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Prediction approach on pedestrian outdoor activity preference under factors of public open space integrated microclimate

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ABSTRACT

This study conducted measurements of microclimates and investigations of spatial environments and human activities in six typical waterfront public spaces in Shanghai. The aim was to explore the synergistic influence mechanism of public open space (POS) integrated microclimate (POSIM) on pedestrians' activities to predict the utilization of public space. The measurement period was during the spring and early summer when outdoor activities were more diversified. 121 observation points were set up in urban waterfront public spaces, and an outdoor activity characteristic database of 25,583 people was established. In addition, multiple linear regression and nonlinear neural network models were introduced to analyze data from different types of activities to calculate the fitness of the models and the influence weights of the variables. The results indicated that the neural network had stronger predictive ability for the spatial integration of microclimate demands of different activities. The prediction degree for strolling and sitting activities was the highest, with R^2 (goodness of fit) of 0.704 and 0.844, respectively, while the prediction degree for viewing and sports activities was lower ($R^2 < 0.5$). This study integrated the synergistic influence of urban waterfront public open spaces and microclimates factors on pedestrian outdoor activities to predict the preference patterns of different activities for spatial types. Focus on the requirements of space occupants, this study analyzed the public space environment from the bottom up and provided reference and inspiration for subsequent design optimization of urban waterfront areas.

1. Introduction

Microclimate is one of the key factors that affect the use of urban outdoor spaces, and people tend to choose comfortable microclimate environments for outdoor activities. A good urban out door environment can promote people to engage in fitness and social activities, thereby improving the utilization of space and enhancing the daily vitality [1,2].

With the rapid development of urbanization, waterfront areas have gradually evolved from the outskirts of cities to the vibrant centers of urban life. Moreover, as the quality of life of urban residents continues to improve, their demand for daily leisure activities and fitness venues is increasing. Urban waterfront public spaces have become one of the important places for residents to engage in a variety of outdoor activities due to their beautiful landscape, comfortable microclimate environments, and the combination of point and line spaces [3–6].

Previous research on space, activity, and microclimate has typically focused only on two of these factors, and has formed a relatively complete system. In contrast, research that integrates all three factors of microclimate, space, and activity is still relatively lacking. Generally, microclimate is influenced by the spatial environment and jointly affects outdoor pedestrian activity. In order to improve the utilization of outdoor space, synergistically optimizing microclimate and spatial factors is a more effective way, which will also help to improve the comfort of outdoor pedestrian activity.

Given the above, the motivation and objectives of this research are formulated as follows: (1) to identify the influencing factors of public open space integrated microclimate (POSIM) on pedestrians' preferences for different types of activities. (2) to explore the synergistic influence mechanism of POSIM on pedestrians' activities to predict the utilization of public space through compares different analytical models. (3) to compare the preferences of the different types of activities. This research contributes to a better understanding of the mechanisms of interaction between environment and pedestrians, thereby providing a scientific basis for the design and optimization of urban public open spaces targeting different types of activities.

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2. Literature review

2.1. Environmental behavior studies (EBS)

Environment-behavior studies (EBS) is a scientific field that investigates the interactive relationship between people and the surrounding spatial environment [7]. Early EBS research has encompassed a variety of disciplines, including environmental sociology, urban planning, architecture, and ergonomics [8]. Nowadays, it has expanded to disciplines such as public environmental health, economics, and educational research. With the continuous development of the discipline, EBS has also gradually begun to focus on the study of pro-environmental behavior, such as climate change, environmental protection, and energy conservation.

Previous research has shown that the factors of public space that affect outdoor activities include spatial forms, visual interface, green configuration, and service facilities [9–15]. With further research, researchers have discovered that microclimate is also an important factor in addition to the physical spatial form that affects activities, and have conducted related discussions. Jan Gehl was the first to study the relationship between outdoor microclimate, thermal comfort, and activity characteristics [1]. Claire Cooper Marcus et al. in "People Places" proposed that microclimate factors such as sunlight, temperature, and airflow velocity have a significant impact on the comfort of square users. Results showed that people's reactions to microclimate were unconscious, which led to differences in people's outdoor activity patterns [2]. However, most of the existing discussions based on environmental behavior studies are qualitative research. The theoretical model of environmental perception-activity proposed by Paul Bell et al. is a more comprehensive theoretical explanation of the interaction between environment and activity (Fig. 1). [16] It suggests that under objective physical environmental stimuli, people obtain environmental information through perception, awaken perception, and then affect their corresponding activities. Currently, the discussion of the relationship between microclimate and activity is to some extent based on this theoretical model.

2.2. Correlation between microclimate and activities

When exploring the influence of microclimate on human activities in urban thermal environment research, two indicator systems are commonly used.

The first system is a comprehensive thermal comfort indicator based mainly on the Predicted Mean Vote (PMV), Universal Thermal Climate Index (UTCI) and Physiological Equivalent Temperature (PET). In 1973, Fanger developed the PMV thermal comfort index based on indoor environmental parameters and energy balance models [17]. This index has been widely used to predict human behavior related to thermal conditions. With increasing concern for urban thermal environments, researchers have aimed to extend this thermal comfort concept to outdoor spaces. From 1998 to 2002, the European Union conducted the "Rediscovering the Urban Realm and Open Spaces" (RUROS) project. Field surveys revealed that while 81% of people considered certain urban environments as "comfortable", only 60% felt comfortable based on calculations using the PMV [18]. This indicates that the actual thermal comfort evaluation by the public in urban spaces does not align with the objective thermal indices predicted by the PMV. As a result, researchers have begun exploring the connection between actual thermal comfort conditions experienced by individuals and objective thermal comfort indicators, aiming to predict human behavioral patterns in spatial settings [19]. In follow-up research, researchers investigate and observe activity characteristics and the thermal adaptability of pedestrians under different microclimates, establishing relationships with comfort indicators. For instance, Lin proposed that in hot and humid climate zones, the PET and the number of square users in the cold season were positively correlated, while they were negatively correlated in the hot season [20].

The second system explores the influences of microclimate indicators such as humidity, temperature, airflow velocity, and radiation on human activities. Some research conclusions have shown that humidity has a relatively small impact on activities, but its influence increases significantly in hot and humid environments [21]. In addition, air temperature has a significant effect on occupant attendance and adaptation behavior in the space [22]. In addition, Yang et al. proposed that wind environments have a certain influence on leisure sports, sitting and rest activities in public open spaces (POS) [23], and many studies have extracted the average and maximum wind speed during a certain period as testing indicators. Solar radiation is also an important factor affecting the way people engage in activities. Providing shading facilities for public spaces is the best way to reduce solar radiation, and the shaded area can reduce up to 432 W/m^2 of solar radiation [24]. In the hot season, over 75% of users prefer to stay in shaded areas, and their stay time is longer than under sunlight [25], as summarized in Table 1. In addition, individual psychological and physiological differences among populations have an impact on their perception of microclimate, leading to various differences in gender [26,27], age [28], emotional state [29], and other aspects.

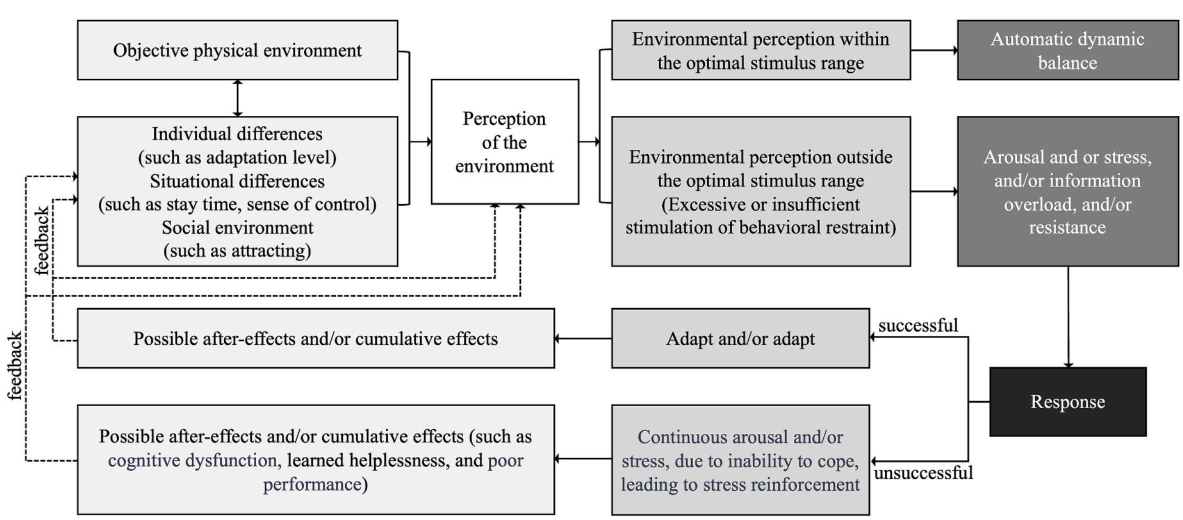


Fig. 1. The integrated model of environmental perception-behavior theories.

