Heat and Park Attendance: Evidence from "Small Data" and "Big Data" in Hong Kong

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Abstract

Urban heat disrupts the use of parks, although the extent of such disruptions remains disputed. Literature relies on "small data" methods, such as questionnaires, field studies, or human-subject experiments, to capture the behavioural response to heat. Their findings are often in contradiction with each other, possibly due to the small sample sizes, the short study period, or the few sites available in a single study. The rise of "big data" such as social media offers new opportunities, yet its reliability and usefulness remain unknown. This paper describes a study using Twitter data (tweets) to study park attendance under the influence of hot weather. Some 20,000 tweets geo-coded within major parks were obtained in Hong Kong over a period of three years. Field studies have been conducted in parallel in a large park covering the hot and cool seasons and some 40,000 attendance were recorded over three months. Both the "small" and "big data" were analyzed and compared to each other. Findings suggest that a 1 °C increase in temperature was associated with some 4% drop in park attendance and some 1% drop in park tweets. The differences between the two data sources be explained by the 'leakage' of indoor tweets to parks caused by GPS drift near buildings. The Universal Thermal Climate Index can better predict self-reported thermal sensations, compared with other biometeorological indicators. This study has contributed to methodologies and new evidence to the study of behaviors and thermal adaptations in an outdoor space, and geo-coded tweets can serve as a powerful data source.

1. Introduction

Hot weather disrupts outdoor activities such as walking and the use of parks, yet the extent and direction of such disruptions remain disputed. Research literature asserts a thermal threshold, defined variably using heat physiology and laboratory experiments, beyond which the levels of thermal comfort are expected to decrease, together with levels of outdoor activities since people tend to 'vote with their feet'. This view has been widely shared by the scientific community and it has been supported by published evidence [1–3]. In contrast, a parallel body of studies has reported stable or even increased levels of park activities when the temperature rose beyond what is considered thermally acceptable [4,5]. This increase is referred to as 'heat coping' [6,7]: a hot park can still be cooler than its surrounding neighbourhoods, especially when air conditioning is not in use. The above inconsistency undercuts the credibility of a unified theory of outdoor thermal comfort. It also works against the rationale of climate resilience planning, which promotes urban parks as means against heatwaves.

Existing studies of outdoor thermal comfort and behavior are limited by the "small data" approach. The majority of studies in the last two decades employed field studies, on-site measurement, questionnaires and interviews. The process, despite the merits, is labor-intensive and can only cover a few sites over a limited period of time. The "small data" approach is limited by the sample size, which can be statistically underpowered. Nor is the accumulation of "small data" evidence helpful, since the data collection protocols often vary by study, making their finding difficult to be compared with others [8]. Controversies in the literature are expected to persist, unless new methods emerge which can yield robust evidence, in compensation to the many drawbacks of "small data."

Social media offers new opportunities to study human behavior in the digital age. Popular platforms such as Twitter, Facebook, and Weibo have attracted large quantities of contents shared by diverse population groups. Many users share the GPS coordinates by default, allowing for tracking of their behaviors with spatial-temporal precision. A sizable proportion can be traced within urban parks. Social media data can be collected en masse at a significantly lower cost than traditional means, such as field surveys, and for this reason, they have been used in the study of environmental behavior, social sciences, and health [9], except in the field of thermal comfort in parks. Like other new data sources, social media data are also considered vulnerable to sampling biases and distortion from commercial incentives [10,11]. Questions remain as to whether social media data can reliably capture park attendance under the influence of thermal conditions. And if yes, what implications does it provide in research and policy?

This paper describes the first study to use social media to quantify park attendance in response to hot weather conditions. The objectives are 1) to evaluate whether tweets can reliably monitor outdoor activities in parks, and 2) to compare the performance of biometeorological indicators[1] in explaining thermal sensations during the study conditions. A large sample of geo-coded Twitter data (tweets) were collected, with a subsample consisted of tweets geo-coded within major urban parks. Concurrent field studies were conducted in a large urban park in Hong Kong during hot, temperate and cool seasons. On-site meteorological measurements were conducted using a HOBO weather station. Park attendance data were acquired, and occupant thermal sensation and comfort were captured

[1] A biometeorological indicator measures the extent to which a human body is exposed to a particular thermal environment by accounting for the energy exchanges between a human body and the ambient environment. Many also account for human body thermal regulation and various measures of adaptations.

using a questionnaire. The above datasets were modeled statistically, and the results are compared with each other.

2. Relevant Works

Park attendance under the influence of thermal conditions has been extensively studied in the last two decades. An exhaustive search of published journal articles have been conducted in two databases, the Web of Science Core Collection and Scopus. The keywords used in the search include “outdoor thermal comfort,” “park attendance,” “park visitation,” and “thermal perception,” and a total of 206 entries were returned between 1990 and November 2022. They can be categorized in two: 1) assessment of heat stress in outdoor spaces, and 2) park attendance and temperature. The research gaps have been identified in relation to the opportunities afforded by “big data”, such as social media data, mobile phone and WIFI scanners.

2.1. Assessing Heat Stress in Outdoor Spaces

A large number of mathematical models, known as human biometeorological indices in literature, have been developed to assess human body energy balance and thermal regulations in outdoor environments. They rely on heat transfer and conservation equations to solve the heat gains/losses of an individual in an outdoor park, influenced by meteorological factors such as solar radiation, wind, air temperature, and humidity. They are also based on principles of human heat physiology and biological characteristics, such as the metabolic rate, external work, and clothing insulation, to determine the level of heat stress experienced by an individual. Many indices can be traced to their indoor equivalence, codified in the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standards 55 and adopted globally [12].

An early example is the Wet Bulb Globe Temperature (WBGT), a simple, empirically derived formula to classify levels of heat stress in an outdoor environment. The ranges of heat stress are consistently defined: a WBGT value <18 °C is considered suitable for unlimited sporting activities, while all trainings should be stopped if the value exceeds 30 °C. Originally developed to reduce heat diseases occurring in the US Army, WBGT has been adopted by civil authorities from Australia to Hong Kong as an advisory guideline for the public to determine the suitability of outdoor activities [13]. Two later examples include the Physiologically Equivalent Temperature (PET) [14] and the Outdoor Standard Effective Temperature (OUT_SET*) [15,16], both are based on a sophisticated two-node human body heat balance and thermal regulation models, which can be solved as non-linear equations or numerical simulations. For PET, the range of 18-23 °C is considered comfortable, 23-29 °C with slight heat stress, and further above with moderate and strong heat stress [17]. The Universal Thermal Climate Index (UTCI) is the latest bio-meteorological indicator, which is based off the 16-node Active System Model to simulate the responses of the human thermoregulatory system [18]. As its name implies, the UTCI index defines the range between 9 and 26 °C as free from thermal stress, above this range various levels of heat stress are expected to incur. These indices are considered ‘universal’ because they are derived from extensive laboratory data at standard conditions, which is applicable to the majority of thermal conditions.

However, considerable discrepancies were found between model prediction and field evidence collected from urban parks. Researchers used mobile weather stations to measure the in-situ thermal conditions, based on which they computed the biometeorological indices. They also captured the thermal sensations reported by occupants in open spaces of real cities, not in laboratories. For the PET index, park occupants in tropical and subtropical cities have reported a much warmer 'neutral zone' than those specified by laboratory data: it was found between 27 and 29°C in PET in Hong Kong [19], around 28.1°C in Singapore [20], or between 29.5 and 32.5°C in Dhaka, Bangladesh [21], all were significantly higher than the original range between 18 and 23 °C. Similarly, the zone of 'thermal comfort' for Universal Thermal Climate Index was found to vary between 15.2-28.8°C in Wuhan [2], 19-33°C in Hong Kong [22], all are significantly different from the 18-26°C in its original definition in Europe [23]. So far, the research community remains divided over the validity claims of the universal' human biometeorological indices and their range of application across climate zones.

2.2. Park Attendance and Temperature

Park attendance under the influence of thermal environment, or hot and cold weather conditions in particular, has long been recognized in behavioural studies. Classic urban theorists, from William Holly Whyte [24] to Jan Gehl [25], have observed in detail how social life in public open spaces, is influenced by sunlight, wind, and shadows from nearby buildings. Later studies, equipped with quantitative evidence, aimed at establishing quantitative relationships between park attendance and temperature, and their findings can be categorized in two:

First, there is a lack of consensus of whether park attendance tends to peak at the thermal conditions which are 'stress-free'. The large body of thermal comfort literature tends to suggest so, yet other behavioural studies argue that park activities can be more complex, beyond the description of human biometeorological models. The first school considers that people are most likely to use parks during the thermal 'neutral zone,' defined by various human biometeorological indices in Section 2.1 above. Deviation from this 'neutral zone', towards either the warm or cold side, resulting in a decline in park activities, since people will 'vote with their feet' and seek other activity venues which are thermally more comfortable. This view has been substantiated by a large quantity of observational studies [2,3,26–31]. For instance, Huang et al. [29] has documented the decline in open space attendances during hot weather conditions in Hong Kong, and virtually all activities have ceased when the Universal Thermal Climate Index (UTCI) equivalent temperature exceeded 39°C. A similar trend has been observed by Klemm et al. [28], in which daily park attendance correlated negatively with the maximum air temperature in urban parks in the Netherlands.

The second school of literature has revealed a more complex behavioural pattern under the influence of heat. They have reported increased park attendance, when the thermal conditions are beyond those considered neutral or stress-free. Lin et al. [4] reported an increase of park visitors in the shaded area of a urban park in Taiwan during the hot period, in which occupants adapted from unshaded area and chose voluntarily to be exposed to the thermal conditions outside of the 'comfort zone' prescribed by existing theories. Kabisch et al. [5] surveyed park visitors in Leipzig, Germany during hot summer days, and they found a high share of respondents were undisturbed by hot weather and kept using parks during heat waves as frequently as usual, albeit adjusting their visit schedule. Similarly, Jaung and Carrasco [32] reported a growing number of visitors in a park in Singapore under hot weather conditions, and there was no decline in headcounts in parks even if the air temperature reached as high as 31.7 ℃. An explanation for this, referred to as the heat-coping theory, is that parks are used as cooling spots for residents without access to air conditioning at home. They have been practiced by residents of lower income, poor living conditions [33], or the older population sticking to their habits formulated prior to the advent of home air conditioning [34].

2.3. Research gaps

Despite the abundance of theory and evidence in the field, two important knowledge gaps remain. The rise of social media provides new opportunities in the study of park attendance under the influence of heat stress.

