Capturing park-use behavior patterns using volunteered street view imagery: Does the likelihood increase with the volume of contributions

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Abstract

Analyzing how citizens experience urban parks can provide valuable information for evaluating the effectiveness of park planning and management decisions to encourage park use. Although crowd-sourced data from social media have been reported to be useful for reflecting park visitations, limited user information from social media posts makes it challenging to understand the detailed characteristics of visitor behavior. To address this issue, this study evaluates the reliability of volunteered street view imagery (VSVI), a dataset of geo-tagged street-level images containing motion information from volunteers, as a proxy for park-use behavior, using metropolitan parks in the 23-ward of Tokyo as a case study. Several indicators of park-use behavior, including park visitor count, spatio-temporal distribution, and path characteristics were calculated using VSVI data and reference datasets to investigate data reliability. The results suggest that VSVI may serve as a complementary open dataset for identifying park-use patterns in parks with sufficient contribution volume, while also revealing contribution self-selection toward photography-oriented scenic or tourist parks. This study provides new insights for future research on modelling citizen activities using volunteered geographic information data.

1. Introduction

As important places for outdoor recreation in cities, urban parks provide opportunities for city dwellers to experience nature, engage in social interactions, and participate in physical activities, ultimately contributing to physical and mental health benefits (Chiesura, 2004; Coutts et al., 2010; Wolch et al., 2014; Coldwell & Evans, 2018; Carver et al., 2024). To design parks that encourage park use, it is essential to collect current and detailed visitor-use data to evaluate the effects of park planning and management decisions and make the necessary adjustments. Knowing whether visitor numbers are increasing or decreasing is an important step toward better funding, management, and allocation of natural resources to recreational sites (Loomis, 2000; Sessions et al., 2016). Understanding the detailed spatial distribution of users is crucial for park setting and facility planning, especially those aimed at mitigating the negative impacts of overcrowding while maintaining opportunities for high-quality visitor experiences or natural area conservation (Orsi & Geneletti, 2013; Zhai et al., 2018). Finally, understanding mobility patterns (e.g., travel trajectory characteristics) is critical for improving detailed park route recommendations to manage capacity, improve retail profits, and increase tourist satisfaction (Rajaram & Ahmadi, 2003; Tsai & Chung, 2012; Zhang et al., 2017).

In the early stages of measuring park-use behavior, studies typically relied on surveys, such as manual observations (Arnberger, 2006), interviews or questionnaires (Huang & Wu, 2012), and experiments recording the GPS tracks of specific participants (Shoval & Isaacson, 2007; Orellana et al., 2012; Birenboim et al, 2013; Meijles et al., 2014). Such time-consuming and costly methods posed obstacles to large-scale surveys and continuous data updates in practical park management applications. Although the rise of high-precision and portable GPS devices (e.g., mobile phones and cameras) has made it possible to obtain large-scale data (Filazzola et al., 2022), these datasets are collected and processed by specific companies and are often expensive, thereby notably limiting their widespread use in research.

Recently, with the emergence of Web 2.0, various types of geotagged online big data—collected and shared by individuals in a bottom-up manner—have been utilized to capture park visitor behavior on a large scale. One representative example is social media posts, which have become a prominent data source for monitoring user behavior in parks and other recreational destinations (Wood et al., 2013; Sessions et al., 2016; Walden-Schreiner et al., 2018; Song et al., 2020a; Wilkins et al., 2021). However, social media posts tend to provide very few visitor records (Park et al., 2021). As a result, studies using such data are often limited to macroscale measures, such as visit frequency (Sessions et al., 2016; Song et al., 2020a) rather than microscale spatial distribution or movement patterns (e.g., visit duration), which are critical for microscale park design policies. Although the kernel density of Flickr photographs has been mapped to measure spatial and temporal distribution patterns of visitor use in mountain-protected areas, such as in the study by Walden-Schreiner et al. (2018), the effectiveness of such data in reflecting actual activities has received little attention. Therefore, identifying easily accessible data sources that reflect actual visit behavior is crucial for the efficient analysis of park-use behavior.

