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Deciphering urban bike-sharing patterns: An in-depth analysis of natural environment and visual quality in New York's Citi bike system

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ABSTRACT

Bike-sharing offers a convenient and sustainable mode of transportation. Numerous studies have investigated the influence of temporal variations in the natural environment on cycling, as well as the impact of physical street characteristics like networks and infrastructures. However, few studies integrated and compared the effects of natural environment and street visual quality on cycling in the spatial dimension. As a case study, we focused on the impact of these two factors on Citi Bike system on weekdays and weekends in New York City, while accounting for sociodemographic and functional factors. This study employed machine learning and multiscale geographically weighted regression models at both station and neighborhood scales for a comprehensive analysis of their relationships. The results reveal that the natural environment factors, particularly visibility, are more important factors associated with bike-sharing use. Among the visual quality factors, motorized traffic has a negative impact on both weekday and weekend cycling. When considering geographical location, sky openness exhibits an unfavorable influence on weekday cycling in specific areas. By combining natural environment and visual quality factors, our study promotes optimal resource allocation and the development of bike-friendly cities.

1. Introduction

Cycling is vital in urban transportation, sustainability, and public health (Pucher and Buehler, 2017; Neves and Brand, 2019; Oja et al., 2011). It has drawn considerable interest from researchers and policymakers due to its potential to ease road congestion, lower carbon emissions, and encourage active lives (Buehler, 2012; Chau et al., 2015; Götschi et al., 2016). In recent years, the factors affecting bike-sharing have been extensively investigated, such as weather conditions, air quality, built environment, and sociodemographic attributes (Wu et al., 2021; An et al., 2019; He et al., 2023).

Natural environment factors such as weather conditions and air quality have been widely investigated in terms of their influence on bike-sharing demand (Noland, 2021; Morton, 2020). Nevertheless, these studies have mainly focused on the temporal scales and large spatial units, ignoring the variation in the spatial dimension across different areas within the city, especially weather conditions. It has been recognized that some weather conditions such as temperature and wind speed can exhibit local variations within a city due to factors like urban form and landscape (Elnahas, 2003; Gago et al., 2013). Furthermore, given that riding behavior takes place within a spatial area, it is reasonable to infer that the connection between natural environment factors and cycling could exhibit localized variations within that particular region. This has been exemplified in previous literature on public transit ridership, revealing that the influence of weather within a city is defined by spatial location, rather than being a constant global factor (Wei, 2022).

The visual quality of streets affects people's perception, which is an important part of the cycling experience. Limited by constraints in measuring and assessing the impact of visual quality, there exists an insufficient understanding of how fine-scale design factors specifically influence cycling (Wang et al., 2023). Street View images (SVIs) and Computer Vision (CV) have yielded opportunities for the research of cycling, enabling the capture of detailed visual data on urban streetscapes (Ito and Biljecki, 2021). Existing research, however, has mainly examined how the element of greenery in SVIs affects cycling (Chen et al., 2020; Wang et al., 2020b), with relatively little attention paid to the effects of other visual quality features.

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Many previous studies have analyzed the factors influencing cycling at the bike-sharing station level, focusing either on built environment factors or natural environment factors (Wang et al., 2018; El-Assi et al., 2017). Collectively, these studies suggest that cycling are not determined by a sole factor but rather by a complex interplay of various forces (Cervero et al., 2019). Moreover, these studies generally rely on traditional linear models, and overlook the consideration of neighboring stations and the effects of spatial heterogeneity. However, the relationship between these factors and active travel tends to be non-linear (Xiao and Wei, 2023; Nosal and Miranda-Moreno, 2014). Daily travel and mobility patterns also vary spatially and defy the stationarity hypothesis (Chen et al., 2019). Therefore, it is essential to integrate and compare the impact of built environment factors, particularly visual quality, which have received less exploration, with natural environment factors on bike-sharing use in the spatial dimension and it is crucial to address non-linear relationships and spatial autocorrelation as key considerations when evaluating the relationship between bike-sharing use and influencing factors.

In this study, we aim to address the following research questions: (1) How do spatial differences in visual quality and natural environment factors including weather and air quality affect bike-sharing usage at the station level within a city? (2) Specifically, which attribute group of these two categories, and which specific features, are more strongly associated with bike-sharing usage? In the temporal dimension, how do their impacts differ on weekdays and weekends? Taking Citi Bike in New York City (NYC) as a case study, we focused on the impact of the natural environment and visual quality factors on the Citi Bike system on weekdays and weekends, while considering functional factors that influence the visual appeal of streets and sociodemographic characteristics. This study provides a more detailed understanding by setting up a series of experiments to compare the effects of these factors, using machine learning (ML) models to explore non-linear association at the bike-sharing station scale and multiscale geographically weighted regression (MGWR) models to explore spatial variation relationships at the neighborhood scale. The utilization of two spatial analysis units stemmed from the necessity to account for potential demand disparities between two distinct groups. Bike-sharing companies benefit from precise machine learning models for each station, enabling accurate predictions and efficient resource scheduling. Conversely, transportation and urban planners, along with policymakers, may find it more advantageous to adopt a macro perspective. This broader viewpoint aids in understanding the utilization of bike-sharing in various neighborhoods while accounting for geographical factors. It facilitates planning and regulation on a larger scale, thereby promoting a bike-friendly city and transportation system.

The following sections of this study are organized as follows. Section 2 reviews the literature on the relationship between various factors and cycling. Section 3 introduces the data and methodologies. Section 4 summarizes the key research results. In section 5, we make discussions and possible implications. Finally, conclusions and limitations are presented in Section 6.

2. Literature review

2.1. Natural environment factors

Weather conditions play a pivotal role in influencing the utilization of bike-sharing. Extensive research has focused on investigating the impact of various weather factors, including temperature, precipitation, relative humidity, and wind speed, on travel patterns at temporal scales (Eren and Uz, 2020). Typically, there exists a positive correlation between daily temperature and bike-sharing usage, as warmer weather tends to encourage people to travel by bike (Kutela and Teng, 2019). On the other hand, precipitation, low temperatures, wind, snow, and fog are generally regarded as having a negative impact on bicycle travel (Nosal and Miranda-Moreno, 2014; Sears et al., 2012). However, certain studies have indicated that adverse weather does not invariably impede cycling in specific situations. For instance, commuting trips are usually less influenced by weather conditions compared to recreational trips. Rainfall may not always dissuade people from cycling to work, potentially due to the shorter duration and distance of typical commuter trips (Nankervis, 1999). Furthermore, different demographic groups may exhibit varying levels of sensitivity to weather conditions. Several studies have demonstrated that the transportation disadvantaged, such as individuals with low income, those over 30 years old, and women, may face limited alternatives during severe weather conditions. They are less inclined to switch to motorized modes of transportation and are likely to continue cycling even in unfavorable weather (Zhao et al., 2018).

Previous literature has been devoted to studying the connection between air quality levels and cycling as part of the efforts to foster more sustainable transportation and develop environmental policies. It has been widely proven that high levels of air pollution often lead to a reduction in outdoor activities among individuals. For example, a study conducted in London revealed that ozone concentration levels had a detrimental effect on cycling demand (Morton, 2020), and a case study in Sydney indicated that air quality alerts led to a reduction in cycling activities (Saberian et al., 2017). Nevertheless, the impact of air quality levels on cycling has been a subject of debate in certain studies. For instance, a study conducted in Montreal revealed a positive correlation between the number of bicyclists and the concentration levels of local air pollutants (Strauss et al., 2012). These studies generally conclude that while exposure to air pollution poses health risks, the positive health effects of bicycling typically outweigh the negative effects (Tainio et al., 2016; Willberg et al., 2023). Public perceptions of air quality and its health effects can also influence bike-sharing use, with individuals with lower air pollution awareness likely to be more insensitive to air quality (Anowar et al., 2017).

2.2. Visual quality and functional factors

Bike-sharing usage is influenced by a multitude of factors, with built environment characteristics receiving significant attention due to their potential for intervention and impact through urban planning and policy implementation. In recent years, urban studies using SVIs and CV techniques have proliferated, but less attention has been paid to cycling, particularly the impact of visual quality features on bike-sharing usage at the station level. Current research on visual quality and cycling has primarily concentrated on the influence of eye-level street greenery, which is widely acknowledged to encourage cycling (Chen et al., 2020; Wang et al., 2020b). Yet there are relatively few studies conducted on other visual quality elements. A prior study proved that the proportion of sky and building frontage has high explanatory power for bike-sharing use in Shanghai, and streets with a higher sense of enclosure are positively correlated with cycling (Wang et al., 2023). However, these studies have predominantly focused on dockless bike-sharing systems, and the influence of the visual quality surrounding docked stations on bike-sharing usage has not been thoroughly examined.

In addition, Points of Interest (POIs) play a crucial role in bike-sharing usage, and different functional types have varying effects on the visual quality of the streets. The combination of visual quality and functional factors can also promote the cycling experience at specific stations. Typically, bike-sharing is encouraged by the presence of bike stations in residential and commercial areas, as many individuals prefer cycling for their daily commutes (Dehdari Ebrahimi et al., 2022; Noland et al., 2019). However, there is inconsistency among studies regarding the impact of educational facilities on bike-sharing use. For example, bike-sharing stations near university campuses show a positive correlation with bike-sharing use (Wang et al., 2018), while the presence of after-school program facilities is associated with a decrease in bike-sharing trips in certain areas (Qin et al., 2018).