Table 1
Climate zones, seasons, indicators, activities, factors, and data collection methods in existing relevant studies.

Climate characteristics	Seasons	Sub-factors	Evaluation indicators	Activity types	Activity indicators	Data collection methods		Source
						Microclimate	Activity	
Subtropical oceanic climate (Taiwan, China)	Spring, Summer, Autumn, Winter	Air temperature, mean radiant temperature	–	Outdoor activity	Number of people	Field measurement	Taking photos every 10 min from a high place.	[20]
Subtropical maritime climate (Curitiba, Brazil)	Summer, Autumn, Winter	–	UTCI	Walking	Clothing parameters	Field measurement	Questionnaire survey	[30]
Temperate continental climate (New York, USA)	Spring, Summer	Solar radiation	–	Walking	Walking volume, street selection	Meteorological station	Video recording	[31]
Tropical Rainforest Climate (Malaysia)	Winter	Air temperature	–	Physical activity	Types	Field measurement	Observation, recording and interviewing	[32]
Temperate monsoon climate (Xi'an, China)	Summer	–	PET, URCI	Physical activity	Intensities	Field measurement	Physiological measurements and survey questionnaires	[33]
Subtropical monsoon climate (Nanning, China)	Summer	Air temperature, relative humidity, black globe temperature, wind speed	UTCI	Outdoor activity	Number of people, location of activities	Field measurement	Observation, recording	[34]
Mediterranean climate (Adelaide, Australia) Temperate oceanic climate (Melbourne, Sydney, Australia)	Summer, Autumn	–	UTCI, PET, OUT_SET	Outdoor activity	Activity proportion	Field measurement	Passive activity observation (PAO)	[35]

2.3. *Synergistic influence of POSIM on pedestrians*

Previous studies have gradually begun to explore the synergistic influence of POSIM on human behavior, in order to provide more comfortable activity spaces. For example, existing studies often emphasized the influence of service facilities on activities, such as the quantity and density of seats which can increase the number of people staying to some extent. However, considering the influence of microclimate, researchers proposed that the number of seat settings is less important than temperature and sunlight [42]. Besides, Teixeira proposed that although vegetation can reduce surface temperature and improve microclimate comfort, the number of green spaces and plants does not affect pedestrians' activities as much as the configuration pattern of vegetation [40]. Related studies are summarized in Table 2. Furthermore, with the evolution of technology, relative study has begun to explore the impact of POS factors on pedestrian activities through methods such as video encoding [45] and trajectory modeling [46]. However, there are spatial scale limitations.

Based on the literature review conducted in this study, it is found that research on the relationship between space, microclimate, and human activities has predominantly extended in two directions. Firstly, the objective thermal comfort indicators have gradually expanded to consider diverse thermal perceptions of different population groups, eventually encompassing their impact on human behavior. Secondly,

Table 2
Spatial elements, data acquisition methods, and conclusions in existing studies.

Space elements		Related conclusions	Data acquisition methods		Source
			Microclimate	Activities	
Space layout and interface	Functional distribution	Static activity areas should have ideal microclimate conditions, while dynamic activity areas and traffic areas can be in areas with poor microclimate conditions.	Field measurement	Photography and observational record	[36]
	Enclosure degree	Improving the enclosure degree of open spaces can prolong people's stay outdoors in dense urban environments.	Feature induction	Questionnaire survey and interview	[37]
	Underlying surface material	Different paving materials significantly influence the thermal comfort of pedestrians. In a hot climate, users can sense the outdoor temperature difference between 2 and 3 °C.	Field measurement	Observational record and questionnaire survey	[38]
		In hot seasons, people tend to prefer grassy surfaces as they provide better thermal comfort compared to asphalt pavement. Asphalt surfaces not only reduce thermal comfort but also impact visual comfort.	Field measurement	Questionnaire survey	[39]
Green landscape	Plant configuration	Plant configuration pattern, rather than the quantity of green areas and plants, affects human activities.	Field measurement	Questionnaire survey and observation record	[40]
	Multilayer greening system	The introduction of a multilayer greening system can reduce the average radiation temperature by 1°C–3°C, effectively increasing the time people spend outdoors.	Field measurement and digital simulation	Observation record	[41]
Service facilities	Recreational seating	The influence of air temperature and solar radiation on recreational activities is higher than the quantity of seating.	Field measurements and record of the distribution of sunny and shaded areas	Observational record	[42]
	Activity facilities	Under the same microclimate conditions, activity facilities can act as spatial attractors, causing abrupt changes in pedestrian walking speed at the individual level.	Field measurements	Video shooting, and computer vision technology analysis	[43]
	Shading facilities	Summer shading facilities can provide residents with more opportunities for interaction with the environment.	Field measurements	High-resolution photos taking at fixed angles	[44]

there is an extension of environmental behavior studies (EBS), which explores the combined mechanisms of spatial morphology and microclimate elements on human behavior.

However, there are still some limitations in current research. Firstly, many studies have focused on specific population groups and single types of behaviors. Secondly, quantitative research in this field is relatively limited, often relying on linear models for data analysis [22,45,47]. There is a lack of comparative analysis among models and exploration of complex relationships.

Considering all the aspects, this paper attempts to address these questions. To what extent can space and microclimate factors predict preferences in human behavior? What are their underlying mechanisms of influence? Are these relationships linear or nonlinear? What proportion does microclimate hold in this context? This research aims to broaden the scope and elements of Public Open Spaces (POS), establish a comprehensive profile of the public space utilization, and compare different analytical models. By doing so, it helps us better understand the potential influence of spatial and microclimate factors on preferences for pedestrians' selection of activity spaces. This research aims to achieve a "bottom-up" and "human-oriented" approach in the design of public spaces, providing support for enhancing and optimizing the vitality of public spaces in the future.