The Web 2.0 era also facilitates the collection of volunteered street view imagery (VSVI) (Goodchild, 2007). In previous applications, VSVI has been used as a completely free alternative to traditional SVI, which tends to restrict data use in urban audit studies (Yang et al., 2025; Sánchez & Labib, 2024; Ito et al., 2025; Zheng & Amemiya, 2023; Danish et al., 2025). In addition, utilizing the advantages of data accumulation by volunteers, VSVI has been utilized in current research, primarily for high-precision measurements of urban environments. Applications include the identification and geolocation of traffic signs (Ertler et al., 2020) and the monitoring of vegetation such as crops (d'Andrimont et al., 2018) and street trees (Tsutsumida & Funada, 2023). For behavioral analysis, the most notable difference from geotagged social media users is that VSVI contributors tend to provide sequential geotagged photos trajectories rather than isolated image points. The movement information inherently embedded in these data suggests considerable potential for more continuous and comprehensive behavioral analysis, yet this potential remains largely unexplored.

Unlike conventional datasets, VSVI datasets are often dominated by a small number of active users over limited periods (Ma et al., 2019; Juhasz & Hochmair, 2015; Mahabir et al., 2020), and may therefore reflect the behavior of specific contributors rather than the general public. In addition, VGI contribution behavior is shaped by contributors’ motivations, local knowledge, and community-oriented participation (Budhathoki & Haythornthwaite, 2013). As observed in studies of social media posts, photo contributions in parks may be influenced more by park popularity or attractiveness (Zhang et al., 2018; Song et al., 2020a) than by accessibility-driven daily recreational use (Zhang & Tan, 2019). These self-selection effects are also reflected in spatial and temporal biases in VSVI contributions across locations (Ma et al., 2019; Juhasz & Hochmair, 2015; Seto & Nishimura, 2022; Mahabir et al., 2020). However, previous research also suggests that increasing contribution frequency may help mitigate some aspects of VSVI data bias (Zheng & Amemiya, 2024). Therefore, rather than assuming temporal equivalence among datasets or contributor representativeness, this study evaluates whether long-term accumulated VSVI contributions preserve patterns of park use that are also observable in independent reference datasets, and whether their proxy validity varies with contribution volume.

To evaluate these questions, this study examines the statistical relationships between park-use behavior patterns from long-term accumulated VSVI and those observed in reference data, including commercial GPS tracks and administrative surveys. Specifically, it addressed the following questions: (1) To what extent are VSVI contribution indicators related to park visitor numbers? (2) To what extent do the spatial and temporal distributions of VSVI photo contribution patterns align with the spatial and temporal distributions of park visitors recorded using commercial GPS tracking data? and (3) To what extent do the movement characteristics of VSVI trajectories align with the movement trajectories of park visitors recorded using commercial GPS tracking data? We further examine whether these relationships vary with VSVI contribution volume.

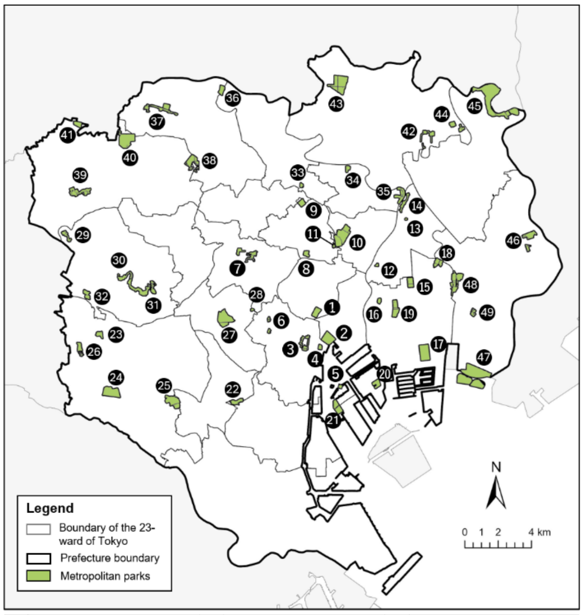
2. Method

2.1 Study Sites

This study was conducted in 49 metropolitan parks in the 23-ward area of Tokyo, Japan (Figure 1). The study area was selected because it is one of the major Mapillary hotspots in Japan, where Mapillary, currently the world’s largest VSVI platform, has accumulated substantial volunteered street-level imagery data (Seto & Nishimura, 2022). These metropolitan parks are generally large, with areas exceeding 10 ha, making them suitable for studying within-park spatial distribution and travel-path characteristics. They have also recently been involved in digital-data-driven changes in park management, which provides a basis for the necessity and importance of this study.

2.2 Data Description

2.2.1 Park Polygon Data: Owing to the lack of park polygon data, this study extracted the areas of each metropolitan park based on park maps using land-use data (obtained from the Tokyo Metropolitan Government in 2021) to create park polygons. In this step, land-use polygons within parks, excluding those for motorized roads, were selected for each park.