Although numerous previous studies have investigated the connection between the built and natural environmental factors and cycling, there remain several research gaps. First, there is less evidence on how the wider visual quality factors influence bike-sharing use, particularly the lack of attention to docked bike stations. Second, existing studies on the relationship between weather conditions, air quality, and bike-sharing usage have primarily focused on the temporal scale, neglecting the spatial variations across different areas within cities. Third, in the spatial dimension, fewer studies have concurrently explored the effects of both the natural environment and visual quality on bike-sharing use, and a comparative analysis of these two categories of factors' influence on cycling is currently lacking. Lastly, by testing two spatial units—stations and neighborhoods—applying machine learning techniques to capture the non-linear relationships at the station scale and MGWR to investigate the spatial heterogeneity at the neighborhood scale, a more in-depth knowledge of how factors affect bike-sharing use can be attained.

3. Data and methodology

3.1. Study area

With a population of 8,804,190 in 2020, NYC holds the distinction of being the largest city in the United States. It is comprised of five boroughs and spans an area of >778.2 km^2. In the 2023 LawnStarter website (Lawnstarter, 2023) rankings of bike-friendly cities in the United States, NYC ranked second position, highlighting its favorable environment for cycling. Presently, Citi Bike stands as the largest public bike-sharing system in NYC, operating stations across Manhattan, as well as parts of areas of Brooklyn, Queens, and The Bronx (Fig. 1a).

3.2. Analytical framework

This study proposes an analytical framework to enhance understanding of the spatial relationship between visual quality, natural environment factors, and bike-sharing usage at stations on both weekdays and weekends (Fig. 2). First, we collected data on the trips of Citi Bike stations in NYC in 2022 and multi-source data on several attribute groups that potentially influence bike-sharing use. Data for natural

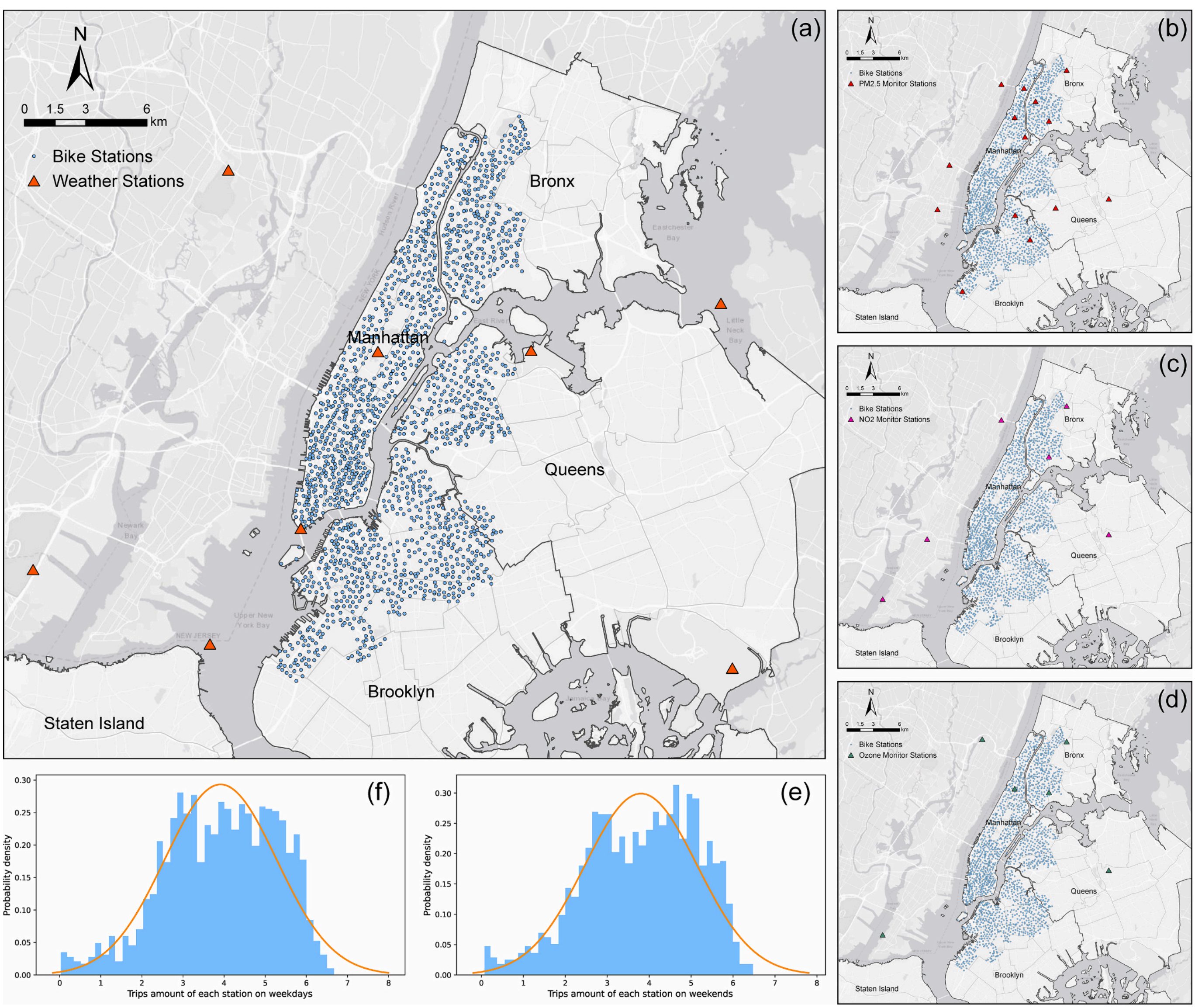

Fig. 1. (a–d) Spatial distribution of Citi Bike stations and weather stations or air quality monitor stations. (e–f) Histogram plots of the trip amount of each bike station after natural logarithm conversion.

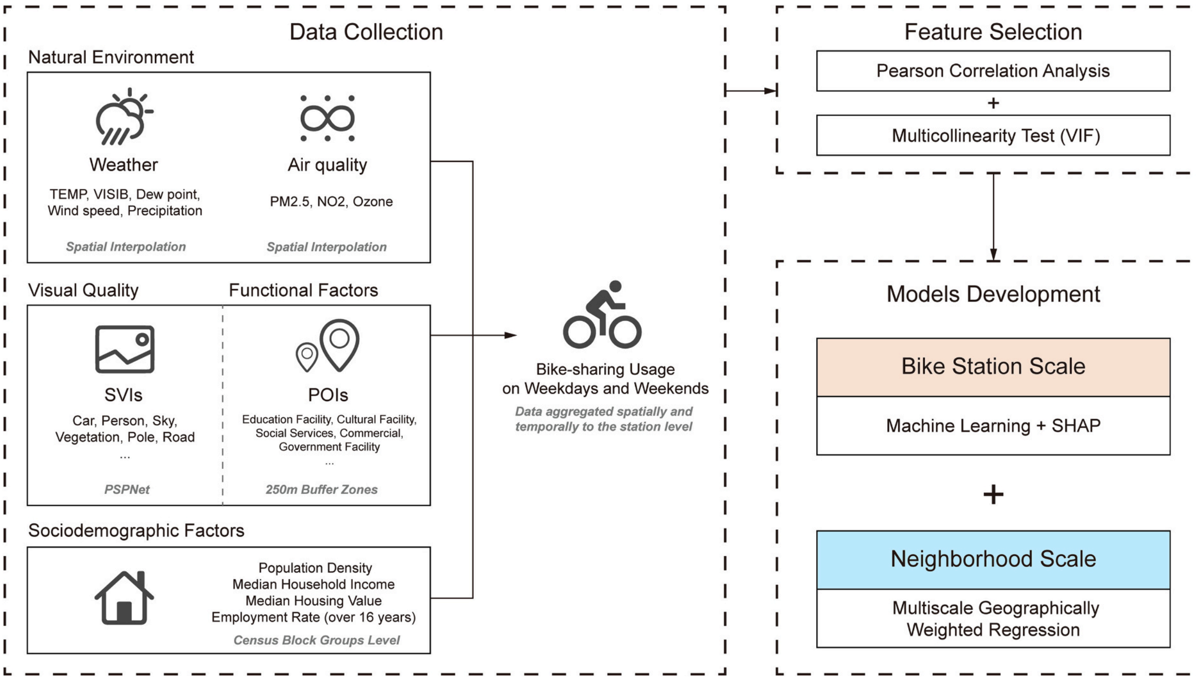

Fig. 2. Analytical framework.

environmental factors were gathered from various weather stations and air quality monitor stations located in and around NYC, followed by a spatial interpolation to compute the average daily weather conditions and air pollutant data on weekdays and weekends in 2022 for each bike station. Visual quality data was obtained from Google SVIs as calculated by Pyramid Scene Parsing Network (PSPNet) and the number of POIs in each category that are within a 250 m buffer of each station was used to determine the functional factor.

Second, we identified features that are likely to have an impact on bike-sharing usage through Pearson correlation analysis and multicollinearity testing. Then, two spatial-scale models were developed using these features. Specifically, we applied ML models to establish a non-linear relationship between features and bike-sharing usage at the station scale and reveal the feature importance using the SHapley Additive exPlanations (SHAP) package. Additionally, MGWR models were utilized to capture spatial non-stationary and reveal quantitative effects of related factors at the neighborhood scale.

