obtained from Instagram posts, whereas the coordinates of city centers—the central business district of each city—were extracted from Google Maps.

2.4. Covariates

In the analysis, we included three covariates that may affect greenspace use. The four case cities lie in different climate zones; hence, weather data during the study period were collected. These weather records were converted into two covariates: weekly average temperature and outdoor-suitable days in a week. Here, an "outdoor-suitable day" is defined as a day with mild weather (e.g., sunny,

overcast, cloudy, or light rain) and with temperature between 5 and 35 °C. In contrast, an "unsuitable day" is defined as a day with heavy precipitation, strong wind, or temperature below 5 °C or above 35 °C. Moreover, as each city follows its own holiday calendar, holidays may likely induce greenspace visits. Hence, the proportion of holidays and weekends in a week was used as the third covariate.

2.5. Statistical analysis

Corresponding to the two dataset structures (one each based on users and greenspaces), two panel data analyses were conducted. In Analysis 1, individual Instagram users were the unit of analysis. We examined how the propensity of visiting greenspaces changed when the outbreak entered Stages 1 and 2 and studied the influence of weekly new cases on greenspace visit behaviors. A mixed effects logistic regression model was used to predict the odds of a user visiting a greenspace at least once during a given week (1 = visited greenspace, 0 = not) against explanatory variables and covariates (Eq. (1)). We incorporated a random intercept for each user.

According to the reported booming use of parks in the news in the case cities, we hypothesize an increased park use entering Stage 1 and 2 comparing to Stage 0. We also hypothesize the weekly COVID-19 new cases to be positively associated with park use. For the covariates, we expect the outdoor suitability to be positively associated with park visitation, so are the weekly temperature and weekly holiday proportion.

In Analysis 2, greenspaces were the unit of analysis. We examined how the characteristics of a greenspace affect its use. A mixed effects
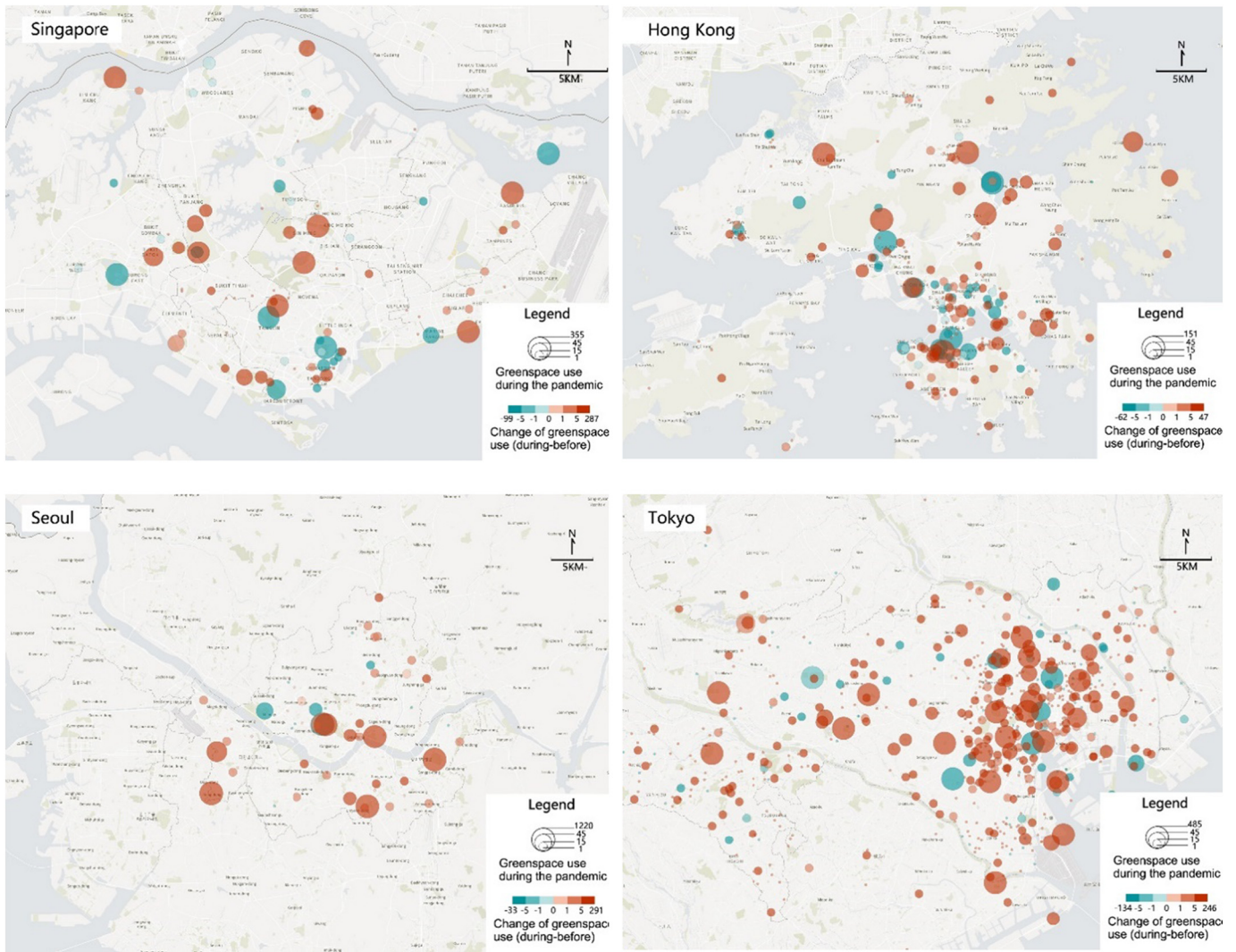
Fig. 3. Greenspace use during the pandemic and the change of greenspace use. Note. The size of a circle represents the total number of uses of a greenspace, while the color represents the change of use during the pandemic, compared with that before the pandemic (blue: decrease; red: increase).

negative binomial regression model was used to predict total greenspace use in a given week for each greenspace, against explanatory variables and covariates (Eq. (2)). The dependent variable, greenspace use, was obtained by summing the number of posts with a *location ID* of each greenspace in a week. This counting accepts multiple visits by the same user on different days, but not on the same date. In this analysis, the random intercept is the parks.