1	Hibiya Park	18	Kameido Central Park	34	Ogunohara Park
2	Hama-rikyu Gardens	19	Kiba Park	35	Shioiri Park
3	Shiba Park	20	The Tokyo Rinkai Disaster Prevention Park	36	Ukima Park
4	Kyu-Shiba-rikyu Gardens	21	Shiokaze Park	37	Akatsuka Park
5	Daiba Park	22	Rinshi-no-mori Park	38	Johoku-Chuo Park
6	Aoyama Park	23	Roka Koshun-en Gardens	39	Shakujii Park
7	Toyama Park	24	Kinuta Park	40	Hikarigaoka Park
8	Koishikawa Korakuen Garden	25	Komazawa Olympic Park	41	Oizumi Central Park
9	Rikugien Gardens	26	Soshigaya Park	42	Higashi-Ayase Park
10	Ueno Park	27	Yoyogi Park	43	Toneri Park
11	Kyu-Iwasaki-Tei Gardens	28	Meji Park	44	Nakagawa Park
12	Yokoamicho Park	29	Zempukuji Park	45	Mizumoto Park
13	Mukojima-Hyakkaen Gardens	30	Zenpukujigawa Park	46	Shinozaki Park
14	Higashi-Shirahige Park	31	Wadabori Park	47	Kasai Rinkai Park
15	Sarue Park	32	Takaido Park	48	Oshima Komatsugawa Park
16	Kiyosumi Gardens	33	Kyu-Furukawa Gardens	49	Ukita Park
17	Yumenoshima Park				

Figure 1. Metropolitan park locations in the 23-ward of Tokyo.

2.2.2 Reference Data: For reference park visitor counts, Tokyo Metropolitan Parks publish annual estimates of park visitation. This estimate is based on daily routes and fixed-point observations (Takeuchi & Hisama, 2021). Because the latest published data are for 2020, we used the total number of visitors in 2019 to avoid the influence of the COVID-19 outbreak. To evaluate the spatio-temporal distribution and trajectory patterns of visitors, *Real People Flow Data* (May 2023; hereinafter referred to as *PeopleFlow*), provided by GeoTechnologies Inc., were used as reference data. This dataset collects location information from users via mobile applications. The entire dataset in Tokyo includes 869,840 users, representing ~6 % of the population of Tokyo and ensuring the reliability of the dataset in reflecting the activity of citizens. The dataset contains ~3 million trips and 65 million records per day in Tokyo, and each record point is assigned attributes such as age group, gender, tripID, and travel mode. The GPS data were cleaned and pre-processed for further analysis. Firstly, 6,932,062 points assigned into 519,652 trips within park boundaries and with “on foot” attributes were extracted to pinpoint park visitors. Because of GPS location errors and other factors (e.g., points outside boundaries were removed), trips containing points with relatively large intervals may lead to an overestimation of dwell time in the spatio-temporal analysis. Additionally, trips spanning multiple parks can affect the evaluation of trajectory characteristics within a park. To address this, we reassigned the tripID whenever there was a gap exceeding 120 s or 250 m, or when points belonged to different parks. After these steps, the points assigned to 523,057 trips were used for the analysis.

2.2.3 Volunteered Street View Imagery Data: The VSVI metadata used here were extracted through the Mapillary API. Mapillary provides openly accessible street-level imagery under a Creative Commons licence. A total of 255,810 points in 2,741 sequences were contributed by 45 users from 2014 to March 2024 within the park areas. The downloaded photo metadata included where it was taken (longitude and latitude), when it was taken (captured at), creator ID, image ID, and sequence ID. In the data cleaning process, we first excluded one image with incorrectly captured time information, and then excluded photo points taken in vehicles or on bicycles. As Mapillary does not provide information on the mode of transport, the identification was based on the GPS information of the images, applying the two rules proposed by Gong et al. (2012): (1) the 85th percentile of the speed of all points is ≤15 km/h and (2) the average speed of all points is ≤6 km/h. The speed of each image point was calculated using the Calculate Motion Statistics tool in ArcGIS Pro 3.5. Furthermore, the issues of sequences spanning multiple parks and with large gaps were addressed using the rules described in Section 2.2.2. In total, 242,534 photographs belonging to 2,007 sequences were extracted for further analysis.