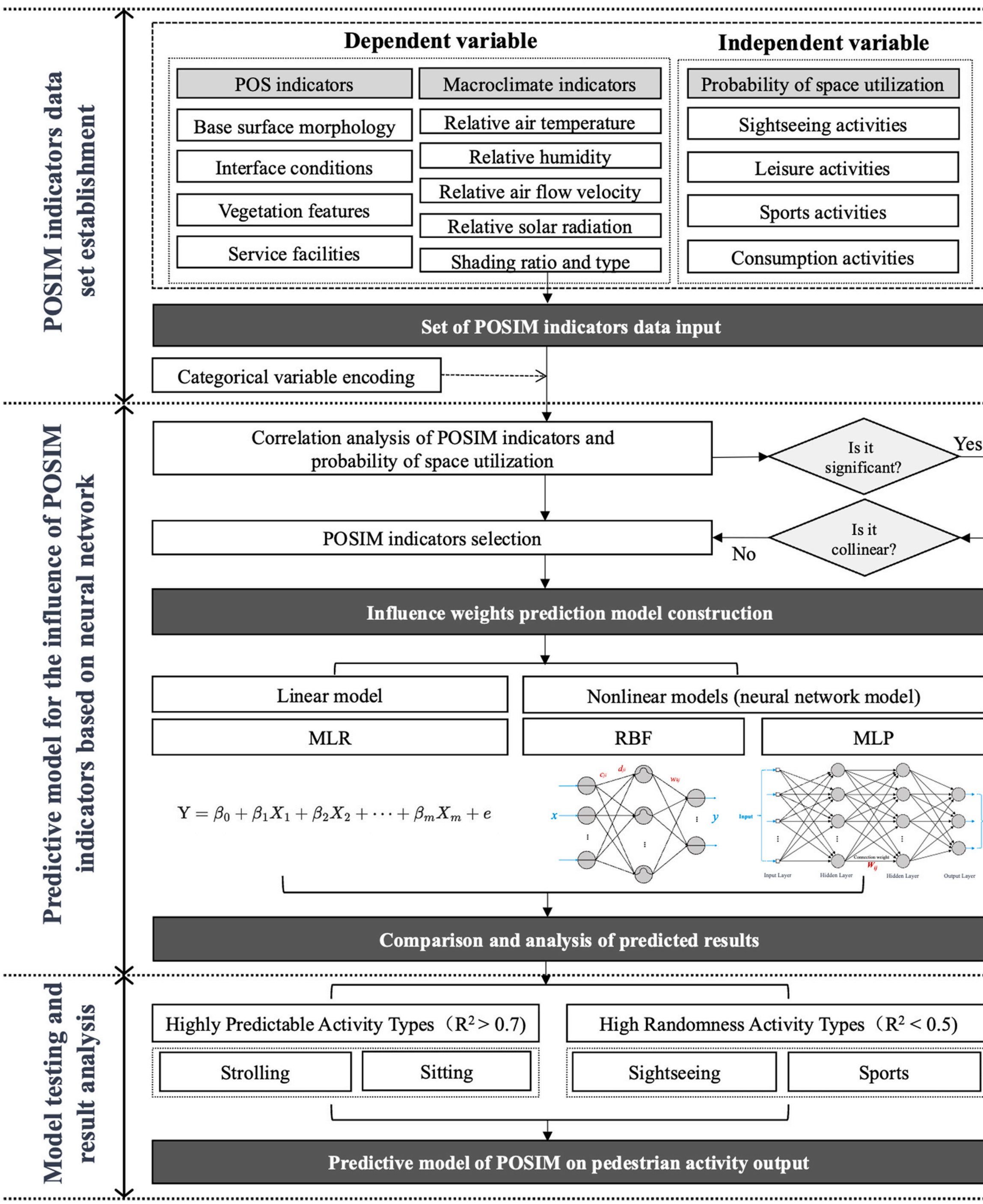


Fig. 2. The framework of the research workflow.

3. Methodology

For this study, six typical waterfront spaces located along the Huangpu River in Shanghai were selected as cases, and a one-year site investigation and measurement were conducted, which led to a microclimate and activity characteristic database. Multiple linear regression and multilayer perceptron (MLP) neural network were used for data analysis and prediction. Finally, the model with the highest explanatory was selected as the prediction result through the comparison of the fitting degree. The specific framework of the study is shown in Fig. 2.

3.1. Study area

Shanghai is in the subtropical monsoon climate zone with distinct seasonal differences. According to the Köppen climate classification system, Shanghai belongs to the subtropical monsoon climate (Cfa), with warm and humid summers, relatively cold and dry winters, and large temperature differences in spring and autumn. Meteorological data shows that the daily average temperature in Shanghai reaches its highest point in July (28.6 °C), and its lowest point in January (4.8 °C). The annual average relative humidity ranges from 71% to 79% (Fig. 3). [48].

3.2. Measurements

3.2.1. Public space selection and measurement points

Field trials were conducted on waterfront public space in Shanghai, China, which offers a variety of activities such as sightseeing, leisure, and commercial activities, making it significant for comprehensive analysis and comparison of activities. Additionally, it features diverse spatial forms, including linear and planar spaces. Compared to urban streets, waterfront public spaces provide pedestrians with independent flow lines free from vehicle interference. Furthermore, previous studies have indicated that urban blue spaces can effectively improve people's emotional well-being and promote physical activities [3–6]. Therefore, six testing fields were selected based on feasibility (Fig. 4).

3.2.2. Microclimate measurement

Based on the spatial characteristics of the tested area, the 6 survey sites were divided into 121 subspaces. Firstly, the study summarizes the material spatial characteristics of the site, including four aspects: basic surface morphology, green configuration, visual interfaces, and service facilities. Microclimate measurement are placed at the geometric center of each section, with instrument height at 1.5 m above the ground, and data recording conducted every 30 min. As shown in Table 3, the recorded indicators include shading ratio, shading type, air temperature, relative humidity, air flow velocity, and solar radiation.

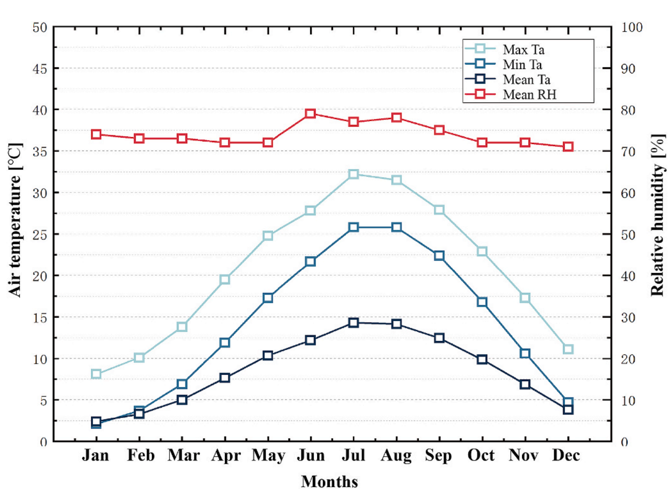


Fig. 3. Monthly mean/maximum/minimum Ta and mean RH in Shanghai.

3.2.3. Activity selection and measurements

In general, the purpose of pedestrian activity determines its requirements and preferences in a specific environment [25,43]. Activities in this study can be roughly divided into four major categories: sightseeing, recreation, sports, and consumption, which can be further divided into eleven sub-categories. The characteristics, duration, and metabolic rate of different activities are shown in Table 4.

The study employed a combination of manual observations and panoramic camera recordings. The utilization of panoramic camera recordings provided objective, detailed, and replicable data for subsequent analysis. The camera positions are illustrated in Fig. 4. During the recording process, the researchers ensured the capture of the pedestrians' locations, actions and postures, age characteristics, and durations of stay (Fig. 5). The time interval for behavior recording was set to 30 min, which was the same as the microclimate measurement. The testing period was divided into four stages: morning (8:00a.m.–11:00a.m.), noon (11:00a.m.–14:00p.m.), afternoon (14:00p.m.–17:00p.m.), and evening (17:00p.m.–20:00p.m.). To ensure the richness of the statistical result, the data recorded was overlapped and accumulated every 30 min to improve reliability.

The observations and measurements lasted for one year. The research included a total of 36 measurements across six sites. Within each season (transitional season, summer, and winter) and weather condition (clear days), two measurements were conducted, one on a weekday and the other on a weekend, to ensure the completeness and comprehensiveness of recording pedestrian activities. Spring and early Summer, during which there were more pedestrians and diverse types of activities, were selected as the main discussion seasons. The research and measurements were conducted between 8:00a.m. and 5:00p.m., which corresponded to the microclimate measurement (Fig. 6).

3.3. Statistic analysis

3.3.1. Independent variable

The independent variables of this research mainly include two aspects: public space factors and microclimate indicators.

Regarding the microclimate indicators, the study reduces errors caused by different measurement times, weather conditions, and operating habits by calculating the difference between the recorded values at different measurement points and the average values of all points in the site. This approach more clearly highlights the changes and differences in microclimate environments at different measurement points during the same period. Taking relative air temperature as an example, it can be calculated by Eq. (1).

$$\Delta T = T - \frac{1}{n}\sum_{i=1}^{n} T_i \tag{1}$$

Wherein, △T represents the relative air temperature during the survey period in the tested site, T represents the measured temperature in the space, and n represents the number of subspaces in the surveyed field.

The study summarized the POS factors that affect outdoor activities through literature review. The final selected independent variables and their corresponding value ranges in different aspects are shown in Table 5.

3.3.2. Dependent variable

Quantitative indicators for pedestrian activity in public spaces currently include pedestrian attendance and crowd density. However, in narrow areas such as waterfront public spaces, pedestrian attendance can vary significantly due to factors such as transportation accessibility and spatial function. To balance the influence of macro factors on the results, this study uses spatial probability of crowd distribution to measure the spatial selection of different activities, which can be