First, the abundance of research publications in the field is largely due to the accumulation of "small data," such as field studies, questionnaire and measurement. Despite the merit, the technique is nevertheless limited in temporal-spatial coverage, resulting in variable sample sizes and data noises. A by-product of the near monopoly of the "small data" is the lack of consensus on the technical protocols [8,35]. For instance, researchers tend to choose the human biometeorological indices at will, with little consensus over which can better explain park attendance influenced by thermal environments. Controversies in the literature are expected to persist, unless new data collection methods emerge which can yield robust evidence, in compensation to the many drawbacks of "small data."

Second, innovations in data collection are rare, and there is a need for novel techniques to obtain large research samples, to cover many sites simultaneously for an extended period of time. A survey of recent publications yielded only a trio of outliers: Reinhart et al. [36] used WI-FI scanners to collect the usage of a campus open space under the influence of temperature. The findings suggest that WIFI scanners can capture attendance patterns in meaningful ways and lower the cost of data collection. In another example, Jaung and Carrasco [32] used mobile phone data to investigate weather and holiday impacts on visitors in a protected area in Singapore. They concluded that the mobile phone data is cost-effective, compared with on-site questionnaires. Yang et al. [37] used travel data to study walking and cycling behaviours under the influence of urban microclimate in New York. They concluded that variations in the thermal environment measured by UTCI can explain up to 4% changes in the choice of active travel modes, such as walking or cycling. A drawback to the above "big data" studies, is the lack of comparison with their "small data" counterparts. Without such comparison, it is difficult to evaluate whether "big data" evidence can reliably capture behavioral patterns, or whether their samples are representative and unbiased.

The rise of social media as a 21st century phenomenon provided new opportunities in the study of human behaviours in open spaces. Large quantities of social media data generated from popular platforms, such as Twitter, Instagram, Weibo, etc., have been used by researchers in tracking the preferences and frequency of park visits [38,39], mapping the perceived mental images of an urban environment [40], and in capturing crowd activity patterns [41]. However, social media alone has well-known many drawbacks, they were found to have exaggerated or misrepresented real-world events, not to mention that social media platforms tend to oversample those who are young, tech-savvy, well-educated, and affluent [42]. To the authors' knowledge, social media data has not been used in the study of park attendance under the influences of hot weather.

In sum, there is a need for a robust, comprehensive study combining "small data" and "big data" to quantify the magnitude of potential biases, to triangulate findings, and to derive appropriate data processing protocols required to achieve meaningful results. Such a study can contribute an innovative methodology and novel research evidence to the field.

3. Method

Occupant attendance data were recorded in field studies conducted in a large urban park in Hong Kong; ambient thermal environments were measured, and self-reported thermal sensations and comfort information were captured using a questionnaire. Geo-coded tweets were retrieved for a period of three years in Hong Kong.

3.1. "Small Data" Studies

Field studies were conducted in Sun Yat-Sen Memorial Park, a large public open space in Hong Kong. The Park was located in the Western District, covering an area of some 30,000 m^2 and it consists of a waterfront promenade, pond plaza, a lawn, a jogging track, seating areas and a children's playground. On-site measurement and questionnaires interviews were conducted simultaneously on 25 study days from September to October in 2021 (Table 2). Attendance in the park were recorded concurrently. The study period covered both hot and cool seasons, including a variety of weather conditions.

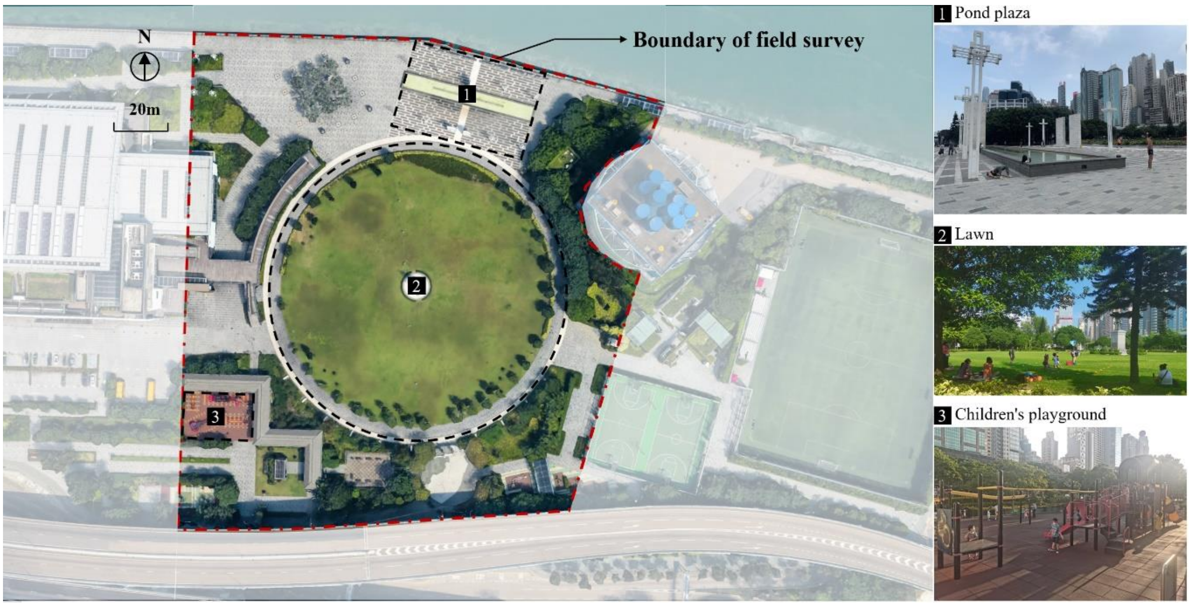

Fig. 1 Left: The study area of Sun Yat-Sen Memorial Park in Hong Kong (Source: Google Map); right: site photos of three venues in the same park (photos taken in September 2021).

Park attendance data were measured on-site by a trained researcher. On each study day, the attendance for occupants present in the park was recorded on an hourly basis from 9:00 to 22:00. Photographic records were also taken at the hourly interval for verification.

A questionnaire was administrated on-site to capture the perceived thermal sensation of park occupants. It was measured using the 7-point ASHRAE scale (from -3 to +3). The age group, gender, clothing conditions, and behavioral preferences of each participant were also recorded. The participants were enrolled voluntarily. To protect the privacy and anonymity of participants, the questionnaire was vetted and approved by the research ethics committee of the authors' institution. A full copy of the questionnaire was provided in Appendix 1.

The outdoor thermal environment in the park was measured using a mobile HOBO weather station as well as a network of ground-based weather stations of the Hong Kong Observatory (HKO). The mobile weather station, including a temperature and relative humidity sensor (S-THC-M008), a wind speed sensor (S-WSB-M003), was mounted on a tripod at 1.5m above ground (Fig. 2). The range and accuracy of these above sensors are presented in Table 1. Data were continuously recorded by a HOBO data logger (RX3000) at 5-min intervals during the study period. Concurrent meteorological data, including solar radiation and cloud cover were acquired from the nearest station from the HKO network. A rain event log was recorded to control for the effect of precipitation on park attendance.

Fig. 2 A photo of the HOBO weather station installed on-site (Photo taken September 9, 2021)

Table 1 Descriptions of the HOBO weather station and sensors

Sensor	Weather parameter	Measurement range	Accuracy	Resolution
S-THC-M008	Temperature/Relative Humidity	-40 ~ +75 ℃	±0.20°C, ±2.5%	0.02°C,0.01%RH
S-WSB-M003	Wind speed	0 ~76 m/s	± 1.1 m/s	0.5 m/s

Thermal indices were used to represent the outdoor thermal environment relating to the perceived heat stress in the park. This approach allows for a unified index, measured in equivalent temperature, to represent the variable radiation, temperature, humidity, and wind conditions in an outdoor environment. Four bio-meteorological indicators commonly used in research literature were chosen in this study, including UTCI, PET, the OUT_SET* and WBGT. The aim was to compare the performance of each index in explaining variations in the perceived thermal sensation of the study subjects in Hong Kong.

The UTCI equivalent temperature at a particular hour can be expressed as a function of the on-site air temperature (T_a), the relative humidity (RH), wind speed (V_a) at a reference height of 10m (V_{10}), and the mean radiant temperature (T_{mrt}), as it is expressed in Equation 1. The calculation was implemented using the polynomial approximation method developed by Brode & Wojtach [43]. Similarly, the PET and OUT_SET* indices were computed using the same set of input variables with wind speed at a reference height of 1.5m ($V_{1.5}$), implemented using the RayMan Pro software [44].

$$Y = f(T_a, V_a, RH, T_{mrt}) \tag{1}$$

where T_a, RH , and wind speed ($V_{1.5}$) were taken from on-site measurements; T_{mrt} was simulated using the CityComfort+ method [45], which takes into account direct, diffuse, and reflection short-wave radiation as well as long-wave radiation from the atmosphere and solid surfaces. The required input data includes 3D urban geometries and solar radiation, which are obtained from the Hong Kong Lands Department [46] and the Hong Kong Observatory [47] respectively.

The WBGT index was computed following the established approach by Yaglou & Minaed [48], and the WBGT can be expressed as a function of air temperature, humidity, wind speed and radiant heat flux, as it is shown in Equation (2).

$$WBGT = 0.7 \cdot T_{nw} + 0.2 \cdot T_g + 0.1 \cdot T_a \tag{2}$$

where T_{nw} is the neutral wet-bulb temperature, back-calculated using Stull's formula [49] expressed in Equation 3, in which T_{nw} is a function of air temperature (T_a) and relative humidity (RH)

$$T_{nw} = T_a \cdot tan\ (0.152 \cdot (RH + 8.3136)^{0.5}) + \tan\ (T_a + RH) - tan^{-1}(RH - 1.676) + 0.004 \cdot (RH^{1.5}) \cdot tan\ (0.023 \cdot RH) - 4.686 \tag{3}$$

where T_g is the globe temperature, which was back-calculated using on-site T_{mrt} and wind speed following Kuehn's Formula [50] as it is expressed in Equation (4). T_g is a function of the ambient T_{mrt}, the diameter (D= 0.15m) and the emissivity (ε = 0.95) of a globe thermometer. The computation of Equations (2)-(4) was implemented using a script written in Python programming language.

$$T_g = \sqrt[4]{(T_{mrt} + 273.15)^4 - \frac{1.06 \cdot 10^8 \cdot V_a^{0.58}}{\varepsilon \cdot D^{0.42}} \cdot \left(T_g - T_a\right)} - 273.15 \tag{4}$$

3.2. "Big Data" Analytics

A Twitter-based analysis framework was developed to monitor user response to the thermal environment in parks. This novel method presents advantages in the affordance of large sample size (>36,000 per annum from the pilot study) continuously collected from the cyberspace. It is a passive data-collection method compared with traditional ones, i.e., questionnaire or field studies described in section 3.1. Twitter is one of the most popular social media platforms in Hong Kong; active Twitter users account for 28% of the city's population according to a recent survey [51]. The choice of Twitter over other competing social media platforms, such as Facebook, is based on data availability and appropriateness for the study's purposes. Messages on Twitter are open to anyone, allowing researchers to collect the data using Twitter streaming Application Program Interface (API), while messages on Facebook are only visible to a user's friends. Its instant, spontaneous message is limited to 140 characters [52], which captures users' responses at a specific location and time, unlike Facebook where users post organized and delayed messages [53], i.e., the actual event described by a Facebook post took place hours or even days before. The data collection was staged as follows.