For this analysis, we hypothesize distance to city center is negatively associated with park visitation, according to previous studies. We also expect that nature parks (vs. urban park) and large parks are more likely to be visited in our case cities according to the news.

$$\text{logit}(P(\text{PostBinary}_{it} = 1)) = \alpha_i + \beta_0 + \beta_1 Stage_{it} + \beta_2 Cases_{it} + \beta_n Covariates + \varepsilon_{it} \quad (1)$$

$$\text{Greenspace use} = \alpha_i + \beta_0 + \beta_1 Distance_{it} + \beta_2 Area_{it} + \beta_3 ParkType_{it} + \beta_4 Stage_{it} + \beta_5 Cases_{it} + \beta_n Covariates_{it} + \varepsilon_{it} \quad (2)$$

Note. i repesents individuals, t represents the time (i.e., week in our study), ε is the random error of the model, and n is an index of the coefficients for the various covariates.

In both analyses, first, we separately fitted univariable regressions for each variable. Second, we fitted a full model with all of the variables. Third, we fitted three sensitivity analysis models to test the robustness of the results.

Only data from Singapore were used in the first sensitivity analysis (Analysis 1: $n = 329,130$; Analysis 2: $n = 1085$). Singapore has little weather variation and is hence considered to have the least influence from weather changes. The second sensitivity analysis used data from relatively active users and actively used greenspaces in Analysis 1 and 2, respectively. Active users are those who posted at least twice on Instagram during the study period ($n = 285,630$), and actively used greenspaces are those with at least 48 posts during the study period ($n = 4228$). These two thresholds were set considering the fewest number of posts in the first quantile (top 25%) of users and parks, respectively. The third sensitivity analysis used data from Stages 1 and 2 (Analysis 1: $n = 801,856$; Analysis 2: $n = 4634$). Because there were zero weekly new cases in Stage 0, excluding this stage may help more accurately determine the influence of new COVID-19 cases on greenspace visit behavior.

All analyses were conducted using the glmmTMB package (Brooks et al., 2017) in R (version 4.0.1) (R Core Team, 2014). Point estimates (odds ratios and coefficients), their 95% confidence intervals, and

significance levels were reported for all models. Additionally, the coefficients of each variable against greenspace use were plotted to visualize individual effects using the effects package (Fox and Weisberg, 2019). These plots improve our understanding of the associations between different variables and the outcomes.

3. Results

3.1. Descriptive statistics

Fig. 4 shows the number of daily Instagram posts related to the greenspaces. The spikes correspond to weekends and holidays, which had more park visits. Singapore saw a gradual increase in park-related posts, especially during Stages 1 and 2, whereas Hong Kong experienced an M-shaped fluctuation, with a gentle decrease at the beginning of Stage 1 that recovered during the transition from Stage 1 to 2. In contrast, the park-visit curves for Seoul and Tokyo are rather linear, but with a very sharp peak in March.

As listed in Table 1, Tokyo had the most Instagram users ($n = 38,138$) in this study, followed by Singapore ($n = 21,942$), Seoul ($n = 20,867$), and Hong Kong ($n = 19,285$). In Singapore and Hong Kong, the proportion of users visiting greenspaces (i.e., the percentage of total users in the city each week who visited greenspaces at least once) in each of the three stages was steady at approximately 9%, whereas in Seoul (6%, 7%, 13% in Stages 0–2, respectively) and Tokyo (7%, 8%, 16% in Stages 0–2, respectively), this proportion increased sharply in Stage 2.

The rate of growth in average weekly new virus cases (denoted '00) was highest in Singapore (Stage 1 = 0.3, Stage 2 = 2.3), followed by Hong Kong (Stage 1 = 0.2, Stage 2 = 1.8), Tokyo (Stage 1 = 0.1, Stage 2 = 1.2), and Seoul (Stage 1 = 0.2, Stage 2 = 1.0). Hong Kong had more outdoor-suitable days than did the other three cities. Weekly temperature is defined as the average temperature in a given week. Singapore had the highest temperature and the least temperature variation. The weekly holiday proportion is the proportion of holidays (Saturday, Sunday, and public holidays) in a week, which was steady at 0.3 in the four cities throughout the study period.

Table 2 describes the features of the greenspaces which were visited by Instagram users during the study period. More greenspaces were visited by Instagram users in Tokyo than did in three other cities. The average size of those greenspaces was larger in Seoul and Singapore. People in Seoul and Singapore also have larger greenspace area per person. Singapore has the highest proportion of nature parks (vs urban parks), while Tokyo has the highest percentage of urban parks (vs nature parks).

3.2. Propensity of visiting greenspaces (analysis 1)

The Instagram users were more likely to visit greenspaces during the COVID-19 outbreak (Table 3 and Appendix 5). In the full model, the odds of visiting a greenspace in Stage 1 increased by 6% ($p < .001$) compared with those in Stage 0. The odds of visiting a greenspace during Stage 2 increased by 26.5% relative to Stage 0 ($p < .001$). As visualized in Appendix 5, the highest increase is that from Stage 0 to Stage 2, a trend consistent across three sensitivity analyses: for users in Singapore only (sensitivity analysis 1), for active users who posted at least two times during the study period (sensitivity analysis 2), and for Stages 1 and 2 only (sensitivity analysis 3). The effects are more pronounced in sensitivity analyses 1 and 2. The odds of visiting a greenspace in Singapore increased 8.8% from Stage 0 to 1 and 31.9% from Stage 0 to 2, whereas the corresponding increase when considering only active users was 24.1% and 54.3%. When considering only Stages 1 and 2, the odds of visiting a greenspace increased 17.7%, slightly less than that in the full model.