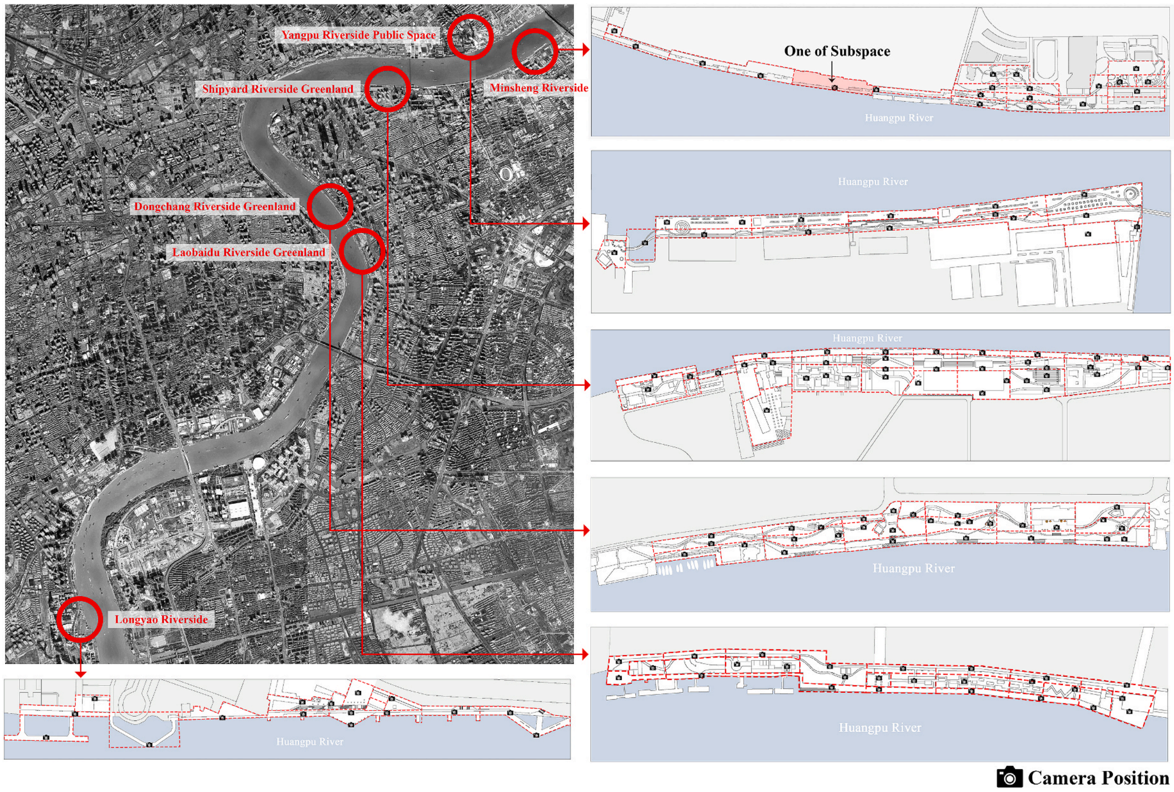


Fig. 4. Study fields location and fragmentation.

Table 3
Information of measuring instruments.

Instruments	Indicators	Range	Accuracy
Testo 410-2	Air temperature	−10~50 °C	±0.4 °C (+1 digit)
	Relative humidity	0~100%RH	±2.5% (+1 digit) (at 25 °C, 10%-90%RH) ±3% (for other ranges)
	Air flow velocity	0.1–20 m/s	± (2% of reading + 0.2 m/s)
TES-1333	Solar radiation	0~2000 W/m^2	±10 W/m^2

calculated by Eq. (2).

$$P = N_{Sub}/N_{Total} \times 100\% \quad (2)$$

Wherein, P represents the probability of the pedestrian of appearing in the subspace, N_{Sub} represents the number of pedestrians of a certain activity type at the subspace, and N_{Total} represents the total number of pedestrians performing the same kind of activity in the test field at the same time.

3.3.3. Analysis methods

This study utilizes both linear and nonlinear analysis models to calculate the influence weight of independent variables. The linear model employs multiple linear regression, while the nonlinear model uses neural network algorithms. Radial basis function (RBF) neural network and multilayer perceptron (MLP) are selected as the training models. Compared to other neural network algorithms, RBF has better computation and generalization ability together with the adaptability to new samples and high stability, while MLP has multiple layers of neurons that can abstract and learn different features of input data. Additionally, more neurons and hidden layers can be added during the model building process to expand complexity and depth, thereby further enhancing accuracy. It enables a better understanding of the decision-making workflow of the dataset. The topological structure and neuron of RBF and MLP are compared in Fig. 7.

Table 4
Behaviors, characteristics, duration, and metabolic rate of different activities.

Activity Type		Characteristics	Duration	Metabolic Rate
Sightseeing activities	Scenery viewing	Static	5min	1.5–2.5 met
	Photographing	Static	2min	1.5–2.5 met
Leisure activities	Strolling	Dynamic	_	2.5–3.5 met
	Standing and talking	Static	3min	1.5–2.5 met
	Sitting and resting	Static	15min	1.0 met
Sports activities	Fitness dancing in the square	Static	60min	3.2–4.5 met
	Exercising	Static	15min	2.5–10.0 met
	Jogging	Dynamic	_	6.0–10.0 met
	Playing	Static	30min	5.0–8.0 met
Consumption activities	Shopping (outdoor)	static	3min	1.5–2.5 met
	Dining (outdoor)	static	90min	1.0 met

4. Results

4.1. Survey and measurement results

4.1.1. Activity statistics results

The study collected activity data from 121 observation points in 6 survey sites, totaling 25,583 samples. The samples were in three age groups: elder group (>65) accounting for 25%, middle age group

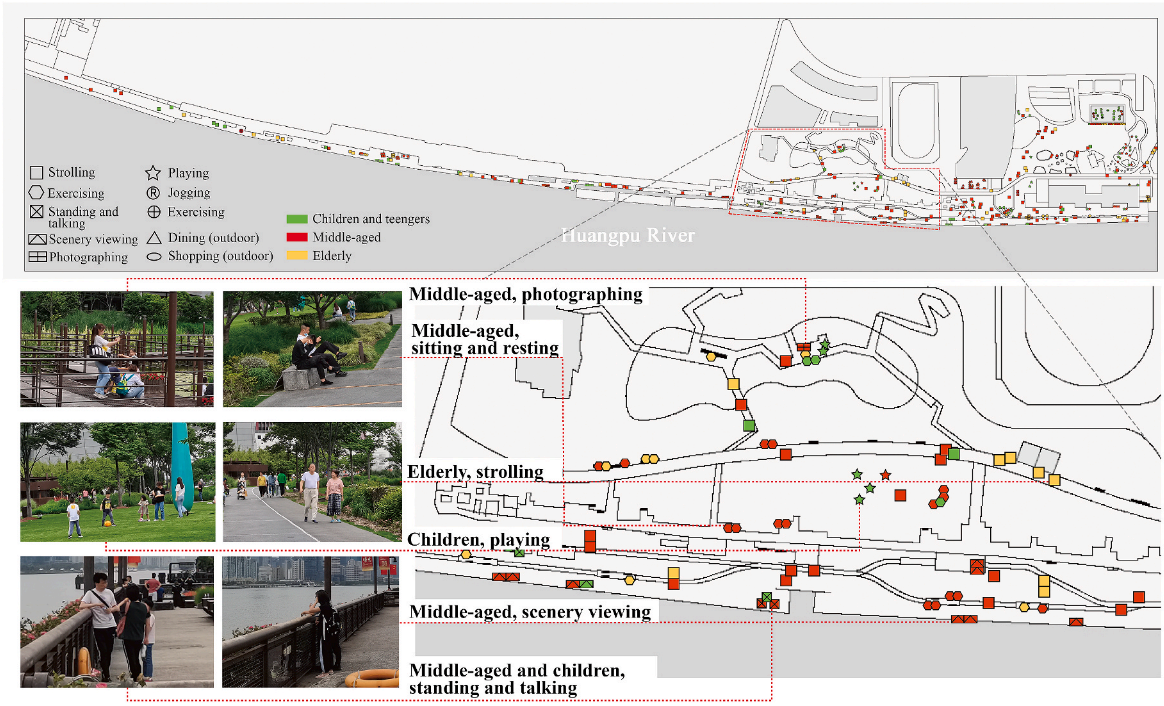


Fig. 5. Recording and identification of pedestrians' behavior (e.g., Yangpu Riverside Public Space).

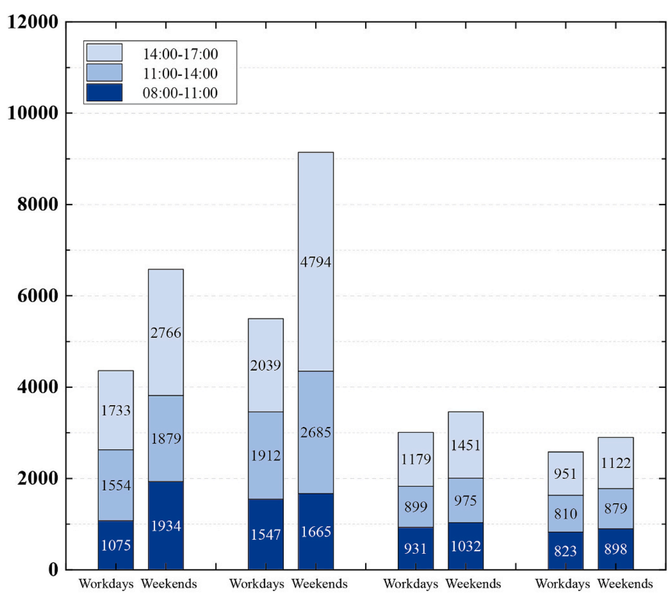


Fig. 6. Number of people in the field during different seasons in survey days.