Twitter data (tweets) have been collected using the Twitter API [52], which allows for an exhaustive sampling of tweets within the designated location as long as the tweets requested do not exceed 1% of the global total [54]. The original data contains text, geographical coordinates and user information. For quality assurance, extensive data cleaning has been performed following a standard filtering process. Tweets were first extracted by their geographical locations inside the boundary of Hong Kong. Repetitive messages, often being advertisements or from fake accounts, were removed to prevent them from influencing the results, following the standard process of existing studies [55]. To discern a fake account from a regular one, we adopted a threshold based on the frequency of posting from a Twitter account: those have posted excessive amount of tweets, i.e., exceeding two standard deviations above the mean used by existing literature [56], or over 60% of geo-locations shared by a Twitter user were identical, an indicator of advertisement ID or bot in technical terms [57]. The top 50 high-frequency Twitter IDs have been manually examined by a trained researcher to robustly verify whether they were authentic users, or they were removed if not. Lastly, the hourly precipitation data in Hong Kong were assessed from Hong Kong Observatory [47] to remove records within rainy hours in the study period. Also, subsamples from Twitter users were tracked and identified to better understand the demographics of the study sample. In this way, impact of large public events (such as holiday parades) which tend to dominate activities on social media can be effectively prevented.

The sub-sample of tweets inside parks have been identified using geo-tagging techniques. An exhaustive list of 807 urban parks in Hong Kong was obtained from government agencies including Leisure and Cultural Services Department, Planning Department, and Lands Department [46]. The list includes a mixture of subcategories such as public gardens, plazas, parks, playgrounds, and sports grounds by official designation. The GPS coordinates of tweets in parks are expected to be more accurate compared with those from a dense built urban area, where the GPS signal weakens thus compromising the accuracy of OSM coordinates. Geo-tagging was performed in the ArcGIS Pro software based on location coordinates.

The thermal environments in all parks on the list were assessed using the ERA5-HEAT dataset [58], which provides modeled global UTCI maps at hourly intervals with a spatial resolution of 0.25° in longitude or latitude (approximately 30 km). The dataset is based on meteorological inputs using the European Centre for Medium-Range Weather Forests datasets [59]. The outputs are UTCI computed using a polynomial approximation method [43] with the above meteorological inputs, and the Mean Radiant Temperature of the same spatial-temporal coverage. The ERA5-HEAT database was retrieved from the Copernicus

Climate Data Store [60]. The hourly UTCI values for the grid covering Hong Kong (114.12°E 22.36°N) between May 2018 and April 2022 were extracted using a script written in Python programming language. Use a single value to represent the hourly thermal environment for all parks in this study brings practical convenience: this means practically any locations on earth can be studied without deploying equipment on the ground, given the global coverage of the ERA5-HEAT dataset. However, the limitation of doing so has been evaluated be comparing the UTCI values in ERA2-HEAT dataset with those computed using field measurement results.

In humid subtropical Hong Kong, park attendance can drop significantly due to rainy weather. It is therefore necessary to control for the influence of precipitation on results. Precipitation records were obtained from the Hong Kong International Airport in the format of Surface Synoptic Observations (CYNOP) and Meteorological Terminal Aviation Routine Weather Report (METAR). The dataset has been robustly cleaned and checked. Park tweets recorded during rainy hours, i.e., the precipitation greater than zero, were dropped from the analysis.

3.3. Statistical Modelling

Statistical regressions were used to model the relationships between park attendance and thermal environments. The Negative Binomial Regression model (NBR) was selected, for its suitability to analyse count data, which are positive integers with wide variability. The NBR is more suitable than the Poisson regression in fitting over-dispersed count datasets, in which the data variance exceeds the mean by definition [81]. Subsequent testing was conducted on data distribution to ensure the suitability of the model of choice. A mathematical expression of NBR in shown in Equation (5)

$$log\ (\mu)\ =\ \beta_1 X + \beta_0 \tag{5}$$

where the μ is the expectation of park attendance; X is the outdoor thermal environment measured in biometeorological indicators; β_1 and β_0 are regression coefficients for the independent variable and constant respectively.

Special attentions were paid to process the large amount of zero values in the dataset. The Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) models are more flexible for dealing with excessive observed zero counts. The headcount dataset of "small data", the hourly park attendance collected in the urban park in Hong Kong, has no zero counts; while in the tweets count dataset from the "big data" method, the Twitter data collected in major open spaces in Hong Kong, large zero values (42% of the total) were observed. Thus, additional statistical testing was conducted to determine whether a zero-inflated model should be selected to tackle the zero counts, following the processes below.

The model selection followed a two-step analysis framework proposed by Fávero et al. [82]. The first step is the over-dispersion test in a dataset, then the Vuong test for zero-inflated models i.e., ZIP and ZINB model. At last, a ZINB model was constructed to fit the tweets count dataset due to the zero counts are inflated. Two ZINB models were constructed to test the robustness of the predictor.

The ZINB was a mixture modelling method that contains two components: a logit model for the binary component and a negative binomial model for the count component. The first model predicts the non-occurrence of a behaviour commonly by logistic regression, which in this study is the zeros in the Twitter dataset. The second model predicts the number of tweets in open spaces. The mathematical Equation (6) of the logit model shows the concept:

$$logit(p) = log\left(\frac{p}{1-p}\right) = \beta_1 X' + \beta_0 \tag{6}$$

where the p is the probability of non-zero counts, X' is variable consistent with zero counts, β_1 and β_0 are estimated regression coefficients for independent variable and constant.

Therefore, the excepted number of tweets in open spaces $E(Y)$ is modeled as a mixture process of the two components, expressed as Equation (7):

$$E(Y) = p * 0 + (1-p) * \mu \tag{7}$$

Regarding people's self-reported thermal perceptions, a linear regression model was used to quantify the correlation between aggregated thermal sensation and outdoor heat exposure. To reduce the variability of the raw thermal sensation votes (TSV), the dataset was aggregated into bins of 1℃ interval and the mean value in each bin was computed [83]. The mathematical equation of the linear regression model was expressed in Equation (8):

$$Y = \beta_1 X + \beta_0 + \varepsilon \tag{8}$$

where Y (response variable) is the expectation of the mean TSV, X (predictor variable) is the mean UTCI in each bin, β_1 is the slope of the regression line, β_0 is the intercept, ε is the random error.

In the above models, a p-value of less than 0.05 was used to indicate statistical significance, while regression coefficients and 95% confidence intervals were reported. All statistical analyses were implemented using the Stata MP 17 software.

4. Results and Discussion

4.1. Data Characteristics

A total of 39,687 attendance and 364 questionnaires were recorded in Sun Yat-Sen Memorial Park on twenty-four fieldwork days in September, November, and December 2021. Table 2 summarized the collected data and the daily average measured weather conditions. The detailed characteristics of questionnaire respondents (gender, age and time of outdoor exposure, etc.) and field measurement were provided in Appendix 2.

Table 2 Schedule, the total records and the weather conditions in the field study.

Month	Date	Park Attendance (ppl.)	Questionnaire (count)	$\overline{T_a}$ (℃)	$\overline{RH}$ (%)	$\overline{V_a}$ (m/s)
Hot (Sept. 2021)	2,3,4,6,9,10,12#,13,14,17,18, 21#,26#,28,30	17,883	157	30.7	76	0.8
Temperate (Nov.2021)	17,19,20,26,30	8,232	162	23.4	69	1.1
Cool (Dec.2021)	4,9,16,18,19#	13,572	45	20.6	59	1.5

Total	—	39,687	364	—	—	—

Public holiday or weekend

After pre-processing, a dataset of 649,952 tweets containing precise GPS coordinates was obtained, of which 22,331 records (3.4% of total tweets) can be geo-coded within the list of open spaces in Hong Kong. Table 3 showed the total number of samples collected in Hong Kong and extracted tweets in major open spaces. Parks with the most Twitter messages include King George V Memorial Park, Tsuen Wan Park, Chai Wan, Kai Tak East Playground and Victoria. A map of collected park tweets over three years was shown in Fig. 3.

Table 3 The total number of tweets retrieved in Hong Kong in this study.