2.3 Indicator Calculations and Statistical Analysis

The framework of this research (Figure 2) is as follows. First, we compared the frequency of Mapillary contributions in the study park sites with the reference number of visitors to validate the strength of VSVI in reflecting park visitor counts (Section 3.1.). Second, we further investigated the behavior patterns of park visitors in terms of their spatio-temporal distribution (Section 3.2) as well as travel path characteristics (Section 3.3) by comparing the VSVI with the reference GPS tracking data. The data processing and indicator calculation were conducted primarily in ArcGIS Pro 3.5, with Python 3.13 used for statistical analysis.

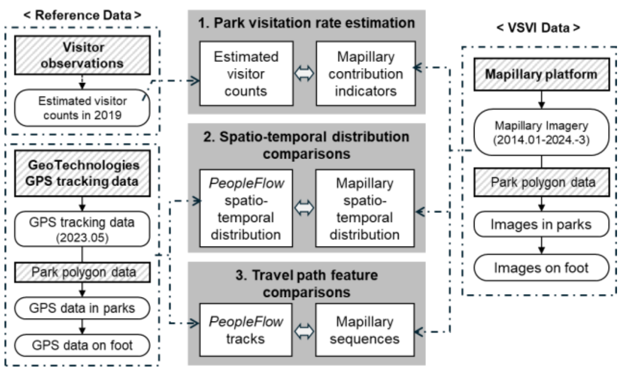


Figure 2. Research framework.

2.3.1 Park Visitor Count Estimation: First, we examined the relationship between the Mapillary-based contribution variables and the reference survey-based visitor numbers to validate the strength of VSVI in estimating park visitation by performing a correlation analysis. To select the Mapillary contribution variables, we assumed that parks with more visitors were more likely to have more Mapillary image contributors. As greater popularity may also contribute to greater image sharing on the Mapillary platform, we included the number of image points, sequences, and photo-user-days (PUD), defined as unique combinations of users and dates used in previous studies (Wood et al., 2013; Sessions et al., 2016). Moreover, to investigate the impact of the VSVI contribution volume on the relationship with reference data, we divided the study parks into low-PUD (n = 29) and high-PUD (n = 20) groups based on the mean value of Mapillary PUD of 5.1 as the threshold and conducted a correlation analysis for each group. The correlation analysis, as well as the subsequent analyses described in Section 2.3.2 and 2.3.3, were all one-tailed, as we only examined the possibility of a positive correlation between VSVI and the reference data.

2.3.2 Spatio-temporal distribution comparisons between VSVI and *PeopleFlow*: We then examined the correlations between Mapillary contributions and *PeopleFlow* reference data in terms of the spatio-temporal distribution of park-use behavior. Given the accuracy and time intervals of the GPS tracks (with a mean interval of 20.9 s between two successive points) and Mapillary sequences (with a mean interval of 1.6 s), we set the grid to 20 × 20 m. Movement information from *PeopleFlow* and Mapillary image points was linked to the grid to provide three grid-level indicators: point counts, dwell time per trip, and average speed. A one-tailed correlation analysis was used to quantify the statistical relationship between the two data sources for all parks at the grid level. We then conducted a park-specific correlation analysis and compared the number of parks with significantly positive correlation results in the high- and low-PUD groups to explore the influence of contribution volume levels.

2.3.3 Travel path characteristic comparisons between VSVI and *PeopleFlow*: Finally, we examined the differences in travel path characteristics between the Mapillary contribution trajectories and reference *PeopleFlow* tracks. We hypothesized that VSVI could effectively reflect the movement trajectories of park visitors. Specifically, we focused on three aspects of trajectory features in terms of temporal features, movement range, and behavioral features based on a previous study (Huang et al., 2020). We incorporated additional data processing steps on the two datasets to ensure that the results reflected park-use behavior. Specifically, we excluded Mapillary and *PeopleFlow* trajectories with durations of <5 min and less than five points. In addition, considering potential errors in the time attributes, trajectories >6 h were excluded. As a result, 1,672 of 2,007 Mapillary sequences and 104,312 of 523,057 *PeopleFlow* trajectories remained for analysis. The definitions and calculation methods for each indicator are outlined below.