(18–64) accounting for 57%, and young age group (5–17) accounting for 18% [49]. Through analysis of the activity data, it can be found that the distribution of pedestrian activities in waterfront public spaces has certain regularity both in time and space.

Firstly, within a day, the proportion of activity types in the site changes with time. As shown in Fig. 8, sports activities have a higher proportion in the morning period (8:00a.m.–11:00a.m.), while consumption, dining activities, are concentrated in the noon and afternoon periods (11:00a.m.–14:00p.m., 14:00p.m.–17:00p.m.). Moreover, with the change of time within a single day, the proportion of pedestrians' stay activities gradually increases from 49% in the morning to 52% in the noon, and finally rises to 55% in the afternoon. Stay activities have the highest proportion in the noon and afternoon of weekends, accounting for 58% and 57%, respectively, while the proportion of dining activities is higher during the same period on workdays, the proportion of stay activities only accounts for 44%, with more strolling activities, accounting for 55%. It is because the linear public space of the waterfront provides a nice strolling place for nearby working people to take a break, which makes the middle aged have the highest proportion (70%) in the same period.

4.1.2. Microclimate measurement results

According to the mean air temperature and relative humidity measured during different time periods at each investigated site within the survey dates, the diurnal temperature and humidity variations of each site were calculated, as shown in Fig. 9. It indicates that the temperature variation trend during a day is roughly the same across all sites, showing a rising and then falling trend with the peak appearing at noon, while the temperature varies due to different weather conditions such as cloudy states in the morning and afternoon. However, the variation of relative humidity shows an opposite trend, that is, the higher the temperature, the lower the relative humidity.

There is no significant regularity in the diurnal average airflow velocity variation, but there are places in each site during different periods of the day where is almost no wind (mean airflow velocity <0.2 m/s). In addition, Fig. 10 shows that the airflow velocity in spring has more outliers and higher volatility, and Fig. 11 shows that the variation trend of diurnal solar radiation is the same as that of air temperature, indicating a trend of first rising and then falling, with the noon period reach the peak (802 W/m^2). Moreover, the mean solar radiation in summer is slightly higher than that in spring.

4.2. Statistical analysis results

4.2.1. Correlation analysis

To ensure the accuracy and interpretability, we first screened the independent variables (POSIM indicators) of the statistical model to ensure there is a correlation and no significant collinearity with the dependent variable (pedestrian distribution probability). Due to many

Table 5
POS factors in different aspects, variable types, and value ranges.

Aspect	Factor	Abbr.	Variable type	Value range
Base surface morphology	Space form	SS	Categorical	1- trail, 2- square
	Total area	TA	Numeric	182.0 m^2–10698.5 m^2
	Active area	AA	Numeric	72.4 m^2–7172.3 m^2
	Distance from river	DR	Numeric	1.5 m–137.9 m (distance from the center points of the site to river)
	Base level	BL	Categorical	1- waterside space, 2- flood control standard space
Visual interface	Underlying surface material	UM	Categorical	1-masonry, 2-concrete, 3-wood, 4-colored asphalt, 5-metal
	Enclosure degree	ED	Categorical	1-none, 2-one side, 3-two sides, 4-three sides, 5-four sides
	Interface composition	IC	Categorical	1-river and vegetations, 2-water and buildings, 3-vegetations, 4-buildings and vegetations
	Interface tortuosity	IT	Numeric	1.0–1.9 (Curved shoreline length/shoreline length)
	Canopy closure	CC	Numeric	0~1 (vertical projected area of the shelter/active area)
	Proportion of river view	VVR	Numeric	0~1 (length of the interface where the river can be see/the total length of the interface)
	Number of visible landmarks	NVL	Numeric	0~3
Vegetation features	Community structure	CS	Categorical	1-none, 2-lawn, 3-shrub, 4-tree, 5-tree and grass, 6-tree, shrub and grass
	Plant disposition	PD	Categorical	1-none, 2-rows, 3-scatter, 4-cluster, 5-group
	Green coverage	GC	Numeric	0.00–0.89 (vertical projected area of green/total area)
Microclimate environment	Relative air temperature	ΔTa	Numeric	−1.41 °C–1.03 °C
	Relative humidity	ΔRH	Numeric	−11.3%–9.3%
	Relative air flow velocity	ΔVa	Numeric	−0.85 m/s~ 1.50 m/s
	Relative solar radiation	ΔSo-R	Numeric	−306.0 w/m^2~ 174.6 w/m^2
	Shading ratio	SR	Numeric	0~1 (shading area of active area/active area)
	Shading type	ST	Categorical	1-plants, 2-facilities, 3-buildings, 4-without shade, 5-cloudy
Service facilities	Vending machine	VM	Categorical	1-yes, 2-no
	Dining area	DA	Categorical	1-yes, 2-no
	Play equipment	PE	Categorical	1-yes, 2-no
	Landscape sculpture	LS	Categorical	1-yes, 2-no
	Shade canopy	SC	Categorical	1-yes, 2-no
	Building facility type	BFT	Categorical	1- closed, 2- none, 3- leisure station, 4- commercial, 5- sports, 6- catering, 7- cultural
	Park bench	PB	Categorical	1-yes, 2-no
	Number of park bench	NPB	Numeric	0~22
	Length of park bench	LPB	Numeric	0.0 m–100.5 m
	Informal seat	IS	Categorical	1-yes, 2-no

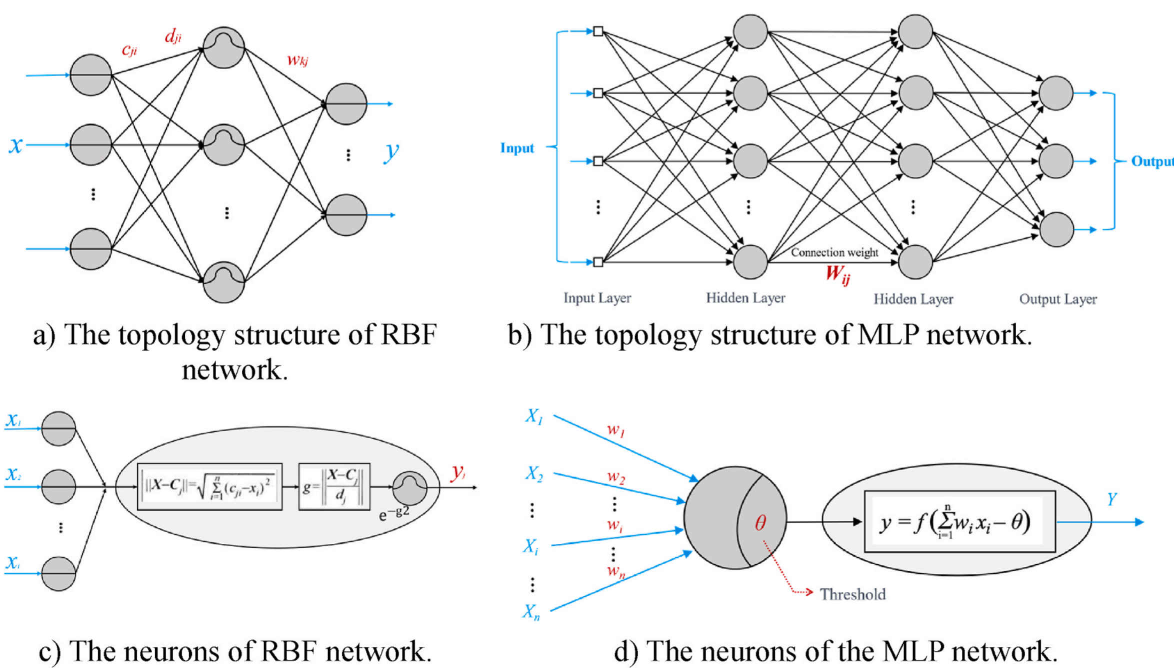


Fig. 7. Comparison of the topology and neurons between RBF and MLP.

POS factors are categorical, the research employed binary data encoding and transformation, with one category chosen as the reference category and the remaining categories converted into indicator variables. This approach allowed the inclusion of categorical variables alongside other continuous variables in subsequent data analysis. The results of the correlation analysis are shown in Fig. 12. We selected the factors that were significantly correlated with the dependent variable and included them in both the multiple linear regression and neural network models.