Year	# of Tweets Retrieved	# of Park Tweets	% of Park Tweets
May.7, 2016-Dec.31, 2018	645,224	21,669	3.4
Aug.2021-April.2022	4,728	662	14.0
Total	649,952	22,331	3.4

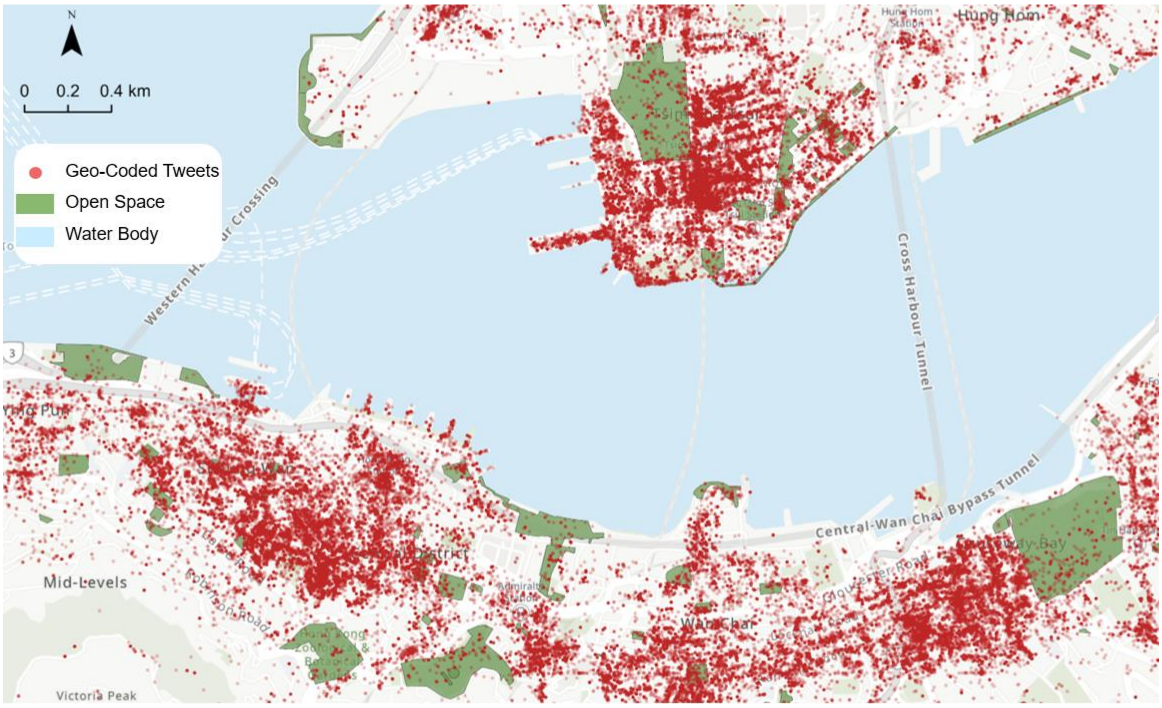

Fig. 3 Geo-coded tweets and urban parks in Hong Kong.

Comparisons of the data range and distribution of both UTCI equivalent temperature and park attendance/tweets in respective “small data” and “big data” were presented in Table 4 & 5.

Table 4 A comparison of data range and distribution between UTCI equivalent temperature in “small data” computed from on-site measurement and the one in “big data” extracted from the ERA5-HEAT database.

UTCI Equivalent Temperature (℃)	“Small Data” (Computed from On-Site Measurement)	“Big Data” (Extracted from ERA5-Heat Database)
Mean	30.4	22.6
Min	6.9	-13.4
Max	46.2	41.4

Variance	68.2	83.2

Table 5 A comparison of data range and distribution between park attendance in "small Data" and park tweets in "big Data".

Count Data (#)	"Small Data" (Park Attendance)	"Big Data" (Park Tweets)
Mean	136	1
Min	7	0
Max	633	21
Variance	8500	2.4

4.2. Comparing "Big Data" to "Small Data"

Both "small data" and "big data" have suggested negative associations between park usage and UTCI equivalent temperature. The Negative Binomial Regression (NBR) models for both have been plotted in Fig. 4 (a) and (b). In general, both attendance and park tweets in logarithmic scale declined during the range of thermal conditions available during the field studies. The regression coefficients for both models are -0.0186 and -0.0043 respectively, which can be interpreted approximately as each 1 °C increase in UTCI equivalent temperature is associated with some 4% drop in park attendance or some 1% drop in park tweets. This suggests that the "small data" and "big data" evidence agreed reasonably well with each other, and also, they are in consistency with a previous study conducted in subtropical cities which had reported the decline of outdoor activities under hot weather conditions [30].

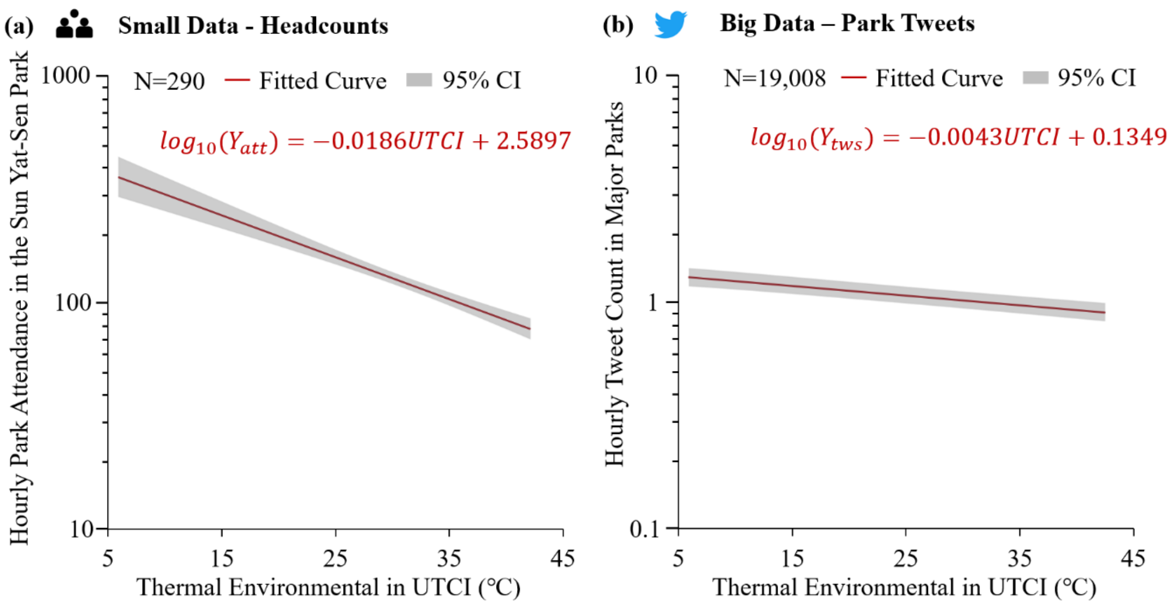

Fig. 4 The park thermal environment in relationship with modeled (a) park attendance and (b) park tweets; the red lines are fitted using Negative Binomial Regression with 95% confidence interval (shown in grey).

Results of the Negative Binomial Regression Model for park attendance and park tweets are shown in Table 4. For "small data", the coefficient of UTCI equals -0.0186 ($p<0.001$), which can be interpreted as each 1 °C increase in UTCI is associated with a 0.0186 decrease in the logs of expected park attendance. In other words, the attendance is expected to shrink by a factor of $10^{-0.0186}$ = 0.9581 at each 1 ℃ increment, or approximately 4% drop per 1 ℃ increase in UTCI. This relationship is statistically significant as it is suggested by the p-values of the Negative Binomial Regression. For “big data”, the coefficient for UTCI in NBR, the count component, is -0.0043 (p<0.001), which can be interpreted as each 1 ℃ increase in UTCI is associated with -0.0043 decrease in the logs of expected park tweets. Converted to ratios, the park tweets are expected to shrink by a factor of $10^{-0.0043}$ = 0.9901 per each 1 ℃ increment, or approximately 1% drop per 1 ℃ increase in UTCI. The The above findings are also supported by the Inflate Component of the ZINB, i.e., the Logit Model. The model coefficient for UTCI is -0.1224, suggesting the log odds of being an excessive zero value decreases by 0.1224 for every 1 ℃ increase in UTCI: in other words, the warmer the thermal condition, the lower the likelihood of excess zeros in park tweets. This relationship is also statistically robust with p-value < 0.001. The robustness of the Negative Binomial Regression model has been tested upon working days, weekends, and public holidays (see Fig. A3 in Appendix 4), with findings similar with the original model reported in Fig. 4, suggesting that the heat-attendance relationship is independent of weekly routine or holidays. Additional details on the statistical models are reported in Table A3 & A4 in Appendix 3.

Table 6 Results of the Negative Binomial Regression Model for “small Data” and “big Data”.

Negative Binomial Regression	“Small Data” (Park Attendance)	“Big Data” (Park Tweets)
Coefficients		
UTCI	-0.0186***	-0.0043***
Constant	2.5897***	0.1349***
alpha (dispersion parameter)	0.2550	0.4402
Number of Observations	290	19,008

*** p<0.001

The “hotspots” of park attendance and tweets, captured using the kernel density map, were largely consistent with each other. Fig. 5 (a) and Fig. 5 (b) have mapped each for Sun Yat-Sen Memorial Park. Attendants concentrated near the Pond Plaza, the Palm Tree Array, and the southern edge of the Circular Lawn. There were discrepancies between the two, for instance, the Children’s Playground was a “hotspot” in park attendance (Fig. 5 (a)), not a Twitter “hotspot” (Fig. 5 (b)) since junior occupants were not yet active on Twitter. Instead, many tweets were found in the sitting area nearby, likely sent by resting parents while watching child play. The spatial overlap of activity “hotspots” indicate support that “big data” and “small data” evidence agreed with each other.

It is worth noting that WIFI hotspots might have contributed to the uncertainties of social media analytics. Fig. 5 (b) shows that some 150 indoor tweets had ‘leaked’ to an outdoor venue near the Viewing Deck. A closer examination of the posted contents, including texts and images, revealed that they were related to swimming events sent from the Swimming Hall nearby. Such ‘leakage’ may have been caused by occupants tweeting when their mobile devices were connected to the local WIFI hotspot, rather than through a mobile network. Their tweets used the coordinates of the WIFI router, in this case, instead of the mobile devices. The leakage of indoor tweets to parks might have added additional data noises, since indoor Twitter users were less likely to respond to the outdoor thermal conditions due to the prevalence of air conditioning. Although the indoor tweets in the Sun Yat-Sen Memorial Park were manually removed from the kernel density mapping, this procedure cannot be scaled up for all other parks, which is another limitation of this study.