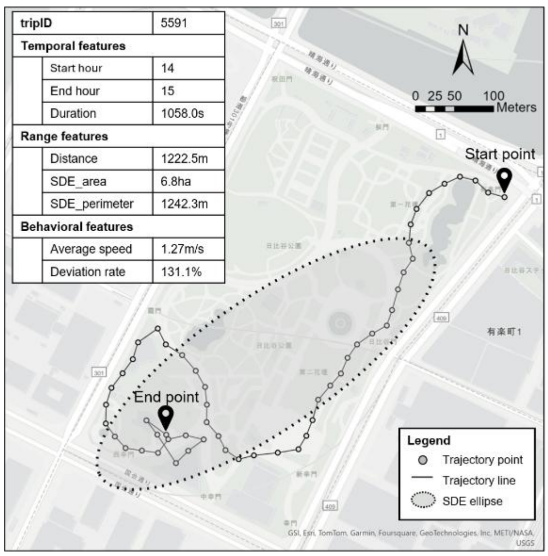


Figure 3. A trajectory example in Hibiya Park.

For temporal features, *start hour*, *end hour*, and *duration* (calculated as the total number of seconds from start time to end time) were used. For movement range features, travel distance refers to the trajectory line length of each visitor. Additionally, we calculated the standard deviation ellipse (SDE) area and perimeter, which represented an ellipse covering ~63 % of the trajectory points. These three indicators (*travel distance*, *SDE area*, and *SDE perimeter*) were standardized by park area to eliminate the influence of park size. Finally, the indicators of *average speed* and *deviation rate* for each trajectory were used to reflect behavioral characteristics. To calculate the *deviation rate*, the difference between the travel distance and Euclidean distance from start to end was first calculated, and the ratio between the difference value and Euclidean distance was calculated (Equation (1)). Figure 3 shows an example of the indicator values for the trajectory.

$$DR = \frac{TD - ED}{ED}, \tag{1}$$

where DR = deviation rate
TD = travel distance
ED = Euclidean distance

After the indicator measures, we calculated the mean values of each park variable to conduct a one-tailed correlation analysis between the Mapillary and *PeopleFlow* datasets at the park level. We further explored the influence of VSVI contribution volumes on effectiveness by conducting a group-specific correlation analysis. Unlike the analysis in Section 2.3.1, parks were divided into low- and high-trip groups based on the number of Mapillary trips rather than PUD because some trips were removed in the data processing described above. Notably, among the 41 parks with available Mapillary trips, 17 parks with fewer than five trips were classified into the low-trip group, whereas the remaining 24 parks with five or more trips were classified into the high-trip group.

3. Results

3.1 Park Visitor Count Estimation

This section examines the statistical relationships between the reference park visitor counts and Mapillary contribution indicators to evaluate the possibility of using VSVI data to estimate park visitation. The correlation analysis results (Table 1) show that none of the indicators are significantly related to reference visitor counts. As shown in Table 2, while all Mapillary indicators remained insignificant for parks in the low-PUD group (n = 29), in the high-PUD group (n = 20), the number of PUDs and creators were found to be moderately correlated with the reference park visitor counts at the 0.05 significance level.

3.2 Spatio-Temporal Distribution Comparisons between VSVI and *PeopleFlow*

In this section, we explore the feasibility of estimating the spatio-temporal distribution of park visit behaviors using Mapillary datasets in terms of three elements: point counts, dwell time per trip, and average speed. At the 20 m grid level, the Mapillary data had lower mean point counts and dwell time per trip than the *PeopleFlow* data, with 28 points and 16.5 s per trip compared with 14,891 points and 21.9 s, respectively. As shown in Table 3, the correlation analysis results using data from all parks showed a significant but weak correlation between *PeopleFlow* and Mapillary data for the number of points (r = 0.147, p < 0.001), dwell time per trip (r = 0.180, p < 0.001), and average speed (r = 0.222, p < 0.001).

	r	*p*
Number of PUD	0.156	0.143
Number of image points	0.033	0.390
Number of image sequences	0.041	0.390
Number of creators	0.237	0.051

Table 1. Spearman's rank correlation between reference park visitation and Mapillary contribution indicators.

	Low-PUD		High-PUD	
	r	*p*	*r*	*p*
Number of PUD	0.048	0.401	0.411	<0.05
Number of image points	0.042	0.415	-0.195	0.204
Number of image sequences	0.119	0.270	-0.296	0.102
Number of creators	0.095	0.312	0.429	<0.05

Table 2. Spearman's rank correlations between reference park visitation and Mapillary contribution indicators by PUD group.

	r	*p*
The number of points	0.147	<0.001
Dwell time per trip	0.180	<0.001
Average speed (m/s)	0.222	<0.001

Table 3. Spearman's rank correlations of spatio-temporal distribution indicators between *PeopleFlow* and Mapillary across all parks.