4.2.2. *Comparison of different analysis models*

Linear and nonlinear models are introduced to analyze the impact of POSIM indicators on different pedestrian activity distributions. The

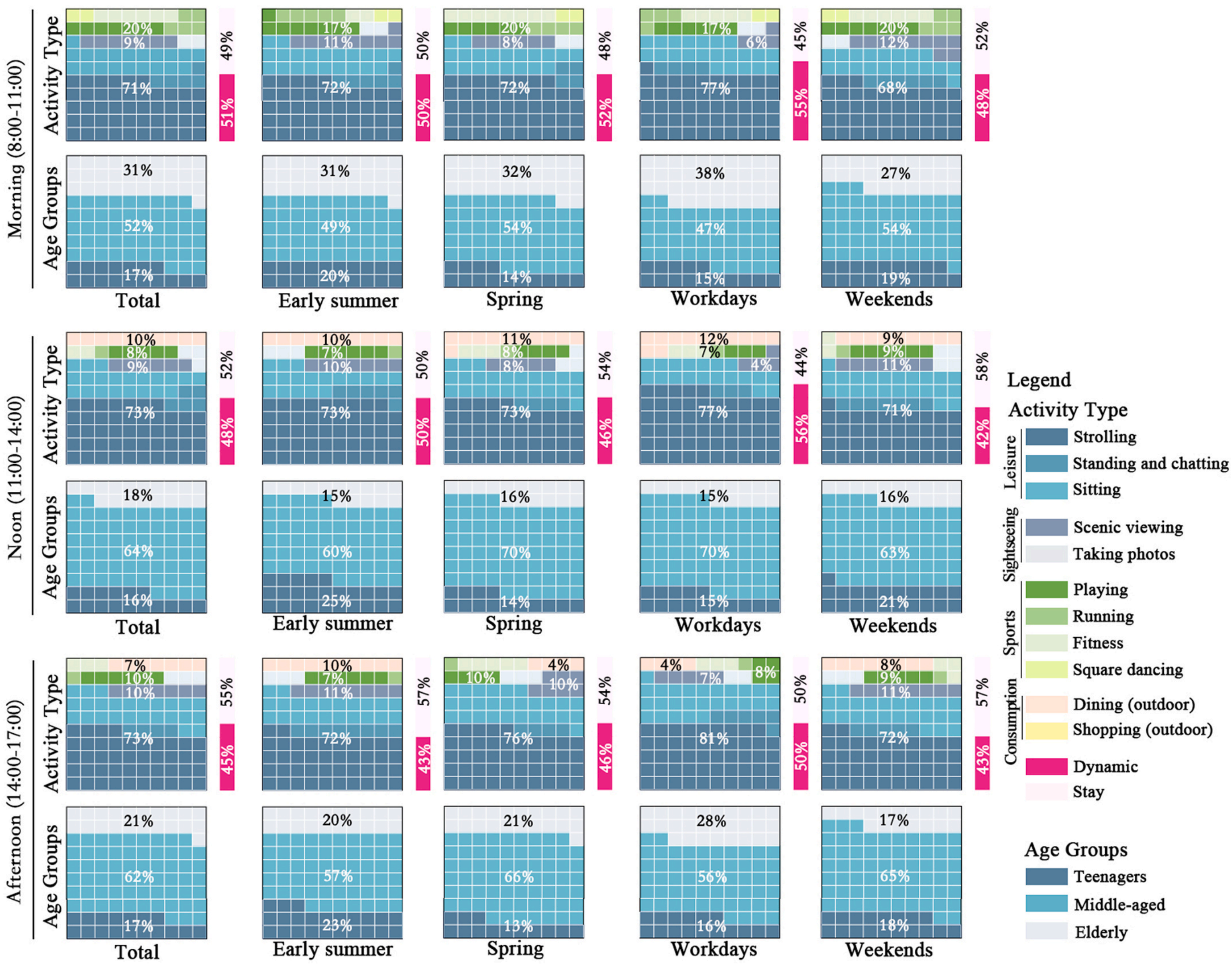


Fig. 8. Activity composition in survey fields.

linear model selected was multiple linear regression analysis (MLR), while the non-linear models included radial basis function (RBF) neural network and multi-layer perceptron (MLP) neural network. This research evaluates the predictive ability of the model using relative error and goodness of fit. Relative error refers to a measure of the discrepancy between predicted values and the true values, expressed as a ratio or percentage. It is used to assess the performance and accuracy of a model. A smaller relative error indicates that the predicted results are closer to the true values, indicating higher model accuracy. Goodness of fit reflects the degree of explanation that the predicted values provide for the actual values. A higher goodness of fit signifies a better predictive capability of the model. Fig. 13 shows the performance of different models in analyzing the results. Among them, the MLP neural network had the highest prediction accuracy for the pedestrian distribution probability, and the prediction accuracy of the RBF neural network was mostly lower than that of the MLR. Compared with the linear model, the MLP neural network showed the highest improvement in the prediction of sedentary activities with $R^2 = 0.331$.

Furthermore, modifying the training sample proportion of the nonlinear models can optimize the reliability of the prediction results to a certain extent. Table 6 shows the comparison of R^2 under different training sample proportions. It is known that MLP neural network is used in this study to predict both strolling and sitting activities with $R^2 > 0.7$, and the sitting activities has a higher prediction accuracy of 0.844. However, the prediction accuracy for sightseeing and sports activities is relatively limited ($R^2 < 0.5$), indicating a strong randomness in the distribution of these activities. Nonetheless, sightseeing and sports activities accounted for only a small fraction (<32%) of all surveyed activities. Finally, based on the survey results and the prediction results of different activity types, the overall prediction accuracy of each survey site is calculated and showed in Fig. 14. The prediction accuracy of all six survey sites can reach above 60%, indicating that MLP neural network can achieve good accuracy for outdoor activities prediction.

4.2.3. *Analysis of prediction results*

The influential weights of factors predicted by MLP neural network were analyzed for different activity types, as shown in Fig. 15. The weight of service facilities factor was the highest (5%–57%), while microclimate factor accounted for 3%–29% of the total. Based on the predictability, this study classified the activities into two categories: predictable activities ($R^2 \geq 0.6$) and random activities ($R^2 < 0.6$), and their respective characteristics were explained below.

4.3. *Analysis of predictable activity*

Currently, activities with a predictability greater than 0.6 are mainly composed of three types: strolling, sitting and dining. Among them, dining activities are largely determined by the distribution of catering

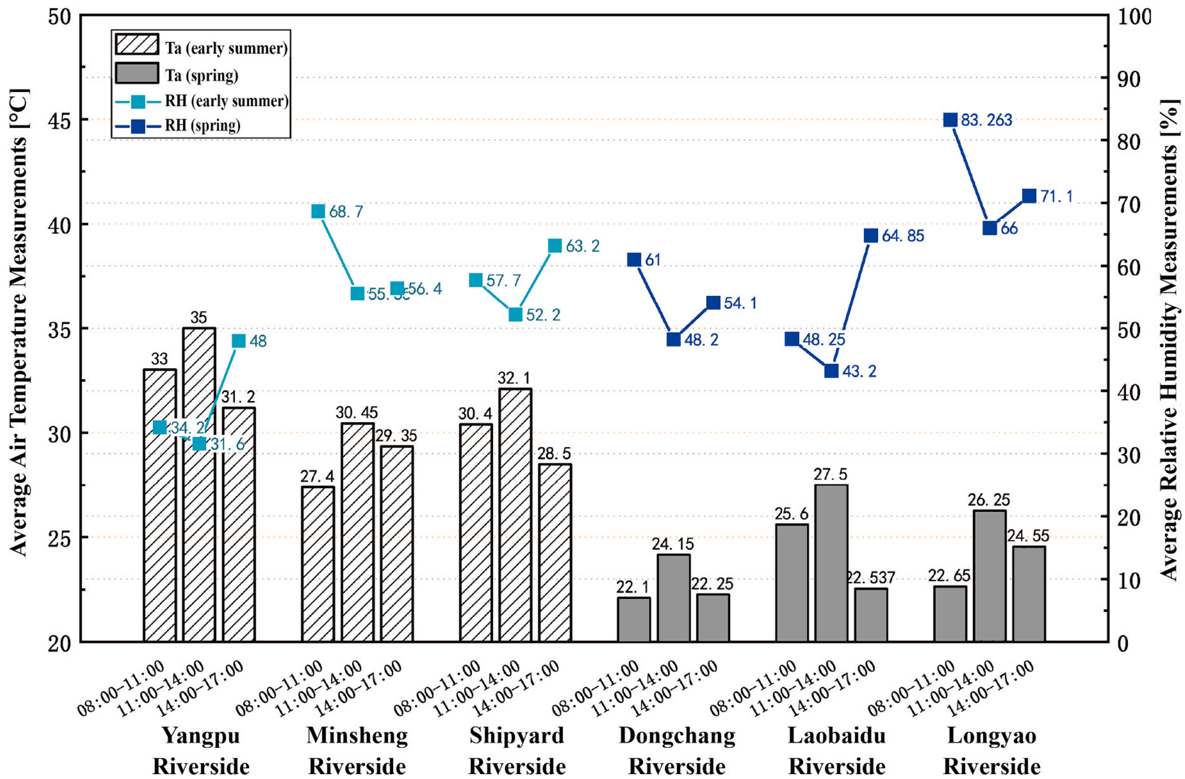


Fig. 9. The diurnal variation of air temperature and relative humidity.