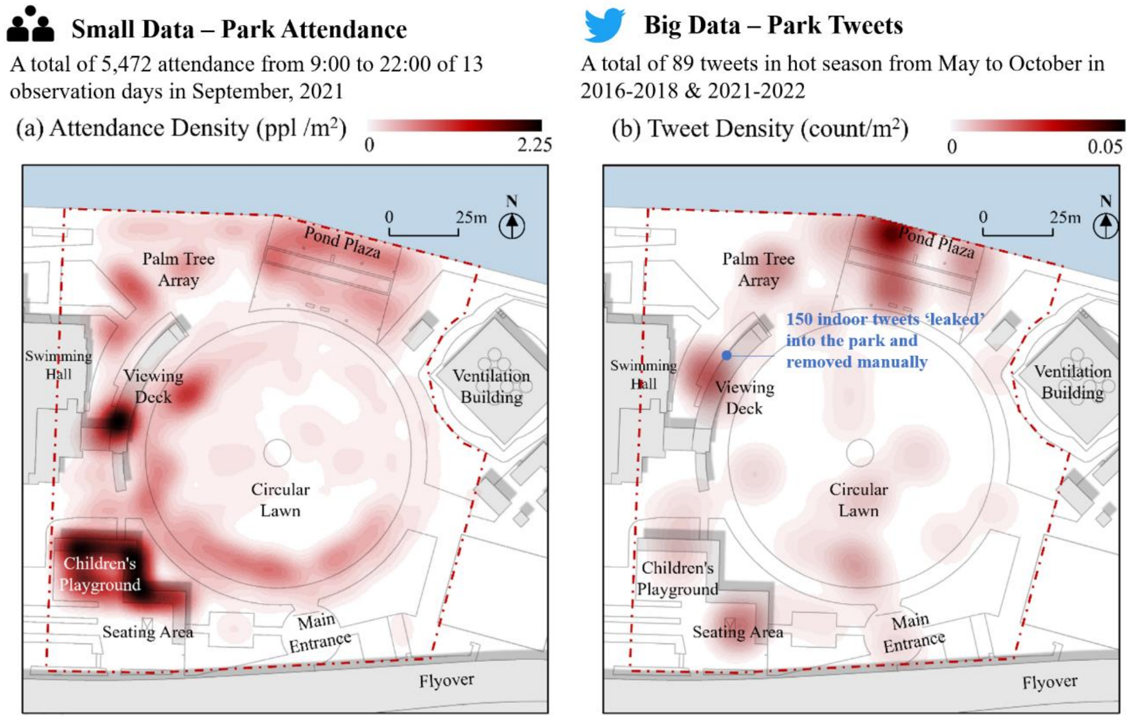

Fig. 5 The kernel density of occupant activities in Sun Yat-Sen Memorial Park using (a) attendance records in September 2021, and (b) geo-coded tweets in hot seasons (May 1-October 31) between 2016 and 2021.

4.3. Comparison of Biometeorological Indicators

The four biometeorological indicators, UTCI, PET, OUT_SET* and WBGT, were compared with each other in relation to their performances in explaining self-reported thermal sensations. The four bio-meteorological indicators were plotted against self-reported thermal sensations, as it is shown in Fig. 6 (a) (b) (c) and (d). The mean Thermal Sensation Vote was aggregated within 1 °C bins, and the scatterplots were fitted linearly with straight lines. In general, all four models showed positive associations between the *X* and *Y* variables, suggesting warming sensations correspond with higher values in biometeorological indicators. The four models differ, however, in the degree of scattering around the fitted line. The R^2 value, or the "goodness of fit", is the highest for UTCI at 0.74, suggesting that UTCI equivalent temperature can explain 74% of the variations in self-reported thermal sensation. The second highest R^2 value was found for the WBGT model at 0.72, followed by OUT_SET* at 0.52 and PET at 0.47. The result supports the choice of UTCI as an appropriate index in capturing self-reported thermal sensations in outdoor spaces in Hong Kong. On this point, the findings of this study do not differ from other published studies [18,61,62] that UTCI, a state-of-the-art bio-meteorological indicator, can better predict the perceived thermal sensation in outdoor spaces.

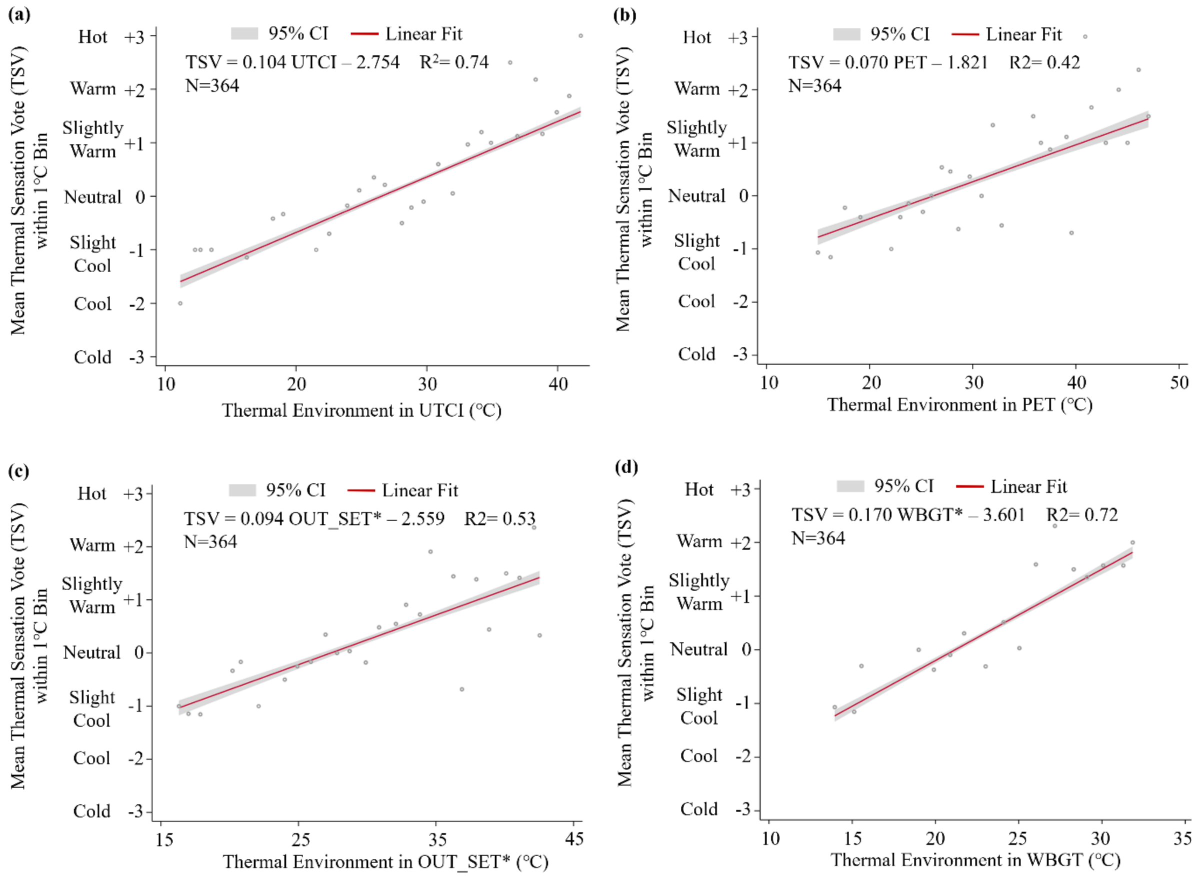

Fig. 6 Mean Thermal Sensation Vote against thermal environment in (a) UTCI, (b) PET, (c) OUT_SET* (d) WBGT.

4.4. Discussion

The results from this study reveal that the “big data” from social media can be a promising measurement of human responses to thermal conditions in outdoor activities. The findings have both theoretical and practical implications in park design. The limitations of this study and future research are also discussed.

The study has contributed to the literature in two important aspects. First, geo-coded Twitter data sent in urban parks, once cleaned and robustly checked, can be used to monitor the level of activities in parks. It is the first attempt to do so in the field, and results suggest that Twitter data analytics agreed reasonably well with those from “small data”. Data analytics protocol established in this paper can therefore be of value to follow-up studies in other climate zones, using data from Twitter or alternative platforms such as Weibo in mainland China or Muloqot.uz in Uzbekistan. As long as the analytical workflow was applied consistently, as is demonstrated in this study, one can expect that evidence obtained across societies and climate zones can be meaningfully compared with each other.

The strength of the “big data” approach lies in its efficiency and the ability to sample numerous parks in a large geographical area for an extended period of time. Twitter data streaming can continuously monitor activities in a neighborhood or an entire city, covering a large twitter-active population. Compared with the “small data” method, this is a marked advantage compared with the “small data” methods of field studies and questionnaires, which is labor intensive and costly. The advantage led to a significant increase in the statistical power of the study sample, provided that the datasets are robust cleaning and checked to ensure meaningful results.

Its uncertainties can be summarized in three: first, the quantity of park tweets is a fraction of those of the attendance, and it can only serve as a proxy of the latter. Only a proportion of park users were Twitter-active, less would tweet in a park, and even fewer volunteered to share their precise GPS coordinates. In this sense, park tweets are sparse signals with a low sampling rate, i.e., the time interval between tweets from the same user can be days. In comparison, mobile phone data had a higher sampling rate, with users' geo-locations information obtained in the frequency of minutes. The disparity can be reflected in Fig. 4, whereas the count of tweets from major parks in Hong Kong (b) can be orders of magnitude lower than actual attendance data obtained from a single park (a). Although the low sampling rate of tweets can be compensated by perhaps a long sampling period – years in this study – and by the zero-inflated statistical models employed, yet this drawback can be critical when applied in places with extremely low user penetration, such as mainland China or Uzbekistan. The local equivalent of Twitter, such as Weibo and Muloqot.uz in each country, should be used instead, if at all.

A second uncertainty is possible GPS positioning error due to the interference of local WIFI hotspots or GPS drift. A sizable number of indoor tweets were found in this study, which should have been geo-coded to the nearby indoor swimming hall. Adding on top of this is the well-known GPS drift, especially when the mobile phone GPS receivers are near buildings. The range of accuracy for GPS positioning is usually <5m, it can increase to up to 30m in a density city [63], which could severely limit its application for small urban parks, with dimensions close to or even smaller than the range of GPS accuracy.

Lastly, social media data are mostly anonymous, with users' age, gender, and occupation unknown to researchers, although certain studies have claimed that such information can be 'guested' using machine learning algorithms [64]. Social media users may be over-represented by young, male, well-educated, and tech-savvy [42]. This drawback makes it difficult to compare the behavioral responses to thermal fluctuations by age, gender, or socio-economic groups. As far as evidence from this study suggests that this risk is minor in Hong Kong since the two data sources generally agree with each other. However, this may not be guaranteed in other cities with different demographics and usage patterns of social media platforms.

The study has practical implications. First, both Twitter and attendance data confirm that heat stress correlated negatively with park attendance in Hong Kong. By the same token, a cooler park with extensive shading, water features, and generous greenery, as far as the evidence of this paper suggests, can attract more attendance. The results also foretell that continued urban warming and more frequent heatwaves are expected to further disrupt the use of parks, and there is a need for interventions in light of growing heatwave events and temperature extremes in the future. A second implication is for the weather forecasting service operated by the Hong Kong Observatory, which currently relies on WBGT in support of the Hong Kong Heat Index. Findings of this study suggest that UTCI may be a promising alternative, which can better explain self-reported thermal sensation from field questionnaires.