	Low-PUD	High-PUD
The number of points	10 (34.5%)	15 (75.0%)
Dwell time per trip	8 (40.0%)	16 (80.0%)
Average speed (m/s)	5 (25.0%)	11 (55.0%)

Table 5. The number of parks with significant and positive results for low- and high-PUD groups.

	N	*r*	*p*
Temporal features			
Start Time (hour)	41	0.034	0.417
End Time (hour)	41	0.023	0.443
Duration (s)	41	0.003	0.493
Standardized range features			
Travel distance (m/ha)	40	0.905	<0.001
SDE area	40	0.724	<0.001
SDE perimeter (m/ha)	40	0.942	<0.001
Behavioral features			
Average speed (m/s)	41	0.554	<0.001
Deviation rate	41	0.001	0.499

Table 6. Spearman's rank correlation analysis of trajectory characteristics based on *PeopleFlow* and Mapillary.

	Low-Trip		High-Trip	
	r	*p*	*r*	*p*
Temporal features				
Start Time (hour)	0.158	0.272	-0.073	1.000
End Time (hour)	0.210	0.209	-0.126	1.000
Duration (s)	-0.081	1.000	0.239	0.130
Standardized range features				
Travel distance (m/ha)	0.909	<0.001	0.934	<0.001
SDE area	0.799	<0.001	0.665	<0.001
SDE perimeter (m/ha)	0.931	<0.001	0.967	<0.001
Behavioral features				
Average speed (m/s)	0.321	0.104	0.707	<0.001
Deviation rate	0.346	0.087	-0.021	1.000

Table 7. Spearman's rank correlation analysis of trajectory characteristics based on *PeopleFlow* and Mapillary by PUD groups.

In the park-specific correlation analysis, coefficients varied across parks and were significant for some parks (Table 4). Grid-level point counts showed significant results in 25 parks, ranging from 0.107 ($p < 0.05$) for Toyama Park to 0.691 ($p < 0.001$) for Kyu-Fukukawa Park. Dwell time per trip showed significant correlations in 24 parks, ranging from 0.088 ($p < 0.05$) for Toyama Park to 0.663 ($p < 0.001$) for Mukojima-Hyakkaen Gardens. Average speed showed significant correlations in 16 parks, ranging from 0.113 ($p < 0.05$) for Hibiya Park to 0.460 ($p < 0.001$) for Rikugien Gardens. Table 5 shows the proportion of parks with significant positive correlations between *PeopleFlow* and Mapillary data for the low- and high-PUD groups, following the grouping used in Section 3.1. The proportion was higher in the high-PUD group, especially for point counts (from 34.5–75.0 %) and dwell time per trip (from 40.0–80.0 %), but relatively small for average speed (from 25.0–55.0 %).

3.3 Travel Path Characteristic Comparisons between VSVI and *PeopleFlow*

Finally, we compared travel path characteristics from *PeopleFlow* and Mapillary. Correlation analysis of park-level mean track characteristics (Table 6) revealed significantly positive correlations for standardized travel distance ($r = 0.905$, $p < 0.001$), SDE area ($r = 0.724$, $p < 0.001$), SDE perimeter ($r = 0.942$, $p < 0.001$), and average speed ($r = 0.554$, $p < 0.001$). These results suggest that Mapillary-derived trajectories can capture several aspects of visitor path characteristics. In the group-specific analysis (Table 7), correlations were stronger in high-trip parks for standardized *travel distance* ($r = 0.934$, $p < 0.001$), *SDE perimeter* ($r = 0.967$, $p < 0.001$), and *average speed* ($r = 0.707$, $p < 0.001$), whereas the correlation for standardized *SDE area* was weaker in low-trip parks.