The propensity of visiting a greenspace was positively associated with the number of new virus cases each week. In the full model, the odds of visiting a park increased by 5.3% ($p < .001$) for every 100 new cases in a week, holding other variables constant. As shown in the effects plot (Appendix 5), the number of weekly new cases was positively associated with greenspace visits. This association was significant in the three sensitivity analyses. Particularly, the odds increased by 8.7% ($p < .001$) when considering only Stages 1 and 2, the highest increase among all models, while the odds increased by 2.2% ($p < .05$) for Singapore users and 2.6% ($p < .01$) for active users. Overall, in the four Asian cities studied, people were more likely to visit greenspaces when the pandemic was more severe.

All covariates were significant in the full model and remained significant in most of the sensitivity analyses. Compared with users in
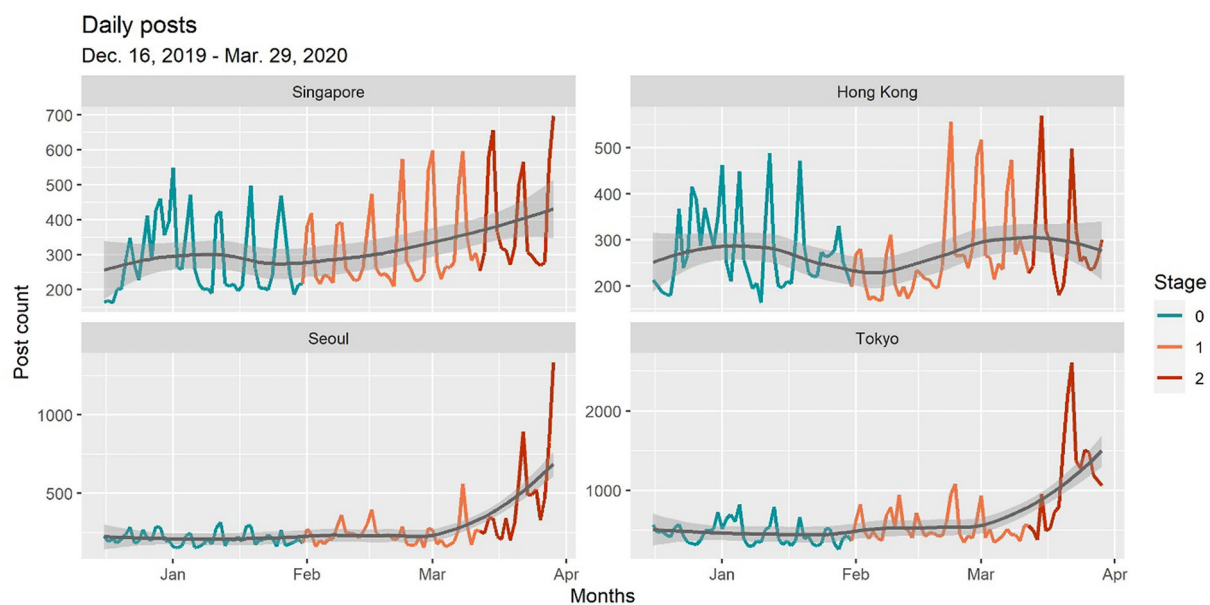

Fig. 4. Daily Instagram posts related to parks in the four case cities. Note. Spikes in the graph are weekends and holidays. Gray lines and bands are shown to help identify the trend, in which gray lines are smoothed conditional means, and gray bands are the 95% confidence intervals of the means.

Table 1
Descriptive statistics of the studied Instagram users, pandemic severity, weather, and holidays in the four case cities ($n = 100,232$).

Variables	Stage 0				Stage 1				Stage 2			
	Singapore	Hong Kong	Seoul	Tokyo	Singapore	Hong Kong	Seoul	Tokyo	Singapore	Hong Kong	Seoul	Tokyo
Users												
Number of users	21,942	19,285	20,867	38,138	21,942	19,285	20,867	38,138	21,942	19,285	20,867	38,138
Percentage of users visiting greenspaces (%)	8.2% (0.0)	8.9% (0.0)	6.3% (0.0)	6.8% (0.0)	8.5% (0.0)	8.4% (0.0)	7.0% (0.0)	7.8% (0.0)	10.4% (0.0)	9.0% (0.0)	13.2% (0.1)	15.7% (0.1)
Pandemic severity												
Weekly new cases ('00) (sd)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.3 (0.1)	0.2 (0.0)	0.2 (0.2)	0.1 (0.1)	2.3 (1.3)	1.8 (1.2)	1.0 (0.2)	1.2 (1.2)
Weather and holidays												
Weekly outdoor-suitable day proportion (sd)	0.5 (0.5)	0.9 (0.9)	0.3 (0.3)	0.7 (0.7)	0.7 (0.7)	0.9 (0.9)	0.5 (0.5)	0.8 (0.8)	0.7 (0.7)	0.9 (0.9)	0.7 (0.7)	0.7 (0.7)
Weekly temperature °C (sd)	29.8 (0.7)	21.3 (1.7)	4.4 (1.8)	10.7 (1.2)	31.1 (0.7)	21.5 (1.8)	6.4 (4.2)	11.9 (1.6)	32.1 (0.7)	24.4 (0.8)	12.5 (2.4)	16.2 (1.1)
Weekly holiday proportion (sd)	0.3 (0.1)	0.4 (0.1)	0.3 (0.1)	0.4 (0.2)	0.3 (0.0)	0.3 (0.0)	0.3 (0.0)	0.3 (0.1)	0.3 (0.0)	0.3 (0.0)	0.3 (0.0)	0.3 (0.1)

Singapore, users in Seoul, Hong Kong, and Tokyo were more likely to visit greenspaces (Appendix 5), in that order. The magnitude of the increase was larger in the full model than in the model considering only active users but similar in the model considering only Stages 1 and 2. Weekly temperature and weekly holiday proportion were positively associated with the odds of visiting greenspaces. The effect of weekly temperature was stronger in the full model than in the active user model and the Stages 1 and 2 model. However, this effect was nonsignificant in the sensitivity analysis with Singapore users. The positive influence of the holiday proportion was rather intense in the Singapore model and the Stages 1 and 2 model. The effect of weekly outdoor-suitable days was mixed: it was positively associated with park visits in the univariate analysis, the sensitivity analysis with Singapore users, and in the active users model, but it was negatively associated with the outcome in the full model and nonsignificant in the sensitivity analysis in Stages 1 and 2.