This study is limited in several aspects. First, the ERA5-HEAT dataset provides a large-scale measurement of thermal environments. It does not account for microclimatic variations among multiple parks, let along the micro-scale variation at the pedestrian level. The geospatial resolution of the ERA5-HEAT dataset is approximately 30km, which is far greater than a typical urban park in Hong Kong (10-1000m), therefore the thermal environments it represents were an average condition for the city, and it cannot reflect the human scale, such as being in the shade or exposed under the direct sun. A more rigorous approach to evaluate thermal environment at the park level would involve a meso or even micro-scale model, say, the use of downscaling technique. This has been extensively studied in urban climate literature, such as the use of Weather Research and Forecasting (WRF) model, taking hourly EAR5-HEAT value as the boundary condition inputs [58]. However, this approach requires detailed urban morphological data and extensive computational power, which can potentially offset the advantages of the proposed "big data" approach, that is a dataset that is low-cost and universally accessible. A comparison between the nominal UTCI values computed using field measurement and from the ERA5-HEAT database is shown in Fig. A1 in Appendix 3. They match each other in trend, but not in absolute values. The latter tends to prescribe a lower nominal UTCI value, by some 4 °C in summer and by up to 7 °C in cool seasons, compared with on-site measurements. This difference can be explained by the microscale modification of an urban thermal environment: a high-density city such as Hong Kong features extensive urban heat island effect, anthropogenic waste heat, the stagnation of air ventilation, each has been well documented in previous studies cited previously and they might have collectively contributed to higher degrees of heat stress experienced in an urban park. Given the possible micro-scale modification of the thermal environment in a city, the negative heat-tweet correlation in parks can be accepted by the consistency in trend, yet the slope of such correlation should not be taken literally.

Another important limitation is the differences in the temporal and spatial coverage of data between the "small data" and "big data" approaches. Ideally, these two should match each other. This would demand a continuous period for field studies in hundreds of urban parks in over two years, given the relative sparsity of twitter data in Hong Kong. Not only is this beyond the source limits of the authors, but also above those of frankly all published "small data" studies in the field. In addition, the current study is also limited in the relatively small sample size obtained from field studies, which cannot adequately cover occupant activities and thermal perception on very cold days. Although this limitation is unlikely to be fatal, given the cold period in Hong Kong is generally short. Further studies covering the cold season should nevertheless be added to expand the "small dataset" of people's thermal perceptions and outdoor behavior. Findings from this study are not expected to be interpreted automatically to places outside of Hong Kong, in which climate, culture and lifestyle may influence park attendance.

Both the spatial and serial autocorrelations have been detected in the geo-coded Twitter dataset, which is a potential limitation of this study. The former has been checked using a consecutive time series analysis [65], while the latter was tested by computing Moran's *I* [66] of tweets grouped by park. The results suggested serial correlation at the lag of the first, seventh, and eighth hour in park tweets ($p<0.05$), but not with other lag values. The latter test revealed a significant spatial autocorrelation in park tweets. In other words, the presence of vibrant twitter activities in one park correlates with higher levels of the same in a nearby park. Although this effect is not expected to alter findings from the current study, which has compressed twitter activities in all urban parks in Hong Kong into a single space. Additional details of the serial autocorrelation test and the Moran's *I* have been included in Appendix 4.

5. Conclusion

The paper describes the use of "big data" in the study of park attendance in response to thermal environments. Social media data were used as a new source of evidence and the results have been compared with those from attendance and questionnaires obtained from a large urban park in Hong Kong. The findings suggest that a 1 ℃ increase in equivalent temperature was associated with 4% drop in park attendance, or 1% drop in geo-coded tweets; the "hotspots" of both agreed reasonably well with each other. The strength of social media data analytics lies in its efficiency and the ability to sample parks in a large geographical area for an extended period of time. This is a marked advantage compared with the "small data" methods of field observations and questionnaires, which is labor intensive and costly. Although Twitter data analytics is vulnerable to uncertainties of GPS positioning, and it may exhibit considerable errors for tweets sent near tall buildings. The Universal Thermal Climate Index compared favorably with the Physiological Equivalent Temperature, the Outdoor Standard Effective Temperature, and the WBGT, due to its ability to predict the thermal sensations from local population. The study has contributed novel methodologies and new evidence to the study of outdoor thermal comfort in urban parks. The data analysis protocols are of value for follow-up studies in the field. Findings have implications for heat-resilient policies in Hong Kong and other cities of sub-tropical climates.

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Appendix 1

Outdoor thermal comfort questionnaire

Date:_____/______/______ time: ______ location:______

1. Gender: (1) Male (2) Female
2. Age: (1) 6-12 (2) 12-18 (3) 18-40 (4) 40-65 (5) >65
3. Are you exposed in direct sunlight? (1) no / (2) yes
4. Clothing (please tick the cloth combination you are wearing at this moment):

   □ T-Shirt (Long-Sleeve) □T-Shirt (Short-Sleeve)

   □Shirt (Long-Sleeve) □ Shirt (Short-Sleeve) □Pants □Shorts □Jacket
5. How long do you stay outdoors each day?

   (1) <30mins (2)30-60mins (3)1-2 hours (4) >2 hours
6. How often will you come here each day?___Times / Day or __Times / Week
7. How long will you stay in this place each time?

   (1)<30mins (2) 30-60mins (3) 1-2 hours (4) >2 hours
8. Your activities have been mainly:

   (1) Babysitting (Sit); (2) Babysitting (Stand); (3) Rest (Sit); (4) Stroll;

   (5) Dance;(6) Board Games; (7) Conversation (Stand); (8) Conversation (Sit); (9) Children's Play; (10) Exercise; (11) Picnic; (12) Others:_____
9. Please circle your **current** thermal sensation

Hot	Warm	Slightly warm	Neutral	Slightly cool	Cool	Cold
+3	+2	+1	0	-1	-2	-3

10. How do you describe the **current** thermal comfort conditions?

    (1) Uncomfortable (2) Acceptable (3) Comfortable
11. Please rank the most important factors for you to use an open space.

Shading	Aesthetic qualities	Facilities	Safety

12. Which aspect of the thermal environment do you think should be improved on this site?

Appendix 2 Summary of Questionnaire Data and Weather Conditions

Table A1 The characteristics of questionnaire respondents.

Item	Sub-groups	Percentage (%)
Gender	Male	40.3
	Female	59.7
Age	Young (age≤65 years old)	87.4
	Elderly (age＞65 years old)	12.6
Frequency	Everyday	30.4
	Every 2 or 3 days	39.7
	Once per week	18.6
	Rarely (⩽once per month)	3.8
	First time	7.4
Time spent in the park	<30 min	12.1
	30-60 min	39.8
	1-2 hour	34.3
	>2 hour	13.7
Outdoor time	<30 min	10.7
	30-60 min	12.6
	1-2 hour	44.8
	>2 hour	31.9
Thermal comfort conditions	Uncomfortable	9.7
	Acceptable	54.1
	Comfortable	36.2

Table A2 Schedule, the total records and the weather conditions in the field study.

Month	Day	Hour	Observation (number)	Questionnaire (number)	$\overline{T_a}$ (℃)	$\overline{RH}$ (%)	$\overline{V_a}$ (m/s)
Sept	2	9:00-22:00	0	21	29.7	77	0.2
	3	11:00-12:00 & 14:00-18:00 & 21:00-22:00	723	7	30.4	75	0.3
	4[#]	9:00-11:00 & 14:00-22:00	1582	12	30.3	77	0.2
	6	9:00-22:00	1293	10	31.0	73	0.7
	9	9:00-22:00	1259	0	31.3	71	0.0
	10	9:00-22:00	1499	0	31.1	69	1.5
	12[##]	9:00-22:00	1775	0	32.6	72	1.3
	13	9:00-22:00	1108	0	31.6	77	0.5
	14	9:00-22:00	1069	0	29.0	85	0.2
	17	9:00-22:00	1313	28	30.5	74	0.1
	18[#]	9:00-13:00 & 19:00-22:00	1344	23	30.6	78	0.0
	21[###]	9:00-22:00	0	13	30.3	80	2.7
	26[##]	9:00-22:00	2420	19	29.7	70	2.1
	28	9:00-22:00	1028	15	30.8	73	0.4
	30	9:00-22:00	1470	10	31.2	94	1.2
Nov	17	9:00-22:00	1651	31	24.2	71	0.2
	19	9:00-22:00	1919	39	23.9	75	0.0
	20[#]	9:00-22:00	2993	36	24.4	75	3.3
	26	9:00-22:00	1669	15	22.4	66	1.2

	30	9:00-12:00 & 14:00-16:00 & 20:00-22:00	0	41	21.9	60	0.7
Dec	4#	9:00-22:00	2262	5	19.7	43	0.0
	9	9:00-22:00	1466	5	21.5	66	1.4
	16	9:00-22:00	1520	10	23.8	80	0.6
	18#	9:00-22:00	3870	15	19.0	56	1.9
	19##	9:00-22:00	4454	10	18.8	49	3.4
Total	—	—	43489	364	—	—	—

Note: #indicates Saturday, ##indicates Sunday; ### indicates festival day; $\overline{T_a}$ indicates mean air temperature, $\overline{RH}$ indicates mean relative humidity, $\overline{V_a}$ indicates mean wind speed during the daily measurement period from 9:00-22:00.

Appendix 3 Detailed Regression Results

Detailed results of the Negative Binominal Regression (NBR) model for park attendance and the Zero-Inflated Negative Binomial (ZINB) regression model for park tweets are shown in Table A3 & Table A4.

Table A3 Results of the Negative Binomial Regression Model for park attendance dataset.