3.3. Data collection

3.3.1. Dependent variables: Bike-sharing usage on weekdays and weekends

We gathered bike-sharing trip data from the Citi Bike website Citi Bike System Data | Citi Bike NYC, n.d.), including 1686 bike-sharing stations located in four boroughs of NYC in 2022 (Fig. 1a). The dataset records the start and end times, as well as the start and end station locations for each trip. We then calculated the average number of trips per day for each Citi Bike station as the bike-sharing usage on both weekdays and weekends.

3.3.2. Natural environment factors

Daily weather data for 2022 was downloaded from the NOAA website (National Centers for Environmental Information (NCEI), n.d.). We obtained daily data from eight weather stations in and around the study area (Fig. 1a), including mean temperature, mean dew point, mean visibility (fog, mist, and smoke related), mean wind speed, and precipitation amount. Then we converted the mean dew point to mean relative humidity by calculating the ratio between the actual water vapor pressure and the saturation water vapor pressure.

Daily air quality data for 2022 was collected from the EPA website (U.S. Environmental Protection Agency | US EPA, 2023). PM2.5, NO2, and Ozone are significant air pollutants in developed countries that have been linked to health problems (Brunekreef and Holgate, 2002). Therefore, daily data for mean PM2.5 of 14 monitor stations (Fig. 1b), maximum 1-h NO2 of six monitor stations (Fig. 1c), and maximum eight-hour Ozone of six monitor stations (Fig. 1d) located in and around the study area were acquired.

Then we calculated the daily mean data of each weather station and air quality monitor station on weekdays and weekends in 2022. Inverse Distance Weighting (IDW) which has been widely used in previous related studies (Ito and Biljecki, 2021; Wei, 2022) was conducted to estimate the daily mean weather and air quality data at each Citi Bike station on weekdays and weekends in the study area.

3.3.3. Visual quality and functional factors

In this paper, visual quality refers to the environmental condition of street space, comprising three-dimensional physical features such as the sky, buildings, and vegetation. In recent years, an increasing number of empirical studies have utilized Street View images and deep learning algorithms to explore visual quality, proving this to be an ideal approach for its assessment (Tang and Long, 2019; Ye et al., 2019). In this study, visual quality data of each bike-sharing station location were collected through the Google Street View API. For each sample point, Google SVIs were downloaded in four directions (headings of 0°, 90°, 180°, and 270°) to cover the overall view of the bike station. The pspnet101_cityscapes model is a variant of the PSPNet architecture with 101 layers (Zhao et al., 2017). It was trained for semantic segmentation tasks on the Cityscapes dataset and was used to identify different objects in the images and their respective proportions. Specifically, this model was trained and generated by PSPNet, which is a scene analysis network constructed with a pyramid pooling module, and has been widely applied in urban studies (Wu et al., 2023; Dong et al., 2023). The Cityscapes dataset was utilized to train the model, and after training, the model achieved dense pixel annotations (97% coverage) for 19 categories, with 8 of them having instance-level segmentation (Kirillov et al., 2019). Subsequently, we computed the average pixel ratio for each physical feature in the four directional SVIs for each sample point.

POIs data that can disclose and classify urban functions was obtained from the NYC Open Data Portal (Points Of Interest, n.d.). We used a search radius of 250 m surrounding each Citi Bike station for these attributes. The 250-m buffer is a commonly used value in the studies of the Citi Bike system given the distances between Citi Bike stations and the dense urban form of NYC (Faghih-Imani and Eluru, 2016; Kumar Dey et al., 2021).

3.3.4. Sociodemographic factors

Sociodemographic data were collected from the 2017–2021 American Community Survey 5-Year Estimates (Census Bureau Data, n.d.), combined at the spatial resolution of Census Block Groups (CBGs). It contains various demographic data and is frequently utilized in socioeconomic and bicycle research (Kang et al., 2021; Wang et al., 2020a). We specifically gathered population, median household income, median housing value, and employment rate (over 16 years) data for each CBG level in the study area, and then calculated population density.

3.4. Data processing

In this study, the dependent variables (bike-sharing usage on weekdays and weekends) were transformed by the natural logarithm, and the processed data generally followed a normal distribution (Fig. 1e-f). Pearson correlation analysis was performed between the independent and dependent variables, and those variables that indicated a statistically significant correlation ($p < 0.05$) with the bike-sharing usage were retained. Variance Inflation Factor (VIF) was calculated to remove variables with multicollinearity (VIF > 7.5). Then we used the Z score method to normalize independent variables in order to transform data of different magnitudes into a uniform measure.

3.5. Model architecture

3.5.1. Station scale

At the station scale, first, we used multiple linear regression (MLR) models to compare the contributions of different attribute groups. The baseline model comprises only sociodemographic factors. We then incorporated visual quality, functional factors, and natural environment factors respectively, and examined the performance of the hybrid model that integrates all attribute groups.

Based on the combination of the best-performing attribute groups, we filtered and optimized the most effective models by evaluating the R-squared (R^2) and Mean Square Error (MSE) values of four ML models, including Gradient Boosting Regression (GBR), Random Forest Regression (RFR), eXtreme Gradient Boosting (XGBR), and Multilayer Perceptron (MLP). Since the selection of hyper-parameters plays a crucial role in the ML models' performance and predictive capability, we use Bayesian optimization, which improves the performance and generalization of the model by continuously evaluating its performance and updating the probability model of hyper-parameters, thus searching for the optimal solution within a limited number of iterations (Snoek et al., 2012). Then we utilized the SHAP package (Lundberg and Lee, 2017) in the Python environment to analyze the contributions of features and their positive and negative effects. Originally proposed by Shapley, SHAP employs game theory to calculate Shapley values, which are used to determine the importance of independent variables.

3.5.2. Neighborhood scale

Regarding the neighborhood scale, we computed the average values of all variables for bike stations on weekdays and weekends within each census tract. This collection of data represents the dataset for that specific census tract. The ordinary least squares regression (OLS) model examines the effects of bike-sharing usage in global terms, but spatial data are often influenced by spatial autocorrelation and spatial heterogeneity (Anselin, 1996). The geographically weighted regression (GWR) model addresses spatial non-stationarity concerns but has a limitation of utilizing a single average bandwidth for all variables to represent the impact range of each variable (Oshan et al., 2019). The MGWR models can produce a more trustworthy result by offering an ideal bandwidth for each independent variable when multiple independent variables operate at different spatial scales are considered (Fotheringham et al., 2017).

In this study, MGWR 2.2 software was used to calculate the results of OLS, GWR, and MGWR models. Five evaluation indexes were employed to assess the performance of different models, including the residual sum of squares (RSS), R^2, adjusted R^2, corrected Akaike information criterion (AICc), and Moran's I test of residuals (Zhou et al., 2023). Better model fit is shown by higher R^2 and adjusted R^2 values and lower RSS and AICc values. In addition, the residuals of a regression model should have a random and independent distribution (Hill, 2012). Therefore, spatial autocorrelation tests were conducted on the residuals of various models using GeoDa software, and the 'rook' approach was used to calculate the spatial weight matrix W.

4. Results

4.1. Descriptive results

According to Pearson correlation analysis (Fig. A1, Fig. A2), four sociodemographic features were significantly ($P < 0.01$) correlated with weekday and weekend bike-sharing use and all these passed the VIF test (Table A1) and thus were included in the final analysis. There was a significant correlation at 0.001 level between most of the natural environment factors and bike-sharing use, but it was worth noting that there was a strong association between some of the weather conditions features. Features exhibiting high multicollinearity were sequentially eliminated based on their VIF values, resulting in the retention of temperature and visibility features. Additionally, all three air quality features were also retained in the analysis.

Eleven visual quality elements with the highest ratios were extracted from SVIs. The analysis revealed that the correlation between fence, rider, and sidewalk and bike-sharing use was weak. Buildings showed a significant negative correlation with sky and vegetation, and walls had a significant positive correlation with vegetation. Therefore, cars, persons, sky, vegetation, poles, and roads were retained as the final set of visual elements. In this study, the association between POIs such as residential, recreational facilities, medical services, and bike-sharing use was found to be limited, and combined with the multicollinearity test, POIs other than educational facilities, cultural facilities, social services, commerce, and government facilities were deleted.

In summary, a total of 20 influencing factors that were significantly associated with bike-sharing use on weekdays and weekends ($p < 0.05$) and passed the VIF test (VIF < 5), were selected in the final modeling. Descriptive statistics of the variables are shown in Table 1.

4.2. Results of station scale

4.2.1. Model comparison of attribute group combinations

Table 2 presents the performance of MLR models using various combinations of attribute groups. Notably, the combination of diverse attribute groups can enhance the model's performance, indicating that these groups contribute various to the understanding of bike-sharing usage from different perspectives. Taking weekday models as an example, the baseline model with only sociodemographic features had an R^2 of 0.12. This value improved to 0.31 when visual quality features were incorporated and further increased to 0.38 with the inclusion of functional features. Additionally, the baseline model incorporating natural environment features achieved an R^2 of 0.51, while the highest R^2 of 0.59 was obtained when all attribute groups were combined.

4.2.2. ML model results

Based on the results from section 4.2.1, which demonstrated that the

Table 1
Summary statistics of all variables included in the models.