3.3. Greenspace characteristics and use (analysis 2)

The full model (Table 4) revealed that greenspace use in Stages 1 and 2 was higher than that in Stage 0. Greenspace use in Stage 1 was 1.095 times ($p < .001$) of expected use in Stage 0, whereas greenspace use in stage 2 was 1.261 times ($p < .001$) if that in stage 0; this upward trend is reflected in the stage-wise plots presented in Appendix 6 and is consistent with the sensitivity analyses for active parks (sensitivity analysis 2) and Stages 1 and 2 (sensitivity analysis 3). However, for Singapore parks, the increase across stages was nonsignificant (sensitivity analysis 1).

Table 2
Descriptive statistics for the greenspaces in the case cities.

Greenspace characteristics	Singapore	Hong Kong	Seoul	Tokyo
Number of greenspaces[a]	115	287	69	714
Average greenspace size (km²)[b]	0.20 (1.1)	0.02 (0.1)	0.57 (1.2)	0.03 (0.1)
Greenspace area/person (m²)	3.95	0.77	4.09	1.54
Distance to city center (km)[c]	8.76 (5.4)	10.08 (8.6)	10.61 (5.6)	18.07 (15.9)
Type				
Urban park	97 (84%)	261 (91%)	66 (96%)	711 (100%)
Nature park	18 (16%)	26 (9%)	3 (4%)	3 (0%)

[a] Number of greenspaces that had Instagram posts during study period.
[b] Average site of the greenspaces defined in a.
[c] Distance to city center is calculated as the distance from the centroid of parks to the CBD of the city.

The number of weekly new cases was also significantly associated with greenspace use. In the full model, expected visits increased by 0.063 times ($p < .001$) for every 100-case increase in new cases, a trend also seen in sensitivity analyses 2 and 3. However, in Singapore, the effect of weekly new cases on park visits was nonsignificant.

Several greenspace characteristics were significantly correlated with total greenspace use. Greenspaces closer to city centers were used more often. Distance to city center was negatively associated with greenspace use in the full model and in sensitivity analyses 2 and 3, but this association was nonsignificant in Singapore. Moreover, larger greenspaces were used more often. Greenspace size (area) was positively associated with greenspace use in the full model and in all three sensitivity analyses. Regarding park type, the full model and sensitivity analyses 1 and 3 revealed that nature parks (predominantly containing natural elements; e.g., country parks and trails) were used more often than were urban parks (containing large man-made elements; e.g., football fields and community parks).

Regarding covariates, greenspaces in Seoul and Tokyo (but not Hong Kong) were used more often than those in Singapore. Both weekly temperature and weekly holiday proportion were positively associated with the total greenspace use. However, the effect of the proportion of outdoor-suitable days on park visits was insignificant, as shown by the broad confidence interval in the plot against outdoor-suitable days in Appendix 6.

4. Discussion

4.1. Principal findings

How urban residents in Asian cities change their urban greenspace use in response to a pandemic with lenient social distancing measures was previously unclear. In this study, we used a longitudinal panel dataset comprising posts from 100,232 Instagram users in Singapore, Hong Kong, Tokyo, and Seoul to examine individual behavioral change in greenspace use before and during the COVID-19 pandemic. After controlling for temperature, weather, and number of holidays, we found that users were more likely to visit urban greenspaces in weeks with more new cases. The propensity of visiting greenspaces increased by 5.3% for every 100-case increase in weekly new cases in the city, holding other variables constant.

4.2. Interpretation and implications

Our findings suggest that urban residents in dense Asian cities may be using greenspaces as a strategy to cope with the COVID-19 pandemic.

Table 3
Multilevel logistic mixed model for predicting the propensity of visiting greenspaces.

Model predictors	Unadjusted model, odds ratio, OR (n = 1,503,480)	Full model OR (95% CI) (n = 1,503,480)	Sensitivity analysis 1[a] OR (95% CI) (n = 329,130)	Sensitivity analysis 2[b] OR (95% CI) (n = 285,630)	Sensitivity analysis 3[c] OR (95% CI) (n = 801,856)
Pandemic severity					
Stages (reference: stage 0)					
Stage 1	1.071 (1.057–1.086)***	1.060 (1.044–1.077)***	1.088 (1.045–1.132)***	1.241 (1.209–1.273)***	*Reference level*
Stage 2	1.818 (1.793–1.844)***	1.265 (1.230–1.300)***	1.319 (1.214–1.433)***	1.543 (1.471–1.619)***	1.177 (1.146–1.208)***
Weekly new cases ('00)	1.226 (1.219–1.234)***	1.053 (1.044–1.063)***	1.022 (1.000–1.044)*	1.026 (1.009–1.043)**	1.087 (1.076–1.097)***
Covariates					
City (reference: Singapore)					
Hong Kong	0.999 (0.981–1.016)	2.020 (1.939–2.105)***		1.238 (1.148–1.335)***	1.781 (1.691–1.875)***
Seoul	0.897 (0.881–0.913)***	5.548 (5.091–6.046)***		1.950 (1.668–2.280)***	5.137 (4.643–5.683)***
Tokyo	1.021 (1.006–1.037)**	4.135 (3.853–4.438)***		1.823 (1.606–2.070)***	3.985 (3.654–4.345)***
Outdoor-suitable days	1.465 (1.432–1.500)***	0.825 (0.797–0.854)***	1.218 (1.125–1.318)***	1.093 (1.028–1.162)**	0.961 (0.910–1.015)
Weekly temperature	1.010 (1.010–1.011)***	1.082 (1.078–1.086)***	0.994 (0.969–1.019)	1.033 (1.026–1.040)***	1.075 (1.070–1.080)***
Weekly holiday proportion	1.762 (1.679–1.850)***	2.995 (2.837–3.163)***	6.527 (4.569–9.322)***	1.963 (1.783–2.162)***	6.338 (5.344–7.518)***