Negative Binomial Regression	Coefficients	95% CI	
UTCI	-0.0186***	[-0.0220	-0.0152]
Constant	2.5897***	[2.4537	2.7257]
Hour[a]			
10:00	0.0094	[-0.0935	0.1122]
11:00	-0.0359	[-0.1660	0.0942]
12:00	-0.0272	[-0.1555	0.1011]
13:00	0.0165	[-0.1134	0.1465]
14:00	0.0457	[-0.1117	0.2032]
15:00	0.1001	[-0.0532	0.2535]
16:00	0.1676**	[0.0372	0.2979]
17:00	0.1653**	[0.0586	0.2720]
18:00	0.0704	[-0.0457	0.1865]
19:00	0.1230**	[0.0119	0.2341]
20:00	0.2278	[0.1137	0.3419]
21:00	0.1750**	[0.0656	0.2844]
22:00	-0.0672	[-0.1767	0.0423]
alpha (dispersion parameter)	0.2550	[0.2193	0.2964]
Number of Observations	290		

*** p<0.001; a. the reference group is hour 9:00; the number of observations is the sample size.

Table A4 Results of the Zero-Inflated Negative Binomial model for park tweets dataset.

Zero-Inflated Negative Binomial Regression	Coefficients	95% CI	
Count (Negative Binomial Regression Model)			
UTCI	-0.0043***	[-0.0052	-0.0034]
Constant	0.1349***	[0.0929	0.1769]
Hour[a]			
2:00	0.0719**	[0.0217	0.1221]
3:00	0.0941***	[0.0442	0.1440]
4:00	0.1372***	[0.0880	0.1865]
5:00	0.1792***	[0.1305	0.2278]
6:00	0.1571***	[0.1083	0.2059]
7:00	0.1617***	[0.1132	0.2101]
8:00	0.1693***	[0.1211	0.2174]
9:00	0.1653***	[0.1174	0.2133]
10:00	0.2353***	[0.1886	0.2820]
11:00	0.2265***	[0.1799	0.2731]
12:00	0.2009***	[0.1540	0.2479]
13:00	0.1812***	[0.1341	0.2284]

14:00	0.1791***	[0.1319	0.2263]
15:00	0.1526***	[0.1051	0.2001]
16:00	0.0015	[-0.0486	0.0515]
17:00	-0.2093***	[-0.2640	-0.1545]
18:00	-0.4298***	[-0.4923	-0.3674]
19:00	-0.6336***	[-0.7060	-0.5612]
20:00	-0.6627***	[-0.7376	-0.5878]
21:00	-0.6398***	[-0.7134	-0.5661]
22:00	-0.5183***	[-0.5855	-0.4512]
23:00	-0.2300***	[-0.2867	-0.1734]
24:00	-0.0970***	[-0.1506	-0.0434]
Inflate (Logit Model)			
UTCI	-0.1224***	[-0.1817	-0.0632]
Constant	-1.4764***	[-2.0177	-0.9351]
alpha (Dispersion Parameter)	0.4402	[0.4129	0.4693]
Number of Non-Zero Observations	10,944		
Zero Observations	8,064		

*** p<0.001; a. the reference group is hour 1:00.

A comparison between the nominal UTCI values computed using field measurement and from the ERA5-HEAT database is shown in Fig. A1.

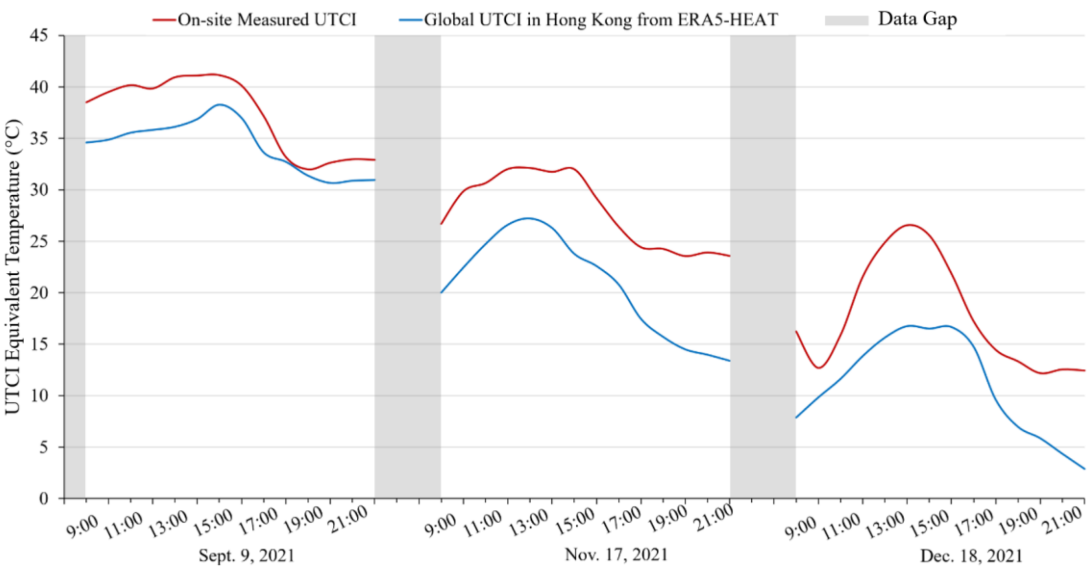

Fig. A1 A comparison of the nominal UTCI values computed from on-site measurement (red line) and ERA5-HEAT dataset (blue line) for a typical summer, intermediate, and cool day in Hong Kong.

Appendix 4 Diagnostics and Statistical Tests for Regression Models

Serial autocorrelation has been detected using a consecutive time series analysis [65]. The results are summarized in Fig. A3 (a) and (b). The former shows a large positive spike at the first lag which revealed significant autocorrelation ($p<0.05$), followed by correlations bouncing around between positive and negative values which none appeared to be statistically significant at a periodicity of 14 lags, or during the 14 observed hours each day. The latter shows a small positive spike at the first lag and a small negative spike at the seventh & eighth lag, which revealed significant autocorrelation ($p<0.05$); followed by correlations that bounced slightly around zero between being positive and negative; against, none is statistically significant. The results rejected the null hypothesis of the existence of serial autocorrelation after the first lag. The time series autocorrelation analysis has been implemented using STATA MP 17 software package.

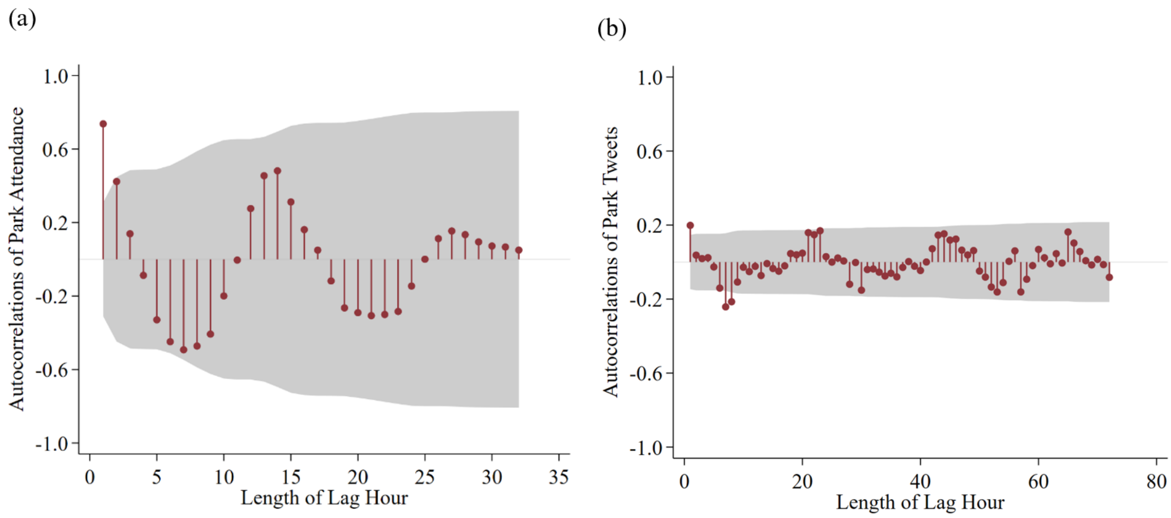

Fig. A2 Plot of autocorrelations of (a) park attendance and (b) park tweets; Sub-samples for park attendance covering hours between 9:00 and 22:00 from Sept.12 to Sept.14, while sub-samples for park tweets covering hours between 1:00 and 24:00 from May.12 to May.18.

The model sensitivity towards the first lag autocorrelation was tested by adding one-lag park tweets as an explanatory variable for park tweets. The results are reported below Table A5. It shows when controlled the effect of previous hour, the associated coefficients of UTCI were -0.0039 which are similar to the results in the original model of -0.0043 in Table 6.

Table A5 Results of the Zero-Inflated Negative Binomial Regression model for the park tweets dataset.

Zero-Inflated Negative Binomial Regression	Coefficients	95% CI	
Count (Negative Binomial Regression Model)			
UTCI	-0.0039***	[-0.0048	-0.0030]
Constant	0.0688***	[0.0265	0.1112]
Lag	0.0596***	[0.0554	0.0638]
Hour[a]			
2:00	0.0560**	[0.0064	0.1056]
3:00	0.0633**	[0.0140	0.1127]
4:00	0.1042***	[0.0555	0.1529]
5:00	0.1374***	[0.0893	0.1855]
6:00	0.1074***	0.0591	0.1558]
7:00	0.1173***	[0.0692	0.1654]

8:00	0.1256***	[0.0778	0.1734]
9:00	0.1173***	[0.0697	0.1648]
10:00	0.1870***	[0.1406	0.2333]
11:00	0.1648***	[0.1183	0.2113]
12:00	0.1363***	[0.0895	0.1831]
13:00	0.1237***	[0.0768	0.1707]
14:00	0.1267***	[0.0797	0.1736]
15:00	0.0964***	[0.0490	0.1439]
16:00	-0.0479**	[-0.0978	0.0021]
17:00	-0.2428***	[-0.2981	-0.1876]
18:00	-0.4673***	[-0.5326	-0.4021]
19:00	-0.6957***	[-0.7750	-0.6164]
20:00	-0.7043***	[-0.7858	-0.6228]
21:00	-0.6829***	[-0.7631	-0.6027]
22:00	-0.5195***	[-0.5893	-0.4498]
23:00	-0.2000***	[-0.2567	-0.1433]
24:00	-0.0821**	[-0.1357	-0.0285]
Inflate (Logit Model)			
UTCI	-0.1093***	[-0.1650	-0.0536]
Constant	-1.3567***	[-1.8515	-0.8619]
alpha (Dispersion Parameter)	0.3905	[0.3640	0.4189]
Number of Non-zero Observations	10,470		
Number of Zero Observations	8,049		

*** p<0.001;** p<0.05; a. the reference group is the reference group is hour 1:00.

Spatial autocorrelation has been tested by grouping geo-coded tweets by park, and computing the Moran's *I* to check the 'spillover' effect. The null hypothesis was that park tweets are spatially uncorrelated with each other. The results suggested a Moran's *I* of 0.017 ($p<0.01$), therefore it rejected the null hypothesis and suggesting a significant spatial autocorrelation in park tweets. In other words, the presence of vibrant twitter activities in one park correlates with higher levels of the same in a nearby park. Although this effect is not expected to alter findings from the current study, which has compressed twitter activities in all urban parks in Hong Kong into a single space. Stata user-written command, 'spatgsa' [67], was used to compute Moran's *I* statistic.