Category		Variables		Description	Mean	S.D.	Min	Max
Sociodemographic factors		Population Density (person/km^2)		The related sociodemographic data of the census block group level where a bike station is located	24,953.833	20,765.960	0.000	176,260.000
		Median Household Income ($)			77,384.270	66,152.905	0.000	250,000.000
		Median Housing Value ($)			552,302.550	665,319.243	0.000	2,000,000.000
		Employment Rate (over 16 years) (%)			0.629	0.232	0.000	1.000
Built environment factors	Visual Quality factors	Car (%)		The average of each feature in SVIs of four directions for a bike station calculated by PSPNet semantic segmentation	0.065	0.052	0.000	0.554
		Person (%)			0.013	0.028	0.000	0.417
		Sky (%)			0.125	0.091	0.000	0.617
		Vegetation (%)			0.151	0.119	0.000	0.742
		Pole (%)			0.002	0.002	0.000	0.032
		Road (%)			0.297	0.076	0.002	0.520
	Functional factors	Education Facility (number)		Number of each category POIs within a 250 m search radius of a bike station	2.668	3.702	0.000	45.000
		Cultural Facility (number)			0.613	1.572	0.000	23.000
		Social Services (number)			0.985	1.224	0.000	8.000
		Commercial (number)			0.965	2.340	0.000	19.000
		Government Facility (number)			0.880	4.329	0.000	76.000
Natural environment factors		TEMP (°F)	Weekdays	Daily mean temperature of a bike station on weekdays/weekends after spatial interpolation	56.377	0.174	56.010	57.067
			Weekends		55.203	0.188	54.770	55.941
		VISIB (miles)	Weekdays	Daily mean visibility of a bike station on weekdays/weekends after spatial interpolation	9.226	0.046	9.126	9.336
			Weekends		9.375	0.015	9.352	9.428
		PM2.5 (ug/m3)	Weekdays	Daily mean PM2.5 concentration of a bike station on weekdays/weekends after spatial interpolation	7.229	0.411	6.175	8.268
			Weekends		6.783	0.338	5.739	7.681
		NO2 (ppb)	Weekdays	Daily max 1-h NO2 concentration of a bike station on weekdays/weekends after spatial interpolation	30.458	0.658	26.843	31.338
			Weekends		24.213	0.423	22.481	25.494
		Ozone (ppm)	Weekdays	Daily max 8-h ozone concentration of a bike station on weekdays/weekends after spatial interpolation	0.035	0.001	0.033	0.036
			Weekends		0.037	0.001	0.035	0.038
Dependent variables		Bike-sharing usage (number)	Weekdays	Daily mean trip amount of a bike station on weekdays/weekends	99.703	116.819	0.019	762.200
			Weekends		36.396	41.403	0.027	264.538

Table 2
MLR models comparison for different combinations of attribute groups.

		SD	SD + BE		SD + NE	All Factors
			SD + VQ	SD + VQ + FP		
Weekdays	R^2	0.12	0.31	0.38	0.51	0.59
	MSE	1.54	1.21	1.08	0.73	0.71
Weekends	R^2	0.12	0.27	0.33	0.44	0.48
	MSE	1.47	1.22	1.12	0.92	0.87

Notes: SD: Sociodemographic factors; BE: Built environment factors, including VQ: Visual quality factors and FP: Functional factors (POIs); NE: Natural environment factors.

model incorporating all attribute groups exhibited the highest performance, thus a total of 20 attributes were utilized in the comparison of different ML models, and the performance of these models on weekdays and weekends is detailed in Table 3. All these models demonstrated superior performance and goodness-of-fit compared to MLR models in section 4.2.1. Specifically, the ensemble method, particularly the random forest, outperformed the other three algorithms with higher R^2 (R^2_weekdays = 0.78, R^2_weekends = 0.77) and lower MSE (MSE_-weekdays = 0.37, MSE_weekdays = 0.37) on the test set, suggesting that the decision tree-based ML approach excelled in modeling non-linear relationships between variables. Therefore, we finally chose the RFR model and initiated the optimization process with 5 random search steps, and continued with 20 iterations of Bayesian optimization. The iterative process is shown in Fig. B1. After optimization, the RFR models showed a notable improvement in terms of MSE and R^2. The R^2 value for the final RFR model was enhanced to 0.80 on weekdays and 0.79 on weekends. The MSE values witnessed a significant reduction to approximately 0.32, indicating the effectiveness of the optimization process.

Table 3
Performance comparison of different ML models on weekdays and weekends.

ML models		Weekdays		Weekends	
		R^2	MSE	R^2	MSE
Ensemble Method	GBR	0.75	0.42	0.73	0.43
	RFR	0.78	0.37	0.77	0.37
	XGB	0.77	0.38	0.73	0.43
Artificial Neural Network	MLP	0.62	0.63	0.56	0.70

4.2.3. Explanation with SHAP

SHAP summary plots allow exploring the direction of the relative importance of variables, thus providing a better understanding of the contribution of variables to the prediction (Fig. 3). Each data point represents a sample and the colors represent the characteristic values (red for high values and blue for low values). Positive SHAP values indicate that the variable has a facilitative effect on bike-sharing use, while negative values indicate a suppressive effect.

The results revealed that the natural environmental factors exhibited stronger explanatory power than visual quality factors. Generally, visibility, ozone, PM2.5, NO2, and temperature were the most important features influencing bike-sharing use on weekdays and weekends. Regarding feature effects on weekdays, visibility had a significant negative impact on the predictions, while ozone and NO2 exhibited a noticeable promoting effect on bike-sharing use. Temperature is also positively correlated with bike-sharing usage during weekdays. On weekends, visibility still maintained a negative impact on the

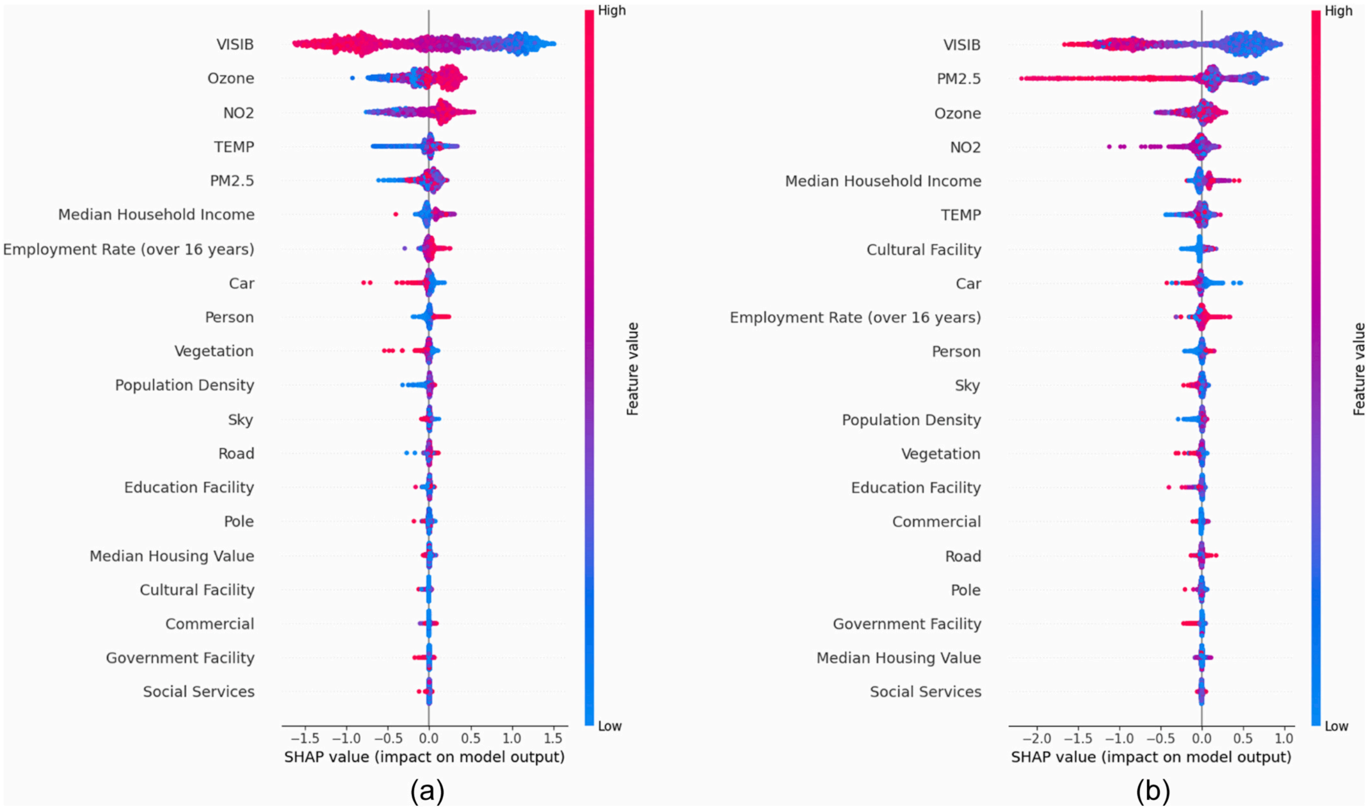

Fig. 3. SHAP summary plots on (a) weekdays and (b) weekends.

predictions, and PM2.5 clearly exhibited an inhibiting effect.

Many visual quality features hold greater importance compared to functional features. Specifically, the ratio of cars, sky, and vegetation had a negative effect on bike-sharing use on both weekdays and weekends, while the ratio of persons had a positive effect. Roads and poles have relatively less impact on cycling. On weekdays, POIs had low predictive power, while on weekends, cultural facilities emerged as the most important built environment factor, positively influencing bike-sharing use. As far as sociodemographic factors, household income, and employment rate demonstrated a positive impact on bike-sharing use on both weekdays and weekends.