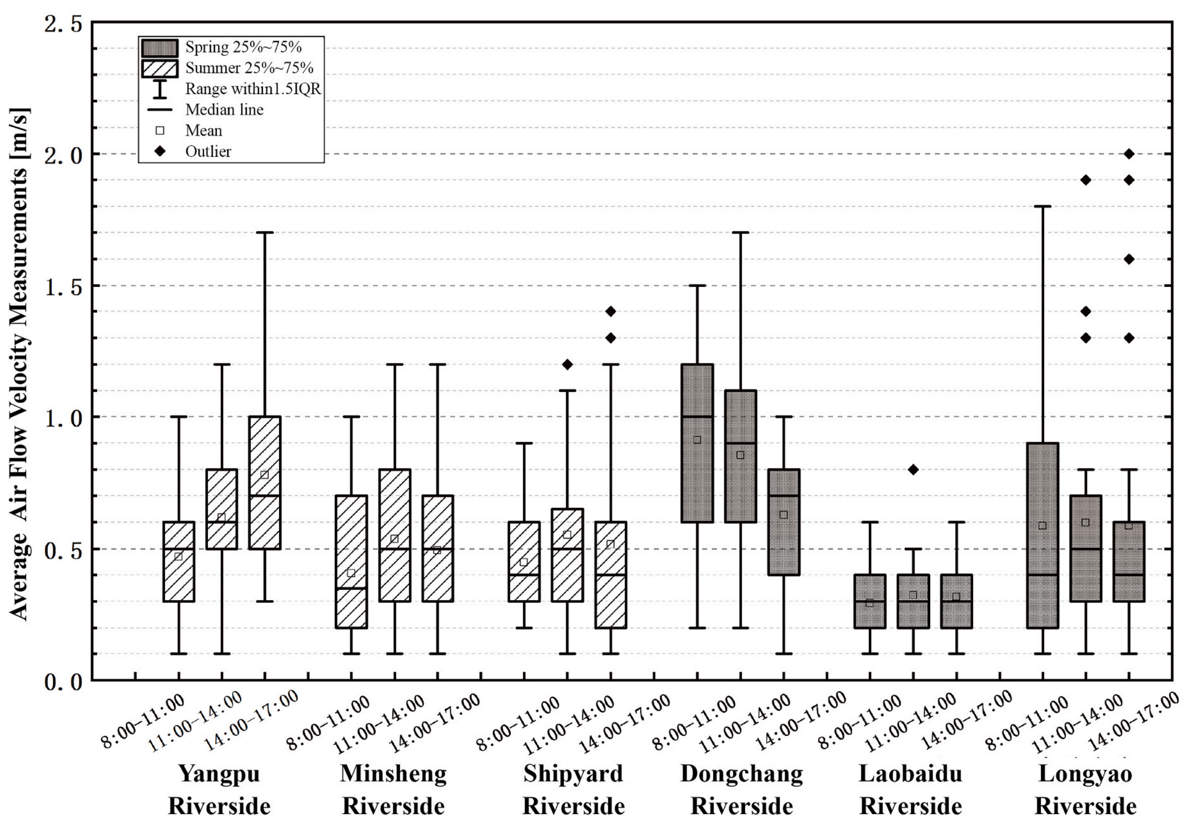


Fig. 10. The diurnal variation of air flow velocity.

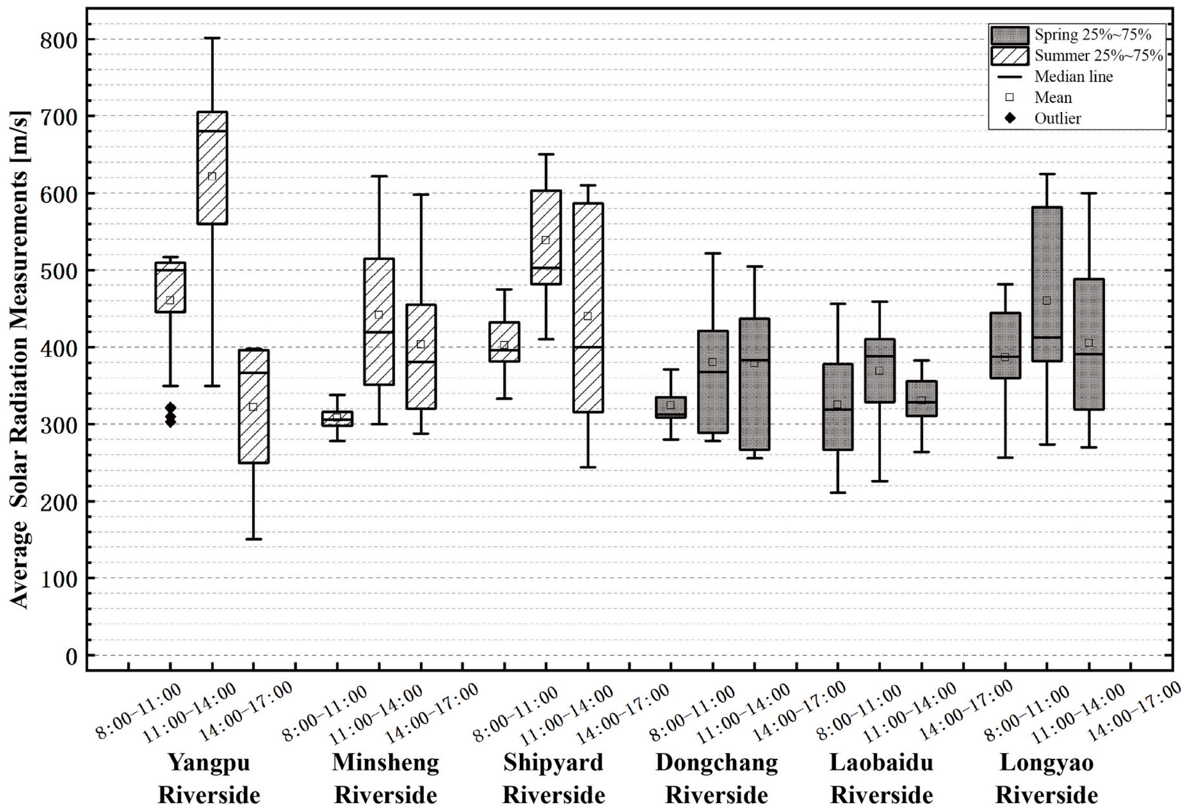


Fig. 11. The diurnal variation of solar radiation.

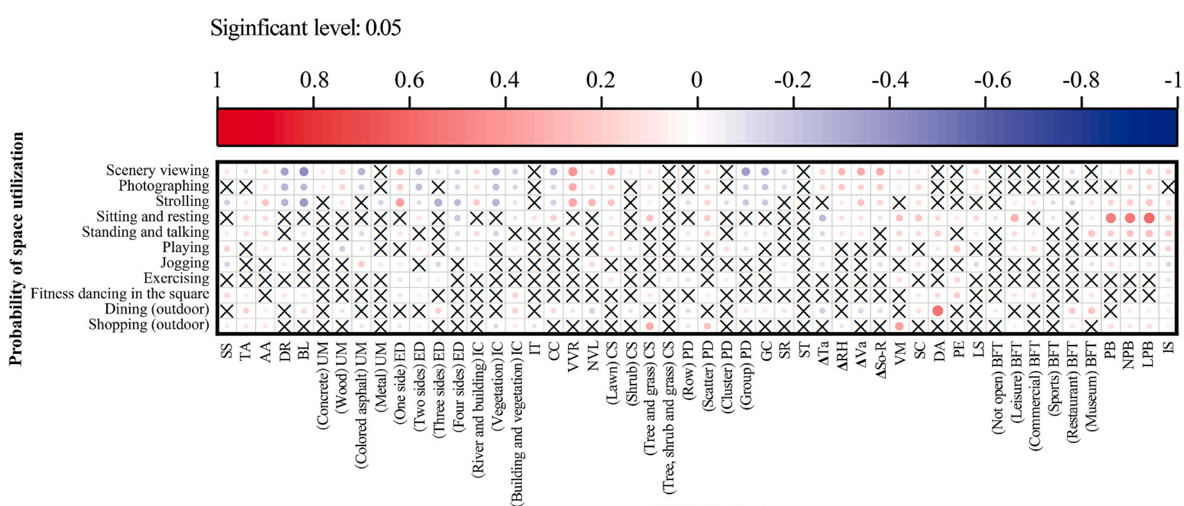


Fig. 12. The result of correlation analysis.

facilities on the site, and share similar characteristics with sitting activities, both of which are dominated by microclimate and service facility configuration. Therefore, sitting activities are taken as representative examples to summarize their features.