Four statistical models have been tested in order to identify a suitable candidate for regression analysis of the tweets dataset. These include the Poisson regression model (PRM), the Negative Binomial regression model (NBR), the Zero-inflated Poisson regression model (ZIP) and the Zero-Inflated Negative Binomial regression model (ZINB). They were evaluated by three fitness tests including Vuong test, likelihood ratio test, and AIC/BIC tests. The detailed results are shown in Table A6 & A7, which supported ZINB is the most suitable mode. Detailed steps include 1) AIC/BIC tests whether a noninflated model can better fit an inflated model. For instance, drop values of AIC & BIC in ZIP/ZINB against PRM (Table A6) indicates zero-inflated models are preferable. 2) Vuong test assesses whether an inflated model is preferable to a noninflated model. For instance, NBR vs ZINB. The p-value less than 0.05 (Table A7) indicates that the ZINB model is preferable to NBR. 3) The likelihood ratio test assesses one zero-inflated model against another. For instance, ZIP vs ZINB. The p-value less than 0.05 (Table A7) indicates that the ZINB model is preferable to ZIP.

Table A6 Results of the estimated parameters and the statistic tests from each of the four tested models for park tweets dataset.

	Variable	PRM	NBR	ZIP	ZINB
Tweets count					
	UTCI	-0.0039***	-0.0039***	-0.0023***	-0.0043***
inflate					

	UTCI	n.a.	n.a.	0.0009***	-0.1224***
Statistics					
	alpha	n.a.	0.445	n.a.	n.a.
	N	19,008	19,008	19,008	19,008
	log-likelihood	-27700	-26600	-27300	-26600
	AIC	55609.951	53389.710	54822.205	53396.944
	BIC	55413.636	53185.542	54610.184	53177.070

***p<0.001.

Table A7 Results of the statistic tests for the Poisson regression model (PRM), Negative Binomial Regression Model (NBR) and zero-inflated models including Zero-inflated Poisson regression model (ZIP) and Zero-inflated Negative Binomial regression model (ZINB) for the park tweets dataset.

Statistics	PRM vs NBR	PRM vs ZIP	NBR vs ZINB	ZIP vs ZINB
Vuong test (p-value)	n.a.	11.839 (0.000)	1.650 (0.050)	n.a.
LR Chi-Square test (p-value)	2230.093 (0.000)	n.a.	n.a.	1435.114 (0.000)

In addition, the robustness of the regression models was tested for the datasets of park attendance (denoted by Y_{att}) and the number of tweets in major open spaces (park tweets, denoted by Y_{tws}) respectively, by controlling the factors of working days, weekends, and public holidays. Detailed results of the tested models are shown in Table A3 & Table A4.

The influences of the weekday,weekends and holidays on park attendance and park tweets have been tested in two steps. The regression analysis for each were reported in Fig. A3 (a) and (b). Compared with the results illustrated in Fig. 4 (a) and (b), both non-holiday weekday and holiday/weenend tweets suggested generally a similar trend along with a rising temperature measured in UTCI. The negative association between park tweets, either on non-holiday weekday or holiday/weekend, and UTCI equivalent temperature were consistent, suggesting that the weekday, weekend or holiday routine is unlikely to have largely influenced the results.

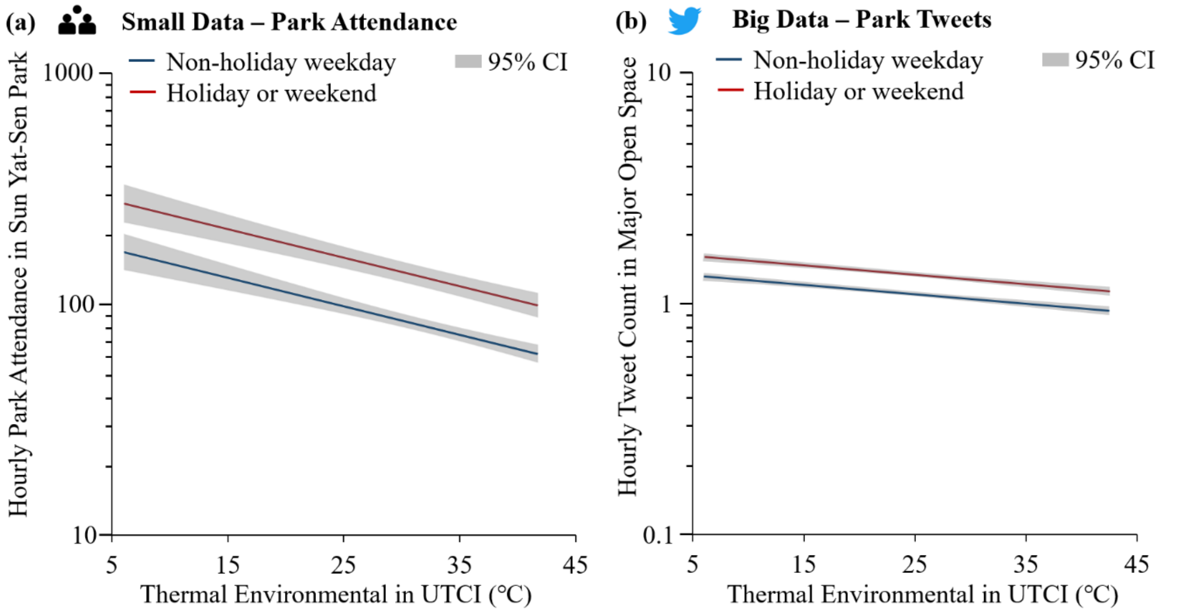

Fig. A3 The effect of the rising thermal environment at 1℃ increments by holiday group on (a) park attendance and (b) park tweets in major open spaces; the lines are fitted using Negative Binomial Regression models with 95% confidence interval shown in grey.

The second step is to consider the potential influence of non-holiday weekday, weekends and holiday on correlation between UTCI and park attendance/tweets by adding an interaction term denoted by UTCI × nonworking. The nonworking = 0 represents the day is a non-holiday weekday from Monday to Friday while nonworking = 1 means the day is a weekend or holiday. The detailed results are shown in Table A8 & Table A9. It shows when controlled interaction effects of weekday and UTCI, the associated coefficients of UTCI were -0.0179 and -0.0067 (the Negative Binomial Regression model of count component), which are similar to the results in the original model of -0.0186 and -0.0043 in Table 6.

Table A8 Results of the Negative Binomial Regression model for the park attendance dataset.

Negative Binomial Regression	Coefficients	95% CI	
UTCI	-0.0179***	[-0.0210	-0.0149]
Constant	2.4930***	[2.3592	2.6269]
UTCI × nonworking[a]	0.0077***	[0.0057	0.0097]
Hour[b]			
10:00	0.0027	[-0.1066	0.1120]
11:00	-0.0677	[-0.1838	0.0484]
12:00	-0.0708	[-0.1879	0.0462]
13:00	-0.0238	[-0.1396	0.0920]
14:00	-0.0077	[-0.1461	0.1308]
15:00	0.0519	[-0.0855	0.1894]
16:00	0.1349**	[0.0136	0.2563]
17:00	0.1616**	[0.0593	0.2638]
18:00	0.0814	[-0.0267	0.1896]
19:00	0.1407**	[0.0247	0.2567]
20:00	0.2509***	[0.1251	0.3768]
21:00	0.2091***	[0.0878	0.3304]
22:00	-0.0459	[-0.1656	0.0738]
alpha (Dispersion Parameter)	0.2000	[0.1718	0.2328]
Number of Observations	290		

*** p<0.001;** p<0.05; a. the reference group is non-holiday weekday from Monday to Friday where nonworking=0; b. the reference group is hour 9:00.

Table A9 Results of the Zero-Inflated Negative Binomial Regression model for the park tweets dataset.

Zero-Inflated Negative Binomial Regression	Coefficients	95% CI	
Count (Negative Binomial Regression Model)			
UTCI	-0.0067***	[-0.0076	-0.0058]
Constant	0.1372***	[0.0956	0.1787]
UTCI × nonworking[a]	0.0064***	[0.0058	0.0070]
Hour[b]			
2:00	0.0690**	[0.0195	0.1186]
3:00	0.0893***	[0.0400	0.1385]
4:00	0.1338***	[0.0852	0.1825]
5:00	0.1766***	[0.1286	0.2247]
6:00	0.1536***	[0.1054	0.2018]
7:00	0.1530***	[0.1052	0.2009]
8:00	0.1591***	[0.1116	0.2067]
9:00	0.1598***	[0.1125	0.2071]
10:00	0.2326***	[0.1865	0.2786]
11:00	0.2243***	[0.1783	0.2702]
12:00	0.2008***	[0.1545	0.2471]
13:00	0.1801***	[0.1336	0.2266]
14:00	0.1783***	[0.1317	0.2248]
15:00	0.1495***	[0.1027	0.1963]
16:00	-0.0004	[-0.0498	0.0490]
17:00	-0.2111***	[-0.2652	-0.1569]
18:00	-0.4322***	[-0.4941	-0.3702]
19:00	-0.6343***	[-0.7063	-0.5623]
20:00	-0.6631***	[-0.7376	-0.5886]
21:00	-0.6408***	[-0.7140	-0.5676]
22:00	-0.5185***	[-0.5852	-0.4518]
23:00	-0.2286***	[-0.2846	-0.1725]

24:00	-0.0969***	[-0.1498	-0.0439]
Inflate (Logit Model)			
UTCI	-0.1171***	[-0.1697	-0.0646]
Constant	-1.3955***	[-1.8723	-0.9186]
alpha (Dispersion Parameter)	0.3992	[0.3730	0.4272]
Number of Non-zero Observations	10,944		
Number of Zero Observations	8,064		

*** p<0.001;** p<0.05; a. the reference group is non-holiday weekday from Monday to Friday where nonworking=0; b. the reference group is the reference group is hour 1:00.