4.3. Results of neighborhood scale

4.3.1. Model comparison

The performance of the OLS, GWR, and MGWR models on weekdays and weekends is shown in Table 4. The goodness of fit of the GWR models was greatly improved compared to the OLS models. However, the results of Moran's I residual test for both the OLS and GWR models indicated that the residuals were spatially correlated ($P < 0.001$) (Fig. 4). The AICc values of the MGWR models were smaller than those of the GWR models and the adjusted R^2 values were higher. There was no spatial correlation between the residuals of the MGWR models (Moran's I index_weekdays = −0.014, P_weekdays = 0.294; Moran's I index_weekends = 0.013, P_weekends = 0.259), suggesting that the models were reliable. As a result, the MGWR models had higher statistical performance, and the OLS and GWR models were not effective in examining the effects of sharing-bike usage on weekdays and weekends.

4.3.2. MGWR results

Table 5 summarizes the statistics of the local parameter estimates for the MGWR models on weekdays and weekends, showing the proportion of significant coefficients (95% level of *t*-Test) and the proportion of significant positive or negative coefficients to the significant coefficients. The findings revealed that on both weekdays and weekends, the intercept, population density, median housing value, employment rate (over 16 years), TEMP, VISIB, NO2, and Ozone were significant. On weekdays, the variables that significantly affected a larger area were the sky, commercial, educational facilities, and cultural facilities, while a few areas were significantly affected by vegetation and social facilities. Median household income, car, and PM2.5 were significant only on weekends.

Fig. 5 and Fig. 6 map the local R^2 based on the MGWR models on weekdays and weekends as well as some of the factors with significant influences to show the spatial distribution of their effects on bike-sharing use. A parameter estimate with a positive sign suggests that the factor has a favorable impact on the utilization of bike sharing, whereas one with a negative sign implies a detrimental impact. The dark

Table 4
Model comparison between the OLS, GWR, and MGWR models.

	OLS		GWR		MGWR	
	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
RSS	489.33	639.62	183.65	178.76	130.56	137.14
R^2	0.61	0.47	0.86	0.85	0.90	0.89
Adjusted R^2	0.60	0.45	0.82	0.81	0.87	0.86
AICc	1850.70	2051.05	1461.70	1469.76	1186.63	1179.23

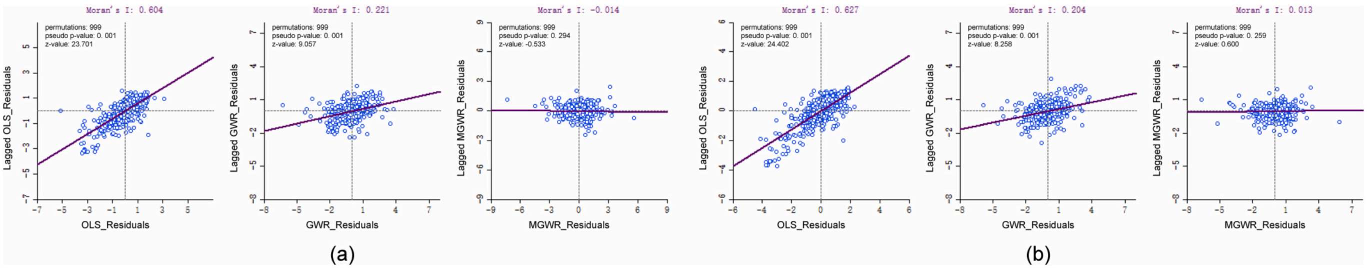

Fig. 4. Moran's I residuals test of the OLS, GWR, and MGWR models on (a) weekdays and (b) weekends.

Table 5
Summary statistics of the local coefficients of the MGWR model on weekdays and weekends.

Variables	Usage on weekdays			Usage on weekends		
	P ≤ 0.05 (%)	+(%)	-(%)	P ≤ 0.05 (%)	+(%)	-(%)
Intercept	93.32	100.00	0.00	100.00	100.00	0.00
Population Density	33.69	100.00	0.00	18.18	100.00	0.00
Median Household Income	0.00	0.00	0.00	31.95	100.00	0.00
Median Housing Value	49.87	0.00	100.00	23.80	0.00	100.00
Employment Rate (over 16 years)	0.13	100.00	0.00	5.48	100.00	0.00
Car	0.00	0.00	0.00	17.78	0.00	100.00
Person	0.00	0.00	0.00	0.00	0.00	0.00
Sky	20.86	0.00	100.00	0.00	0.00	0.00
Vegetation	0.80	0.00	100.00	0.00	0.00	0.00
Pole	0.00	0.00	0.00	0.00	0.00	0.00
Road	0.00	0.00	0.00	0.00	0.00	0.00
Education Facility	6.28	0.13	99.87	0.00	0.00	0.00
Cultural Facility	6.68	100.00	0.00	0.00	0.00	0.00
Social Services	0.27	100.00	0.00	0.00	0.00	0.00
Commercial	100.00	100.00	0.00	0.00	0.00	0.00
Government Facility	0.00	0.00	0.00	0.00	0.00	0.00
TEMP	40.24	100.00	0.00	16.98	0.00	100.00
VISIB	95.32	0.00	100.00	82.49	37.60	62.40
PM2.5	0.00	0.00	0.00	26.74	39.00	61.00
NO2	16.18	0.00	100.00	18.58	35.97	64.03
Ozone	42.51	96.54	3.46	29.01	0.00	100.00

gray represents the area where the variables have no significant effect ($P \leq 0.05$). The coefficients were categorized using ArcGIS pro3.0.0's natural breaks (Jenks) classification approach. As can be seen, the spatial distribution of local R^2 values was similar on weekdays and weekends, with parts of The Bronx, Midtown Manhattan, and Downtown Manhattan having lower R^2 compared to other areas. It implied that these are more intricate places where the use of bike-sharing depends on more potential factors. The spatial distribution of intercept values shows that geographic location had a significant effect on bike-sharing use on weekdays and weekends in the vast majority of areas.

Most natural environmental factors had a significant impact on bike-sharing use on both weekdays and weekends. Visibility had a significant negative effect on weekday and weekend bike-sharing use in most areas, which aligned with the results of the feature importance analysis. In Manhattan, temperature, PM2.5, NO2, and Ozone had no significant association with bike-sharing use on weekdays and weekends. This suggests that people in Manhattan pay relatively little attention to these factors when they ride and that bike-sharing use may be influenced more by other factors. Furthermore, PM2.5 only had a significant effect on bike-sharing use on weekends, mainly with a negative effect in parts of Brooklyn. This indicated that people in some areas are more likely to avoid riding on weekends when there are high levels of PM2.5 in the air, while people in certain areas may be less sensitive to the issue. Cyclists may show varying attitudes toward air pollution, which has been demonstrated in prior literature (Anowar et al., 2017). Ozone showed a negative correlation with weekend bike-sharing use in 29.01% of the region; however, it exhibited a positive correlation with weekday bike-sharing use in parts of Brooklyn. Ground-level vehicle exhaust is one of the major sources of ozone (Liu and Leung, 2008). On weekdays, more people are likely to commute by car and bicycle in these areas, leading to higher traffic volumes, increased exhaust fumes, and higher ozone concentrations. Therefore, there is a positive correlation between ozone levels and cycling. On weekends, if traffic remains high in certain areas, leading to elevated ozone levels, people are less likely to choose to ride in those areas due to the absence of commuting demand.

Among the visual quality features, the ratio of sky mainly had a negative influence on weekday bike-sharing use in some areas of Brooklyn. Similar findings were observed in a study conducted in Shenzhen, China, where the sky openness also showed a negative correlation with weekday cycling but a positive correlation with weekend cycling (Bai et al., 2023). Car primarily had a negative impact on weekend bike-sharing use in parts of Midtown Manhattan and Queens. These regions are probably well-liked weekend getaways for visitors and locals, and the increased traffic volume may cause congestion and lessen the appeal of bike-sharing (Lu et al., 2018). Different from the feature importance results in section 4.2.3, the commercial had a significant positive effect on weekday bike-sharing use and was a global variable with little spatial variation. Dense commercial areas often have a high concentration of business activity and offices, so there are more commuters here on weekdays, which may lead to more bike-share use (Cheng et al., 2020). Previous studies have found a positive correlation between the density of cultural facilities and bicycle station use (Guo et al., 2022), our findings supported it only in 6.68% of the region on weekdays. The education facilities had a significant negative impact on weekday bike-sharing use in some areas of Brooklyn. It may be that there are more after-school program facilities in these areas, resulting in fewer sharing-bike users (Qin et al., 2018). However, each category of POIs did not have a significant impact on weekend bike-sharing use in our study area. Weekend travel may be likely to involve more flexible activities and destinations, and category-specific areas of interest may have less of an impact.