Note.* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
[a] Sensitivity analysis 1: only data from Singapore were included.
[b] Sensitivity analysis 2: only active users who posted at least twice were included. This threshold was determined as the top 25% of the complete dataset.
[c] Sensitivity analysis 3: only data from Stages 1 and 2 were included.

First, our findings complement those from a Norwegian study that reported an increase in greenspace use during the pandemic. In particular, the Norwegian study reported a 291% increase in physical activity in greenspaces (Rice and Pan, 2020; Venter et al., 2020). Similar to Norway, the four cities in this study adopted lenient social distancing measures, without total lockdowns or stay-at-home orders. However, the characteristics of the study subjects differ between the two studies. The subjects in the Norwegian study were mostly sports enthusiasts that used Strava, a mobile sports activity tracking app, whereas the general public comprised the subjects in our study. Nevertheless, the converging findings of the two studies support the generalizability of the behavioral pattern of urban residents under lenient social distancing measures.

However, our result is inconsistent with a Google Mobility Report-based U.S. study which reported that changes in total greenspace use were largely due to seasonality and not the pandemic (Rice and Pan,

2020). This contradiction may be attributed to differences in the urban and social context and in the resolution of the data. More specifically, the four Asian cities in the present study are more densely populated than cities in the U.S. The residential environment is relatively small and confined in Asian cities. In addition, people in Asian cities prefer a more active lifestyle (Bauman et al., 2009). Given the soft social distancing measures in the four cities, people are likely to escape to urban greenspaces as the pandemic becomes more severe. Furthermore, our study used data at the individual level and thus yielded more refined results. In contrast, the Google Community Mobility data were aggregated at the city level, making the tracking of personal behavioral changes difficult.

Second, greenspace use behaviors were associated with weather and holidays. People visited greenspaces more often in weeks with more holidays. Similarly, people visited greenspaces more often on days with higher temperatures, except in Singapore. This exception

Table 4
Negative binomial mixed model for predicting for number of greenspace visits.

Model predictors	Unadjusted model, incidence rate ratio, IRR (n = 8102)	Full model, IRR (n = 8102)	Sensitivity analysis 1[a], IRR (n = 1085)	Sensitivity analysis 2[b], IRR (n = 4228)	Sensitivity analysis 3[c], IRR (n = 4634)
Pandemic severity					
Stages (reference: stage 0)					
Stage 1	1.107 (1.068–1.147)***	1.095 (1.053–1.138)***	1.063 (0.974–1.161)	1.123 (1.071–1.177)***	
Stage 2	1.691 (1.625–1.760)***	1.261 (1.172–1.356)***	1.144 (0.949–1.380)	1.375 (1.254–1.508)***	1.111 (1.032–1.196)**
Weekly new cases ('00)	1.194 (1.172–1.216)***	1.063 (1.038–1.089)***	1.029 (0.979–1.081)	1.042 (1.009–1.076)*	1.084 (1.055–1.113)***
Greenspace characteristics					
Greenspace distance to city center (km)	0.993 (0.987–0.998)**	0.994 (0.988–1.000)*	0.975 (0.924–1.030)	0.986 (0.976–0.997)**	0.994 (0.988–1.000).
Greenspace area (km^2)	1.540 (1.321–1.794)***	1.372 (1.167–1.613)***	1.408 (1.094–1.813)**	1.275 (1.072–1.517)**	1.443 (1.202–1.731)***
Greenspace type (reference: urban park)					
Nature park	3.001 (2.105–4.278)***	2.300 (1.579–3.350)***	3.059 (1.381–6.777)**	1.089 (0.700–1.696)	2.194 (1.476–3.261)***
Covariates					
City (reference: Singapore)					
Hong Kong	0.556 (0.420–0.736)***	0.987 (0.729–1.335)		1.208 (0.801–1.822)	0.875 (0.623–1.228)
Seoul	0.839 (0.569–1.237)	2.680 (1.691–4.245)***		3.566 (1.946–6.532)***	2.429 (1.455–4.054)***
Tokyo	0.484 (0.375–0.625)***	1.456 (1.045–2.028)*		2.212 (1.408–3.474)***	1.236 (0.842–1.815)
Outdoor-suitable days	1.409 (1.294–1.534)***	0.978 (0.886–1.079)	1.227 (1.030–1.461)*	0.971 (0.863–1.093)	1.189 (1.020–1.386)*
Weekly temperature	1.077 (1.071–1.083)***	1.056 (1.045–1.067)***	1.008 (0.953–1.067)	1.063 (1.049–1.076)***	1.047 (1.033–1.061)***
Weekly holiday proportion	1.345 (1.174–1.541)***	2.063 (1.799–2.366)***	5.468 (2.444–12.233)***	2.428 (2.041–2.889)***	2.607 (1.696–4.006)***

Note. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
[a] Sensitivity analysis 1: only data from Singapore were included.
[b] Sensitivity analysis 2: only greenspaces visited at least 48 times were included. This threshold was determined as the top 25% of the complete dataset.
[c] Sensitivity analysis 3: only data from Stage 1 and 2 were included.

in Singapore is not surprising because the daily average temperature is uniform throughout the year, with a high of 28.3 °C in May and June and a low of 26.4 °C in December (Meteorological Service Singapore, 2020). These results are in line with those of previous studies (Rice and Pan, 2020; Rice et al., 2019; Vierikko and Yli-Pelkonen, 2019). People prefer to visit nature during good weather. The COVID-19 pandemic is still ongoing at the time of writing. In cities experiencing severe outbreaks, people should be reminded to take precautions when visiting greenspaces on days with good weather to prevent overcrowding.