Park Name	Category	VSVI PUD	Point Counts		Dwell time per trip		Average speed	
Daiba Parkd	Historic	1	-0.110		0.160		0.128	
Kameido Central Park	Comprehensive	1	0.169		0.007		-0.028	
Takaido Park	Comprehensive	1	0.137		0.281		-0.150	
Shioiri Park	Sports	1	0.111		0.375	*	-0.277	
Ukima Park	Comprehensive	1	0.631	***	0.034		-0.117	
Akatsuka Park	Comprehensive	1	0.200		0.168		0.053	
Yokoamicho Park	Scenic	2	0.231		0.127		0.145	
Roka Koshun-en Gardens	Sports	2	0.085		0.204	*	0.229	*
Okunohara Park	Scenic	2	0.388	***	0.025		-0.126	
Johoku-Chuo Park	Scenic	2	0.424	***	0.089		0.221	*
Oizumi Central Park	Sports	2	0.498	**	-0.217		0.170	
Toneri Park	Sports	2	-0.344		0.235		-0.035	
Ukita Park	Comprehensive	2	-0.082		-0.023		0.102	
Kyu-Iwasaki-Tei Gardens	Comprehensive	3	0.315	*	0.558	***	0.266	*
Yumenoshima Parkd	Sports	3	-0.162		0.028		0.149	
Rinshi-no-mori Park	Historic	3	0.530	***	0.191	**	0.148	*
Zempukuji Park	Comprehensive	3	0.157	*	0.219	**	0.096	
Zenpukujigawa Park	Comprehensive	3	0.219	**	-0.131		0.082	
Oshima Komatsugawa Park	Scenic	3	0.026		0.208	*	-0.191	
Sarue Park	Urban Greenery	4	-0.163		0.005		0.028	
The Tokyo Rinkai Disaster Prevention Park	Comprehensive	4	0.013		0.107		-0.141	
Shiokaze Park	Sports	4	0.066		-0.092		-0.127	
Soshigaya Park	Regional	4	0.449	***	-0.028		0.066	
Mizumoto Park	Scenic	4	0.014		0.135	*	-0.037	
Kasai Rinkai Park	Comprehensive	4	0.135	***	0.181	***	0.454	***
Aoyama Park	Regional	5	-0.110		0.493	*	0.012	
Mukojima-Hyakkaen Gardens	Regional	5	0.368	*	0.663	***	0.259	
Higashi-Shirahige Park	Comprehensive	5	0.424	***	0.191	*	-0.066	
Kiba Park	Zoo and Botanical Gardens	5	0.023		-0.042		-0.063	
Hikarigaoka Park	Comprehensive	5	-0.203		0.116	*	-0.195	
Kyu-Shiba-rikyu Gardens	Comprehensive	6	0.182	*	0.175	*	-0.123	
Koishikawa Korakuen Garden	Comprehensive	6	0.517	***	0.372	***	0.408	***
Rikugien Gardens	Historic	6	0.405	***	0.396	***	0.460	***
Yoyogi Park	Comprehensive	6	0.245	***	0.036		0.068	
Wadabori Park	Historic	6	0.106		0.130	*	0.309	***
Kyu-Furukawa Gardens	Comprehensive	6	0.691	***	0.549	***	0.423	***
Shakujii Park	Comprehensive	7	0.335	***	0.109	*	0.141	**
Hama-rikyu Gardens	Historic	8	0.504	***	0.356	***	0.161	***
Kiyosumi Gardens	Scenic	8	0.352	***	0.361	***	0.414	***
Kinuta Park	Historic	9	0.192	***	0.079		-0.006	
Komazawa Olympic Park	Historic	10	0.193	***	0.060		-0.071	
Toyama Park	Regional	12	0.107	*	0.088	*	0.213	***
Shiba Park	Sports	13	0.017		0.244	***	0.214	**
Hibiya Park	Comprehensive	20	0.284	***	0.143	**	0.113	*
Ueno Park	Comprehensive	39	0.494	***	0.256	***	0.197	***

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. Two parks with no Mapillary contributions were excluded from the analysis.

Table 4. Park-specific Spearman's rank correlations of spatio-temporal distribution indicators between *PeopleFlow* and Mapillary.

4. Discussion

Using geolocation data embedded in street-level imagery from the Mapillary platform in metropolitan parks in the 23-ward of Tokyo as a case study, this study suggests that crowdsourced street-level imagery data can provide a promising but conditional proxy for park-use behavior patterns. However, their interpretation is limited by contributor self-selection and depends on sufficient contribution volume. The study also contributes to ongoing discussions on integrating open and reproducible data sources into urban analytics as alternatives or complements to proprietary datasets (Helbich et al., 2024).

4.1 Park Visitor Count Estimation Using VSVI Data

The first part of the study focused on the possibility of VSVI reflecting park visitations. The results of the correlation analysis between the reference park visitor counts and Mapillary contribution indicators revealed that VSVI data may not be a reliable data source overall, but may become reliable in parks with sufficient VSVI contribution frequency. Such an impact of VSVI contribution volumes on data validity in park visitor estimation may be due to the similar motivation for park visits between VSVI contributors and general park visitors in parks with higher levels of VSVI contributions. Specifically, VSVI users are more inclined to share images in parks with scenic landscapes or tourist attractions, such as historic (e.g., Rikugien Gardens) or scenic (e.g., Shiokaze Park) parks. This finding is supported by previous research on the influence of park attributes on social media contributions (Song et al., 2020b). These parks also tend to attract users with similar motivations such as sightseeing and touring. As a result, both datasets generally follow the trend that the more popular a park, the higher the number of visitors, leading to a stronger correlation.