In terms of sociodemographic factors, many studies have concluded that bike stations situated in densely populated areas tend to attract a larger user base (El-Assi et al., 2017; Rixey, 2013), but our study only partially demonstrated this point (33.69% of the region on weekdays and 18.18% of the region on weekends). Bicycles are not necessarily used more in densely populated areas, especially on weekends, it may be less appealing when there is excessive traffic and crowded streets (Wu et al., 2021). Median Housing Value had a significant negative impact on bike-sharing use on weekdays and weekends in the Upper East Side and Upper West Side, which are affluent residential areas. This finding was consistent with previous literature that concluded that residents of areas with higher housing prices may have more travel options and may prefer

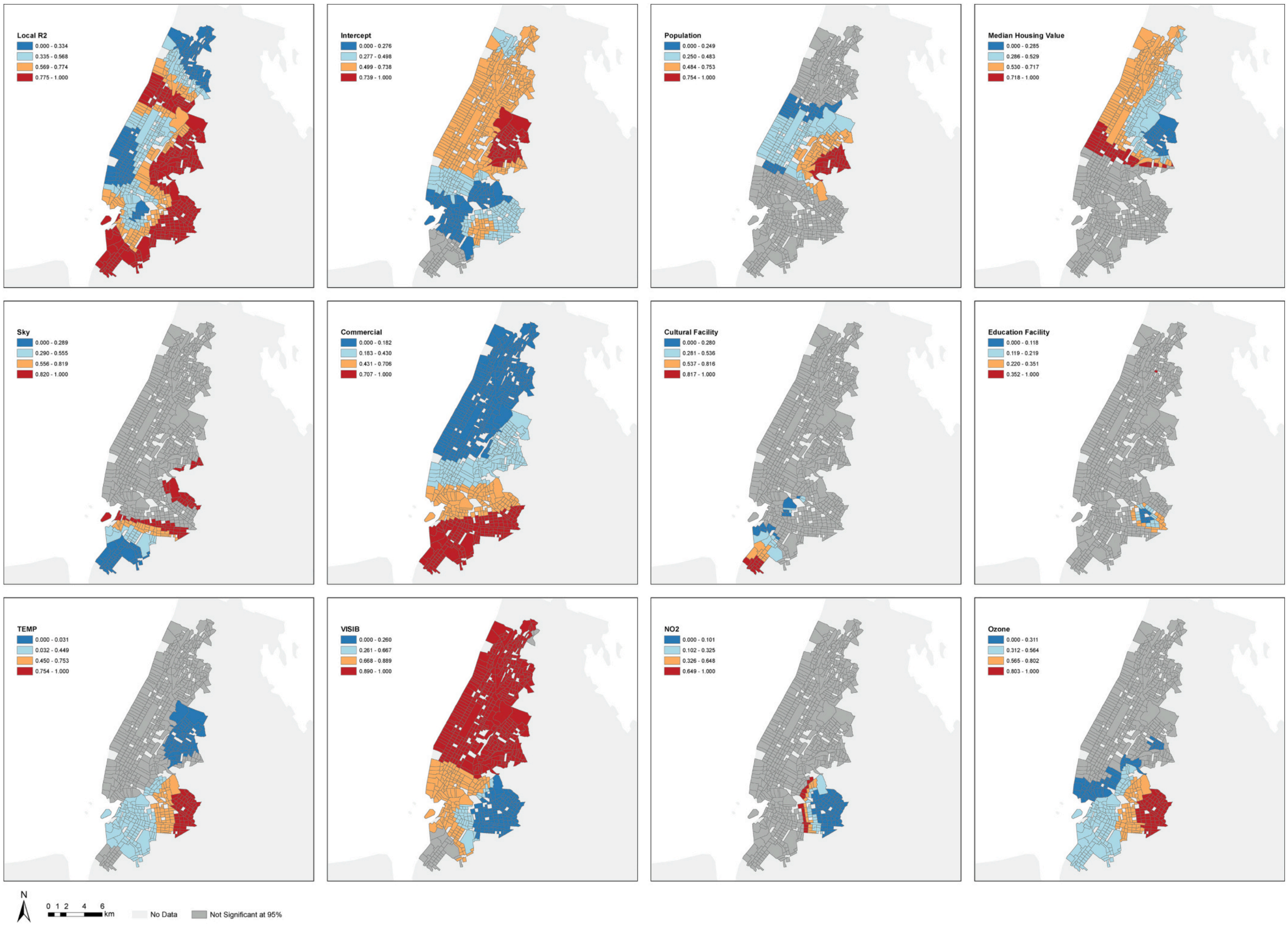

Fig. 5. Spatial distribution of local R^2 and coefficients of influencing factors of the MGWR model on weekdays.

more convenient transportation such as private cars (Liu et al., 2023).

Overall, the results of the MGWR models indicated that the coefficients of each variable and their effects on weekday and weekend bike-sharing use vary spatially and should be modeled on a site-by-site basis. Therefore, it is necessary to model the prediction of weekday and weekend bike-sharing use with explicitly integrated geographical relationships.

5. Discussion

5.1. Effects of natural environment factors

Previous research in the temporal dimension shows that natural environment factors such as weather conditions have a stronger influence on bike-sharing use than built environment factors (An et al., 2019). In this study, natural environment factors in the spatial dimension, including weather conditions and air quality, exhibit strong explanatory power to bike-sharing use and the inclusion of these features significantly enhances the goodness-of-fit of the models when compared to the baseline model. The importance of each natural environment feature surpasses that of the visual quality and functional features, highlighting the significant role played by the natural environment features in different areas within the city when it comes to explaining bike-sharing usage.

The feature importance results indicate that visibility is the most important of all variables, and lower visibility may promote bike-sharing use. In addition, ozone and NO2 have a positive effect on weekday bike-sharing use. These findings challenge the simple expectation that adverse environmental conditions tend to reduce bike-sharing usage, and several reasonable speculations could explain these results. First, low visibility has a significant impact on both automobile travel and public transportation. Studies have demonstrated an increased probability of car accidents in foggy weather, as well as a notable risk of delays or cancellations to public transportation services (Abdel-Aty et al., 2011; Sabir, 2011), so individuals may be less affected when cycling. Second, concerning the road environment, ozone and NO2 originate primarily from emissions from vehicular traffic. Research has indicated that the microenvironment in closest proximity to traffic tends to have the highest levels of directly emitted pollutants (Cepeda et al., 2017; de Nazelle et al., 2012). Consequently, individuals traveling in road vehicles are more exposed, whereas roadside cyclists are likely to be less affected. Third, in the case of necessary commuter travel, individuals may consider that the costs of changing transportation modes surpass the advantages of reducing their exposure to local air pollutants (Nankervis, 1999). Fourth, in adverse weather conditions, individuals who typically walk may opt to switch to alternative modes of transportation in order to minimize travel time and exposure (McCormack et al., 2010; Khattak and De Palma, 1997), potentially resulting in a rise in the usage of shared bicycles. Finally, empirical studies investigating the balance between the health benefits and costs of bicycling have demonstrated that the benefits far outweigh the risks (Panis, 2011; Tainio et al., 2016), so it is understandable that cyclists would perceive cycling as a superior mode of transportation compared to others.

The results of the model at the neighborhood scale reveal spatial

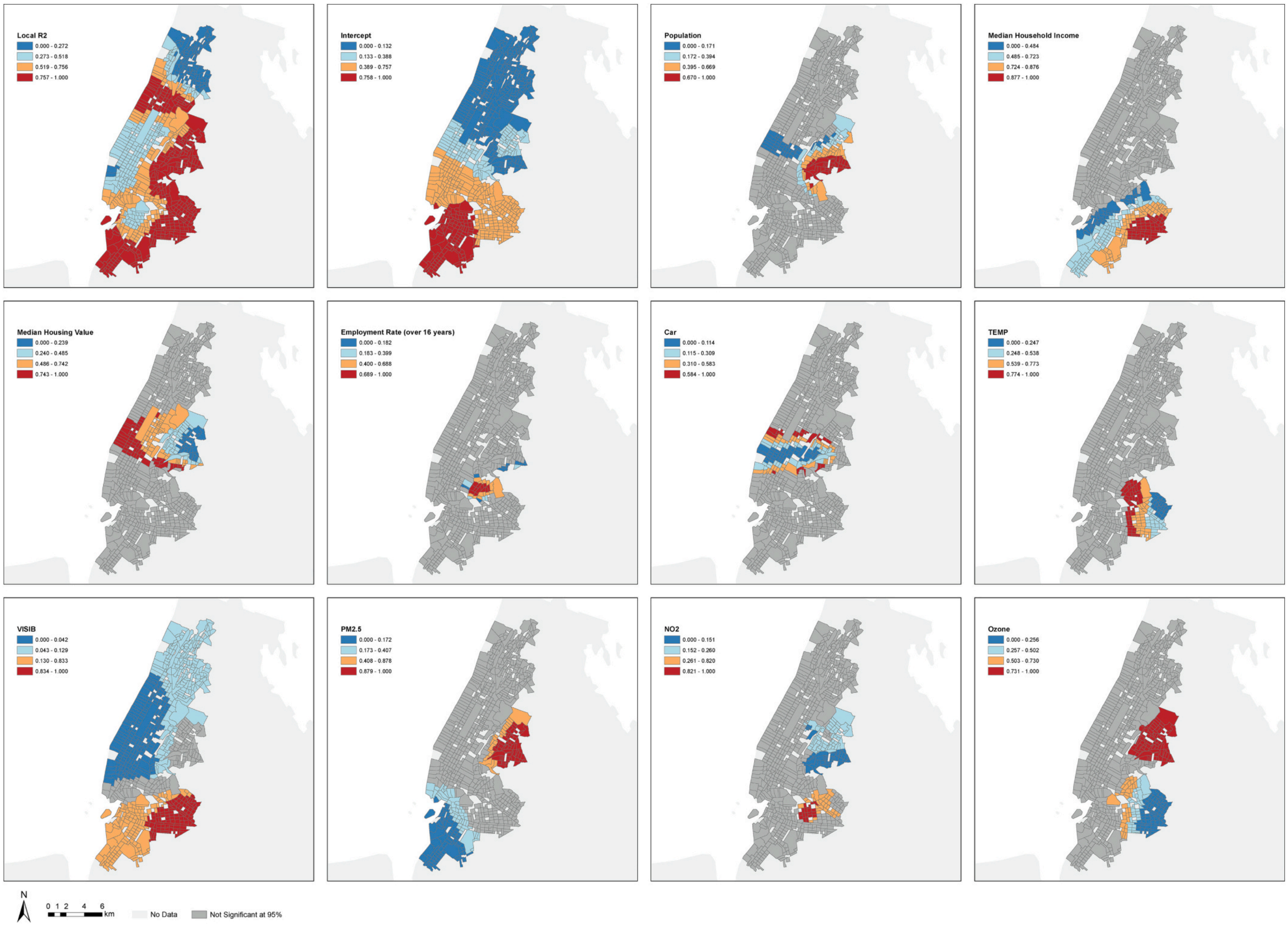

Fig. 6. Spatial distribution of local R^2 and coefficients of influencing factors of the MGWR model on weekends.