Third, greenspace characteristics were related to park use during the pandemic. Greenspaces that are larger and closer to the urban center and nature parks (vs. urban parks) were used more often. These results are largely in line with previous evidence during non-pandemic periods that people prefer large and accessible greenspaces (Cohen et al., 2010; Ekkel and de Vries, 2017; Sugiyama et al., 2010). Our study nevertheless contributes to the literature by revealing that nature parks are more popular than are urban parks in the four Asian cities during the pandemic; similar patterns were observed in Spain and Israel (Rice and Pan, 2020; Ugolini et al., 2020; Xie et al., 2020). According to the attention restoration theory, nature parks are often associated with the feeling of "being away" and "fascination"; hence, these nature parks help urban dwellers reduce stress and recover from mental fatigue (Kaplan, 1995, pp. 174). Nature parks with mountains, forests, and lakes are ideal settings for urban residents to escape from the perceived risk and stress related to the pandemic. Short-term escape to nature parks can be an effective emotion-focused coping strategy for urban residents facing stressful events (Austenfeld and Stanton, 2004; Taylor and Stanton, 2007). Nevertheless, some studies revealed that people also prefer small urban parks in some cities in China and Italy (Rice and Pan, 2020; Ugolini et al., 2020; Xie et al., 2020). The difference in this study and others may be explained by varied cultural and urban contexts across different cities and regions, e.g., availability of nature parks, preferences to nature parks, government policy, and pandemic situation. More studies are needed to explain such regional heterogeneity in park use behaviors.

4.3. Strengths and limitations

This study has the following strengths. Regarding the methodology, we designed a natural experiment study using a longitudinal panel dataset comprising voluntarily submitted social media data. Through this approach, we observed the behavioral change in greenspace use before and during the pandemic among the same subjects. When inferring relationships, this type of panel research design is preferred over cross-sectional design, because the former is enhanced by temporal ordering and can rule out the effects of unobserved individual differences (Frees, 2004). Our large sample size ($n = 100,232$ persons) across four Asian cities and sensitivity analyses improves the reliability and robustness of our findings. To the best of our knowledge, this study is one of the first to demonstrate that people's greenspace visiting is sensitive to pandemic severity. Specifically, in cities with lenient social distancing measures, people visit greenspaces more in weeks with more new virus cases. In addition, certain greenspace characteristics are associated with greenspace popularity during the pandemic. These findings offer insights that future studies on greenspace management and planning as well as on the health benefits of greenspace during the pandemic can build upon.

This study has some limitations. First, identifying a control group was difficult because the COVID-19 pandemic affected almost all cities worldwide. Second, Instagram data have some inherent limitations. Especially, we could not collect individual demographic and socioeconomic data due to data privacy, such as

age, gender, income, vehicle ownership, and transportation mode to greenspace. Although these data are not crucial to panel data analyses, we could not assess the effects of these individual factors on greenspace use (Frees, 2004). Furthermore, it is also difficult to distinguish greenspace use between local residents and no-local travelers, though we expect that the number of travelers was low during the study period. Third, some greenspace characteristics which may influence greenspace use are not available in this study, e.g., facilities, maintenance, landscape design, or solar access. Fourth, although Instagram is among the most used social media apps in these four cities, the user base tends to be young (NapoleonCat, 2020). Hence, our results may not be applicable to older users, who are more prone to COVID-19 and its adverse symptoms. Finally, the motivation, health benefits, and potential harms associated with urban greenspace use during the pandemic were not assessed in this study. As suggested by current evidence, the infection risk associated with greenspace use is relatively low. In a recent study investigating the transmission environments of 7324 infected cases in China, only two cases in one outbreak were linked to outdoor transmission (Qian et al., 2020). Nevertheless, much remains unknown about the potential health benefits and harms during this unprecedented pandemic. Visiting urban greenspaces may be associated with higher infection risk when precautions are not taken (e.g., touching rails, using public toilets and facilities, talking to others with vs. without wearing masks). Additional studies are warranted because understanding these outcomes can inform evidence-based policy making for combating the pandemic.

5. Conclusion

This study is the first to demonstrate that greenspace use during the pandemic is linked to pandemic severity in Asian cities. The propensity of visiting urban greenspaces increased with the number of weekly new COVID-19 cases. Our results show that using social media big data to analyze behavioral changes at the individual level is a feasible and effective research design in which any unobserved individual factors can be controlled for. If our findings are replicated in other cities, they have major policy and urban planning implications. Given the potential health benefits of urban greenspaces, urban planners and public health officials should create more accessible and large greenspaces, especially nature parks, to increase community resilience to crises and pandemics. However, precautions should be taken to mitigate potential harms, such as maintaining social distance, and wearing a mask during social interactions.

CRediT authorship contribution statement

Lu Yi: Conceptualization, Methodology, Writing.
Zhao Jianting: Data collection, data processing, Writing-result.
Wu Xueying: Data collection, Visualization.
Siu Ming Lo: Writing- Reviewing and Editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

Thousands of urban residents flocked to parks and other greenspaces during the peak of the pandemic in Hong Kong (Sun et al., 2020), Singapore (Kimberly Lim, 2020), Tokyo (Kirby, 2020), and Seoul (Chang, 2020).

(a) Hong Kong

(b) Singapore

(c) Tokyo

(d) Seoul

Appendix 2

Social distancing measures implemented in the four cities during the study period.