4.2 Differences in Spatio-Temporal Distribution between VSVI and *PeopleFlow*

In the second part of the study, which focused on the spatio-temporal distribution patterns of park-use behavior, the results of the correlation analysis of grid-level spatio-temporal features between Mapillary data and *PeopleFlow* tracking data showed that although the correlations for all three indicators were generally weak when using data from all parks, the park-specific analysis revealed the differences in data validity among parks. In general, parks with a greater number of PUDs showed stronger correlations with the reference GPS tracking data. This suggests that a higher volume of individual contributions may help mitigate the impact of individual variability. This trend is particularly strong for the spatial distribution of point counts and total dwell time than for the average speed, indicating that the application of crowdsourced street-level data to the average speed is less likely to rely on the accumulation of contribution volumes.

4.3 Travel-Path Characteristic Differences between VSVI and *PeopleFlow*

When comparing path characteristics, the effectiveness of VSVI in reflecting park-use behavior varied between parks and variables. VSVI showed relatively high effectiveness in reflecting movement-range characteristics (including *travel distance*, *SDE area* and *SDE perimeter*) for all parks, regardless of the number of Mapillary PUDs. A possible reason for this is that these attributes are more likely to be influenced by park environments (e.g., route design and pavement) than by individual preferences. For temporal features, no significant correlations were found between Mapillary sequences and *PeopleFlow* tracks, regardless of PUD levels. A possible reason for this is the different nature of the activities between photo-sharing behavior and daily park-use behavior. Meanwhile, the average speed showed significant correlations for all high-PUD parks. This may be because photo-sharing activities generally involve slower movement compared to daily recreational activities, whereas in high-PUD parks, which tend to be parks with tourist spots or beautiful scenery, visitors tend to engage in more photo-sharing activities, thus increasing the correlation.

4.4 Implications

The results provide park planners and designers with novel insights into the possibility of applying open crowd-sourced datasets to park-use behavior evaluations. Specifically, such datasets can be used to estimate park visitation, particularly for tourism-oriented parks such as historic and scenic parks. This could lead to improvements in the managing capacity of parks. Furthermore, VSVI shows potential as a complementary indicator of the distribution of park-use behaviors in parks with sufficient contribution volumes. Point density and movement speed can inform discussions on the association between park layout planning and congestion levels. The spatial distribution of dwell time provides insights into park facility design and retail profit optimization. Finally, movement path characteristics within parks offer detailed insights into individual visitor behavior. This not only helps to assess whether actual visitation patterns are in line with the design intent (e.g., verifying looped travel routes in circuit-style gardens), but also informs path design and route recommendations.

4.5 Limitations and Future Work

This study has some limitations. First, although this study focuses on relative differences in park-use rather than contemporaneous behavioral equivalence, temporal differences among datasets may affect the interpretation of VSVI validity. Specifically, the VSVI data span approximately ten years, including the COVID-19 period, whereas the official counts represent pre-pandemic conditions and the GPS data reflect the post-pandemic period. Future studies should employ temporally aligned datasets to more rigorously evaluate behavioral correspondence. Second, the limited number of contributors (45 users) raises concerns regarding representativeness, as the observed patterns may reflect individual preferences of a small group of active local contributors rather than general park-use behavior. Moreover, Tokyo represents one of the most active Mapillary regions in Japan, the findings may not be directly transferable to areas with lower contribution densities or different contributor communities. Further validation across different geographic contexts and larger contributor populations are therefore needed. Finally, inherent quality issues in the data used, particularly crowdsourced data, related to GPS accuracy, timestamp uncertainty, and contextual heterogeneity (Ma et al., 2019; Zheng & Amemiya, 2024), can influence the results to some extent. The establishment of reliable data processing methods is crucial for future research, especially when dealing with crowd-sourced data of varying quality.

5. Conclusions

This study shows that VSVI can serve as a complementary proxy data source for park-use behavior analysis, particularly in parks with sufficient contribution volumes. However, given the observed concentration of contributions in scenic and tourism-oriented parks, VSVI should not be interpreted as a universally generalizable proxy for park-use behavior. It demonstrates the potential of crowdsourced open street-level imagery to complement proprietary mobility datasets and support evidence-based park management where conventional mobility data are unavailable or costly.

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