heterogeneity in the variables and their impact on bike-sharing use varying across different areas. For instance, in most parts of Manhattan, the natural environment features, apart from visibility, did not exhibit a significant effect. Additionally, PM2.5 only demonstrated a negative effect on weekend bike rides in specific areas. By employing spatial modeling, we gain a more extensive understanding of how these variables influence bike-sharing use in diverse geographic settings.

5.2. Effects of visual quality factors

The inclusion of the visual quality factor in the baseline model (see section 4.2.1) led to a significant enhancement in the model's performance on both weekdays and weekends (R^2_weekdays increased from 0.12 to 0.31; R^2_weekends increased from 0.12 to 0.27). It highlights the effectiveness of visual quality in predicting bike-sharing use, although to a lesser extent compared to the impact of natural environmental factors (R^2 _weekdays increased from 0.12 to 0.51; R^2_weekends increased from 0.12 to 0.44). Based on the feature importance analysis, cars exhibit higher explanatory power on both weekdays and weekends, showing negative associations with bike-sharing use. This finding is supported by previous studies demonstrating a negative correlation between high car traffic and the attractiveness of cycling (Bialkova et al., 2022; Pucher et al., 2011). The positive impact of persons on bike-sharing usage implies that vibrant streets promote cycling and human activity holds appeal for others (Rui and Othengrafen, 2023).

At the neighborhood scale, the analysis considered spatial effects, revealing that the variables exhibit non-stationarity across different areas. On weekdays, the sky openness has a noticeable negative effect on bike-sharing use in certain neighborhoods, while having no significant effects on weekends. The potential explanation could be the difference in the purpose of cycling on weekdays and weekends. During weekdays, individuals may experience commuting pressure, emphasizing safety in their daily journeys (Bai et al., 2023). In general, a high sky ratio implies low enclosure in the street space with a minimal tree canopy and fewer buildings, which might be perceived as an unsafe environment (Harvey et al., 2015; Ma and Ye, 2019), thereby diminishing cycling. Consequently, it is necessary to model the spatial relationship between bike-sharing use and these variables to better explain the underlying factors.

Therefore, alongside the commonly examined built environment factors, such as accessibility and bicycle facilities (Mix et al., 2022; Alcorn and Jiao, 2023), incorporating visual quality factors can enhance the predictive capability of the models and offer a more comprehensive understanding of bike-sharing use. Furthermore, the impacts of these visual quality factors exhibit regional variations, indicating the necessity of region-specific policy interventions to promote active travel.

5.3. Policy implications

For the bike-sharing system, there are several key implications. First, understanding the spatial correlation between weather, air quality, and bike-sharing use is crucial and allows companies to proactively design and adjust schedules to accommodate natural environmental conditions. Second, our findings highlight the spatial variability in the impact of visual quality on bike-sharing use. As a result, bike-sharing firms can optimize the arrangement of bike stations based on visual quality factors, also providing valuable insights for future station siting. Lastly, due to the various relationships between influencing factors and shared bike usage on weekdays and weekends, bike-sharing firms can rationalize and arrange the availability of bikes at stations based on these variations. This flexibility ensures optimal availability and meets the demand on weekdays and weekends.

The negative correlation between bike-sharing use and visibility, as well as the positive correlation with certain air pollutants, indicates several urban public transit and cycling implications. First, policymakers could increase investment in public transit to reduce the probability of delays and cancellations during inclement weather, enabling cyclists to easily shift modes and thereby reduce exposure. Moreover, cyclists may need better information about high local air pollutant concentrations since some pollutants, such as ozone, may not be directly perceived by people. A potential action is to implement programs that enhance cyclists' awareness of local poor air conditions, thus minimizing their exposure and improving public health. For instance, the development of user-friendly mobile apps or websites providing real-time information on weather conditions and air quality indices can empower individuals to make informed decisions regarding cycling conditions.

Additionally, transportation planners should consider traffic flow control and strategically plan road configurations. This may involve measures such as separating bicycle infrastructure from traditional roads or implementing physical barriers, and creating dedicated bicycle lanes or routes to develop bicycle-friendly environments. In certain areas, urban designers should also consider the sky openness when designing the built environment. This consideration can help facilitate a shift in travel patterns toward public transportation and provide favorable environmental conditions that encourage active travel among citizens.

6. Conclusion

Bike-sharing usage is influenced by a complex interplay of personal, locational, natural, and built environment factors. The identification of these factors that impact bike-sharing use at the station level in megacities presents a challenging task. To increase the in-depth understanding of the natural environment and visual quality factors influencing bike-sharing use, this study delves into the possibility of machine learning and geospatial analysis methods for modeling bike-sharing use using multiple sources of data. This study makes three main contributions. First, a broader range of visual quality features, as well as weather and air quality features of different areas within the city, were included as potential factors influencing bike-sharing use in this study. Such a study that synthesized and compared natural environment and visual quality factors in the spatial dimension has been rare in the past and enriches the data sources for future research. Second, a comprehensive framework for analyzing weekday and weekend bike-sharing use was developed by integrating multiple features through big data-driven techniques. This framework utilizes both ML and MGWR models to investigate the relationships between influencing factors and bike-sharing usage at both the station and neighborhood scales, which can be extended to the study of other transportation modes. Third, this study not only focuses on enhancing the accuracy of models but also emphasizes explaining what factors influence bike-sharing use, thereby providing strategic guidelines for sustainable active travel.

The results of this study reveal promising findings in estimating bike-sharing use. First, we conducted a comparative analysis of various models at two spatial scales and provided explanations for the results. Unlike the linear relationship modeled by MLR, the decision tree-based RFR models capture the non-linear relationship between features and bike-sharing use, while the MGWR models account for spatial non-stationary between variables, providing better predictions as well as a more integrative interpretation. This finding highlights the importance of considering local impacts in transportation planning and bicycle studies. By incorporating spatial attributes of variables into the planning and operation of bike-sharing systems, resources can be allocated more rationally, leading to improved operational efficiency of the systems.

Furthermore, the results show a significant improvement in the estimation accuracy of docked bike-sharing use by incorporating a combination of various factors. Among these factors, natural environmental factors such as visibility and ozone exhibit greater importance than visual quality and functional factors. This reinforces the earlier discovery that cycling is very sensitive to weather conditions from the spatial dimension. Furthermore, visual quality features derived from SVIs, like cars and sky, also positively contribute to the understanding of bike-sharing use. These features uncover previously less explored and discussed information, which can inspire bike-sharing companies, policymakers, transportation planners, and urban designers. The findings offer decision support for a comprehensive assessment of bike-sharing use at the station level, the creation of bike-friendly neighborhoods, the promotion of sustainable transportation systems, and the implementation of human-centered transportation planning and management, ultimately contributing to improved public health.

There are some limitations to this study. First, the study was conducted within the confines of NYC, but future research could consider expanding its scope by including a more diverse range of regions. This expansion could help reinforce the examination of spatial heterogeneity in natural factors. Second, there is a need to improve the accuracy of weather and air quality data. In this study, due to the relatively limited distribution of monitoring stations, finer-scale data were not fully utilized. Efforts should be made to enhance the data collection infrastructure and obtain more accurate data for future analyses. Third, the camera angle and the captured moment of the images may impact the integrity of visual quality measurement due to the constraints of available techniques. Fourth, it is difficult for urban planners to significantly improve the natural environmental conditions and to give practical urban design recommendations for the corresponding results. Fifth, streetscape perception has been extensively investigated, and the incorporation of that subjective method within the scope of built environment factors may be explored further. Lastly, future research can delve deeper and provide further interpretation by incorporating time-series data and methodologies. This will enable a more extensive understanding of the relationship between different factors and bike-sharing utilization.