City	Time	Policy
Singapore	2020.03.26	The Ministry of Health promulgated Regulations on Safe Distancing ("Safe-Distancing Regulations").
Hong Kong	2020.01.29	The Leisure and Cultural Services Department (LCSD) announced that all facilities overseen by the department including all public museums, public libraries and sports centers were closed until further notice as a health precaution.
	2020.03.23	All facilities overseen by the department including all public museums, public libraries and sports centers were closed again.
Seoul	2020.02.03	The Ministry of Health and Welfare released "guidelines on the operation of group facilities and facilities frequented by large groups of people".
	2020.02.29	The Korea Centers for Disease Control and Prevention advised citizens to exercise "social distancing" and maintain personal hygiene.
Tokyo	2020.02.27	All schools are closed for about a month.
	2020.03.23	Citizens were urged not to leave their homes at the weekend in order to contain the spread of coronavirus.

Appendix 3

Data sources of covid-19 new cases in the four cities.
Tokyo: https://catalog.data.metro.tokyo.lg.jp/dataset/t000010d0000000068
Seoul: http://www.seoul.go.kr/coronaV/coronaStatus.do
Hong Kong: https://data.gov.hk/en-data/dataset/hk-dh-chpsebcddr-novel-infectious-agent
Singapore: https://www.moh.gov.sg/covid-19

Appendix 4

List of nature parks in four case cities.

| Hong Kong	Singapore	Tokyo	Seoul
Clear Water Bay Country Park	bukit batok nature park	高尾陣場自然公園	북한산국립공원
Pok Fu Lam Country Park	bukit timah nature reserve	滝山自然公園	남산공원
Lam Tsuen Country Park	central catchment nature reserve	多摩丘陵自然公園	관악산도시자연공원
Ma On Shan Country Park	chestnut nature park	狭山自然公園	대모산도시자연공원
Lion Rock Country Park	dairy farm nature park	羽村草花丘陵自然公園	안산도시자연공원
Sai Kung West Country Park	hindhede nature park	秋川丘陵自然公園	봉산도시자연공원
Tai Tam Country Park	springleaf nature park	都立秋川丘陵自然公園	은수도시자연공원
Shing Mun Country Park	windsor nature park	都立狭山自然公園	북악산도시자연공원
Lung Fu Shan Country Park	jurong lake gardens	都立高尾陣場自然公園	불양산도시자연공원
Tai Mo Shan Country Park	pulau ubin	都立滝山自然公園	인왕산도시자연공원
Pat Sin Leng Country Park	coney island park	都立多摩丘陵自然公園	일자산도시자연공원
Lantau South Country Park	sungei buloh wetland reserve	都立羽村草花丘陵自然公園	수락산도시자연공원
Shek O Country Park	bedok reservoir park	大島公園	서오능도시자연공원
Kam Shan Country Park	kranji reservoir park	奥多摩湖畔公園	청계산도시자연공원
Aberdeen Country Park	lower peirce reservoir park	小峰公園	인능도시자연공원
Sai Kung East Country Park	lower seletar reservoir park	多幸湾公園	우면산도시자연공원
Plover Cove Country Park	macritchie reservoir park	八丈植物公園	용마도시자연공원(사가정공원)
Lantau North Country Park	upper peirce reservoir park	羽伏浦公園	
Tai Lam Country Park	upper seletar reservoir park	葛西海浜公園	
Kiu Tsui Country Park		野山北・六道山公園	

Appendix 5

Individual effects of each predictor on the odds of a visiting greenspace in the full model while the other predictors are fixed

Note. Tick marks on the x-axis represent the number of cases at the value of the predictor. Shaded areas and bars represent the pointwise 95% confidence interval.
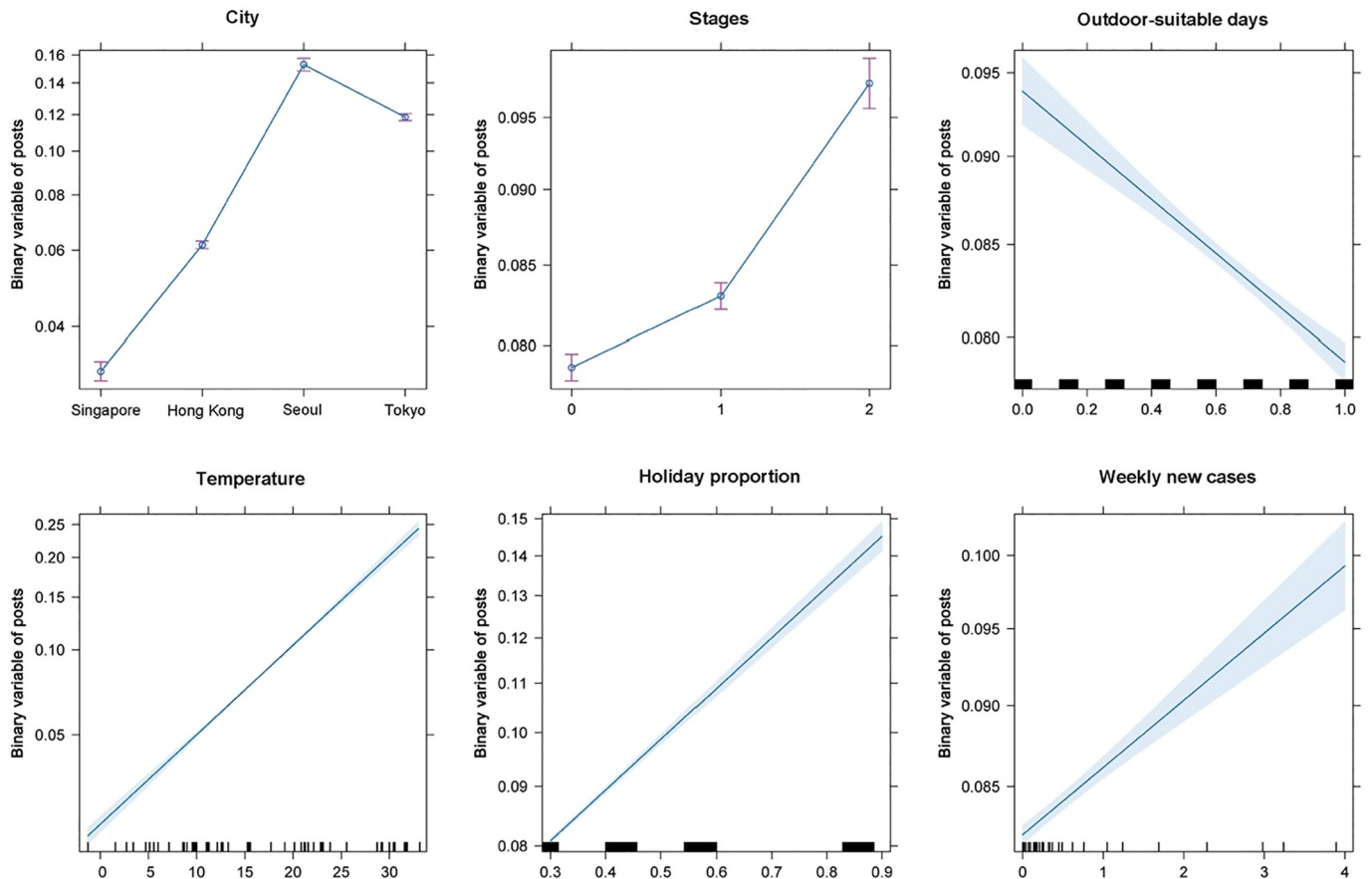
Appendix 6