CRediT authorship contribution statement

Wenjing Gong: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jin Rui:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration. **Tianyu Li:** Visualization, Validation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

Appendix A

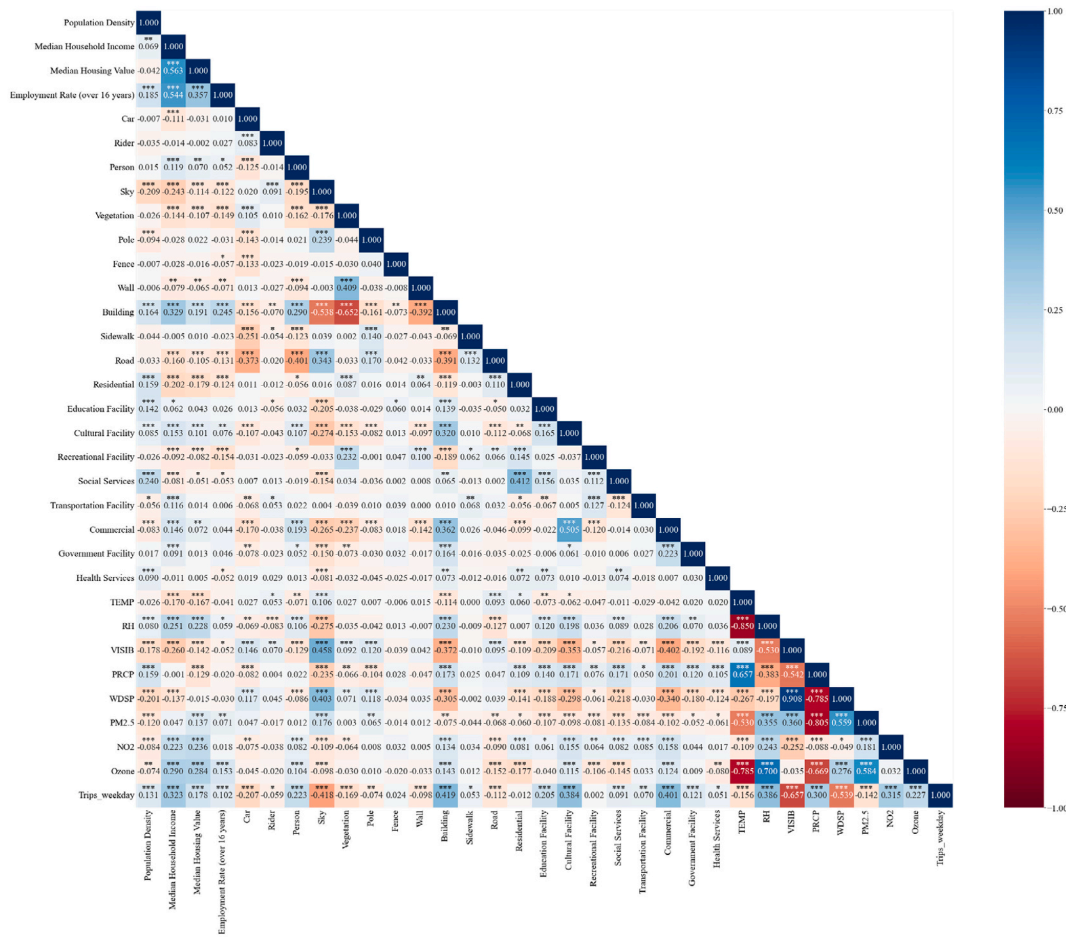

Fig. A1. Pearson correlation analysis of potential variables on weekdays

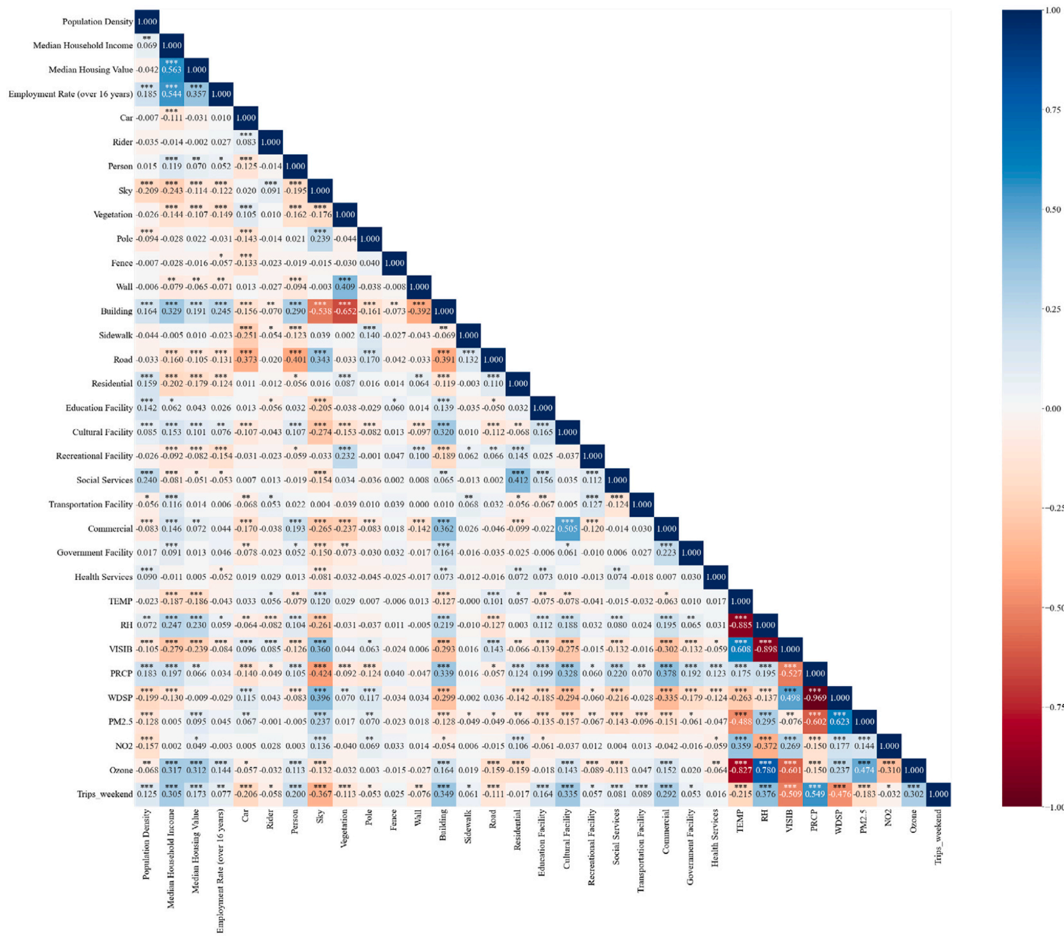

Fig. A2. Pearson correlation analysis of potential variables on weekends.

Table A1
Influencing factors' correlation and VIF values with dependent variables in the final models.

Category		Variables	Pearson Correlation Coefficients		VIF	
			Weekdays	Weekends	Weekdays	Weekends
		Population Density	0.131***	0.125***	1.256	1.262
Sociodemographic factors		Median Household Income	0.323***	0.305***	2.132	2.082
		Median Housing Value	0.178***	0.173***	1.581	1.575
		Employment Rate (over 16 years)	0.102***	0.077**	1.575	1.552
		Car	−0.207***	−0.206***	1.419	1.416
		Person	0.223***	0.200***	1.408	1.408
	Visual Quality factors	Sky	−0.418***	−0.367***	1.788	1.782
		Vegetation	−0.169***	−0.113***	1.256	1.258
		Pole	−0.074**	−0.053*	1.108	1.108
Built environment factors		Road	−0.112***	−0.111***	1.817	1.820
		Education Facility	0.205***	0.164***	1.153	1.151
		Cultural Facility	0.384***	0.335***	1.505	1.504
	Functional factors	Social Services	0.091***	0.081***	1.185	1.181
		Commercial	0.401***	0.292***	1.763	1.725
		Government Facility	0.121***	0.053*	1.092	1.089
		TEMP	−0.156***	−0.215***	3.119	4.409
		VISIB	−0.657***	−0.509***	2.078	2.285
Natural environment factors		PM2.5	−0.142***	−0.183***	2.416	2.119
		NO2	0.315***	−0.032*	1.401	1.502
		Ozone	0.227***	0.302***	3.895	4.475

Notes: *** indicates a significant correlation at level 0.001. ** indicates a significant correlation at level 0.01. * indicates a significant correlation at level 0.05.

Appendix B

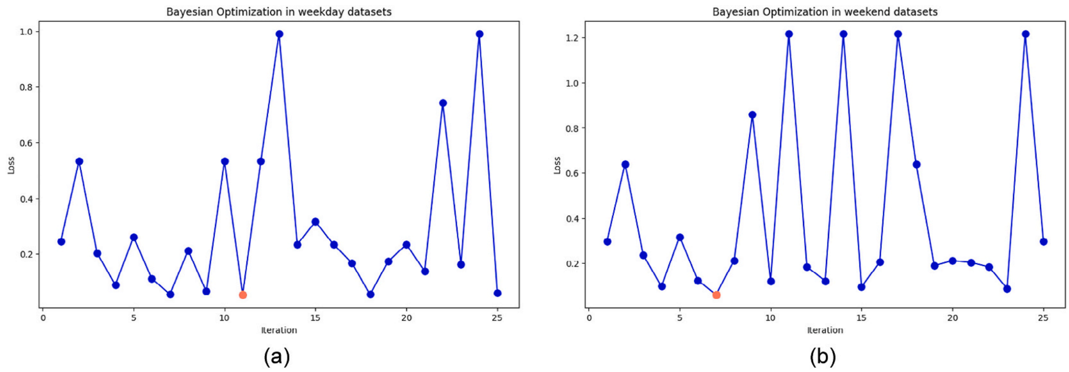

Fig. B1. Interactive process of Bayesian optimization on (a) weekdays and (b) weekends

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