Individual effects of independent variables on the dependent variable in the park-based full model.
Note. Black spikes on the x-axis are values present in the dataset.
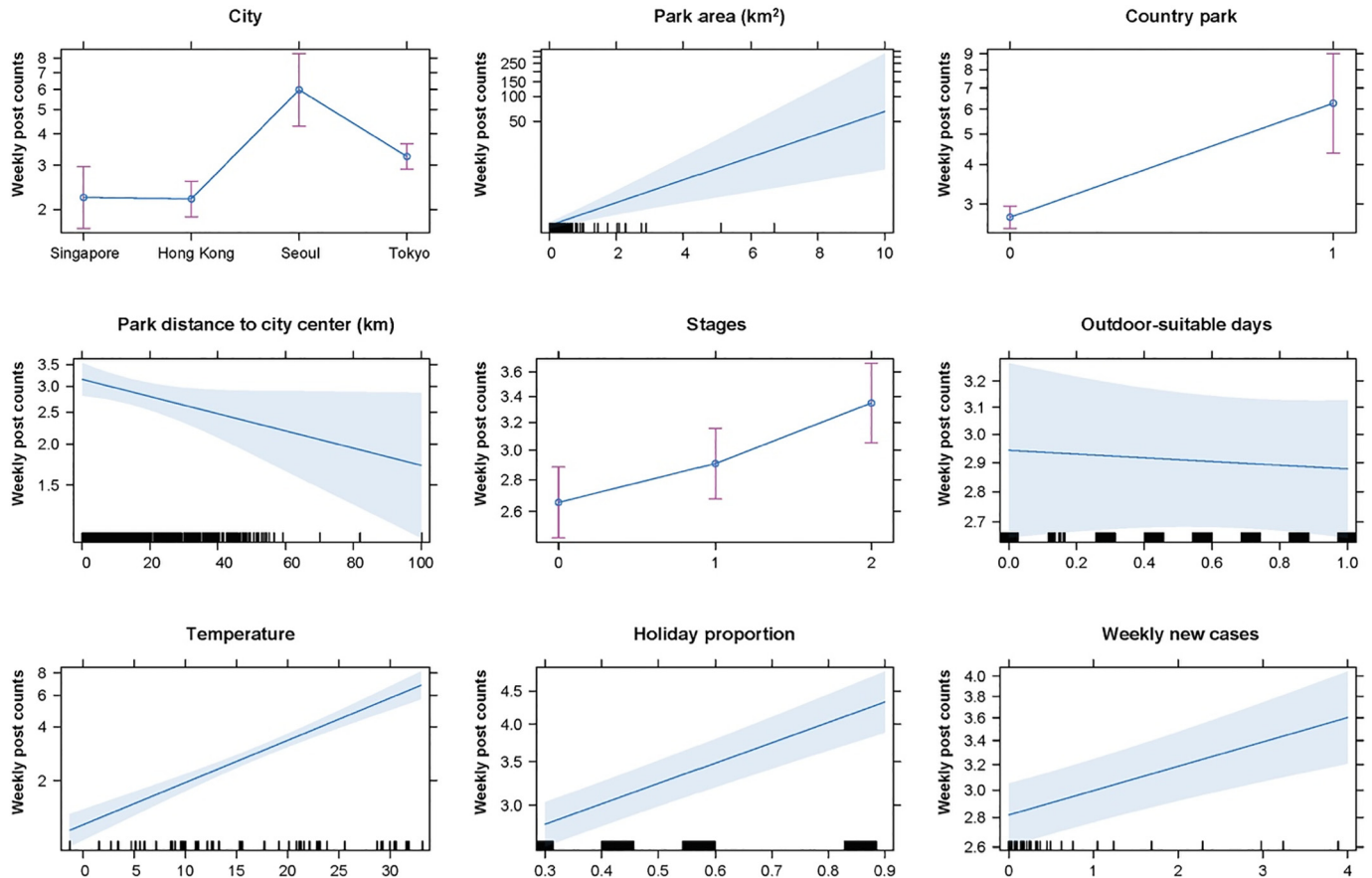
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