4.3.1. *Strolling activities*

Regarding the distribution of strolling activities, the prediction model with a training sample of 90% was used, and the residual and linear fitting results are shown in Fig. 16 (a) and 16 (b). It shows that the majority of residuals are distributed within an absolute value of 5, with an R^2 of 0.704. As strolling activities belong to dynamic activities, their perception of environment is more comprehensive, and the weights of independent variables are relatively evenly distributed. The linear space of waterfront public space provides a coherent viewing experience; thus, the influence weight of visual interface is the highest (0.267), followed by service facilities (0.255). Strolling prefer spatial places with strong water affinity, low enclosure degree, and high river viewing ratio. The influence of microclimate is the lowest, only 0.12, and the relative humidity accounts for the largest proportion. However, according to related studies, pedestrian perception of humidity is small in high temperature and high humidity conditions [21], and people are more influenced by spatial factors during strolling, as shown in Fig. 17.

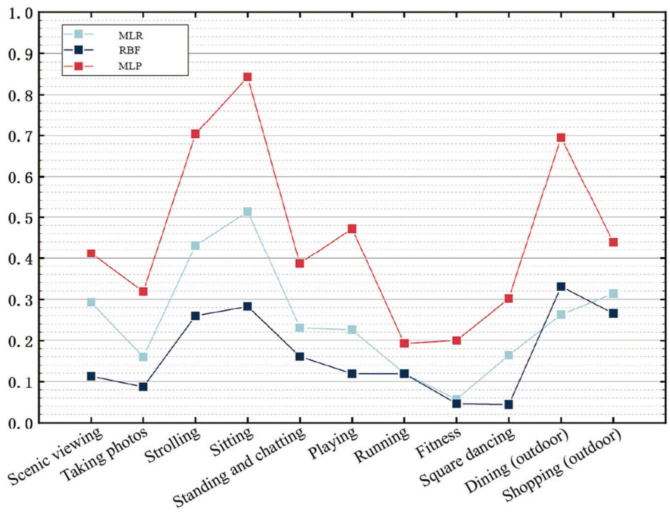


Fig. 13. Model prediction performance (R^2) comparison.

4.3.2. Sitting activities

Besides, the prediction model for sitting activities was trained using 90% of the samples, and the residual and linear fitting results are shown in Fig. 16 (c) and 16 (d). The majority of residuals are distributed within an absolute value of 10, and the R^2 value is 0.844, indicating a nice fit.

For sitting activities, besides providing basic facilities such as park benches, the microclimate environment has a significant influence with a weight of 0.172, where relative temperature and solar radiation both have negative effects. Compared to other activities, different types of shading facilities (e.g., plant shading and landscape shading) have a certain influence on the distribution of sitting activities. Moreover, sitting activities have significantly different requirements for base surface morphology and visual interface compared to other activities. Firstly, in terms of base surface morphology, there is no significant correlation between DR, BL, VVR, NVL, and the distribution of sitting activities. Secondly, in terms of visual interface, sitting activities tend to occur in spaces that are enclosed on two sides and have a high degree of CC. This is partly because spaces with high ED provide stable shading and cooling places for sitting and resting activities. In addition, regarding building types, post stations and cultural buildings are more conducive to the distribution of sitting and resting activities among the pedestrian.

In addition, service facilities and microclimate are two key factors that dominate sitting activities. In public spaces where the microclimate is suitable, providing sufficient park benches will make people more willing to stay and rest. Furthermore, compared to other activity types, sitting, talking, and dining activities all belong to stay activities in the space and have a longer duration with a low metabolic rate. This also determines to some extent the sensitivity of the microclimate. Moreover, their requirements for microclimate are also significantly different from dynamic activities. For example, strolling prefer sites with high Δ So-R, and low ED, while sitting and resting activities prefer sites with shade and cooling, large ΔV_a, high ED, and low Δ So-R.

4.4. Analysis of random activity

4.4.1. Sightseeing activities

According to the comparison results of the prediction models, MLP (80% training samples) and MLP (90% training samples) were finally selected as the prediction models for sightseeing activities and photography activities, respectively. Most residuals are distributed within an absolute value of 20, and the model fitting R^2 are 0.412 and 0.319, respectively, indicating limited predictability. This indicates that in waterfront public spaces, the randomness of pedestrian's sightseeing activities is high, and both linear and nonlinear models are hard to accurately predict.

However, for the scenery viewing, VVR is the most important factor in both linear and non-linear prediction models, indicating that an unobstructed water view can provide sufficient reason for people to gather. In contrast, the photography activity is more sensitive to microclimate, which may be attributed to their need for adequate daylight. Similarly, the increase of CC, ED, GC, and SR will significantly reduce the openness of the view, thereby having a negative impact on both scenery viewing and photography. In addition, compared to photography, scenery viewing activities are also affected by the SS and TA, indicating that the arrangement of the planar node space in the linear waterfront area can expand the view of pedestrians, so as to enhance the spatial perception and exploration desire of the pedestrians, and thus increase the distribution probability of sightseeing activities.

4.4.2. Sport activities

According to the comparison results of the predictive models, the study ultimately chose a MLP (with 80% training samples) as the predictive model for the distribution of playing, jogging, and exercising activities, and MLP (with 70% training samples) as the predictive model of square-dancing activities. The fit of these models is all less than 0.5, indicating that although nonlinear models perform better in predicting sport activities to some extent, however, the predictability is still not enough, especially for jogging activities only with a fit of 0.193.

The high random distribution of sports activities is mainly due to the high-intensity breathing and posture of the crowd, which occupies more attention of the exerciser and reduces their perception ability of the surrounding environment. Besides, when people engage in sports activities, they usually enter a state of "flow" [50], which is an immersive state in the high-intensity exercise itself, and thus the response to external stimulus is relatively weakened, resulting in a decrease in perception of the surrounding spatial environment.

5. Disscussion

5.1. Intervention in the time dimension

In existing literature, factors related to the time dimension are usually discussed as control variables in pedestrian activities studies. However, the findings of this study indicate that although the change of the time of day will affect the total number of pedestrians in the entire site, it will not change the proportion of people in a specific space, that is, it will not affect the selection preference. Based on this, although we collected data during different time periods and on holidays, we can merge them together for final analysis and prediction.

Furthermore, after one year of investigation, the study found significant seasonal variations in space utilization. During the summer, nighttime is the primary period for outdoor activities, and the illumination levels have the most noticeable impact on pedestrians' environmental perception. In contrast, during the winter, although the majority of the population congregates during the daytime, over 80% of individuals pass through the space in a transit manner, with very few instances of stay activities. Generally, the duration of stay by pedestrians significantly influences the vitality and quality of the space. Therefore, waterfront public spaces tend to have lower vitality during winter.

5.2. Influence of age groups

Existing research has indicated significant differences in thermal comfort levels, thermal perception, acceptable thermal range, and thermal preferences based on gender [26], culture [51–53], and age [27, 28]. However, people in public spaces usually travel in groups, so this study selected age groups with significant differences in activity requirements to predict preferences. As shown in Fig. 18, like the prediction of activity types, the MLP neural network still performs the best,

Table 6
Comparison of errors and training sample proportions among different analysis models.

Activity type	Analysis model type	Sample proportion		Relative error		R^2
		Training	Validation	Training	Validation	
Scenery viewing	MLR	–	–	–	–	0.293
	RBF	70%	30%	0.888	0.891	0.111
		80%	20%	0.904	0.801	0.113
		90%	10%	0.905	0.951	0.090
	MLP	70%	30%	0.690	0.709	0.305
		80%	20%	0.613	0.484	0.412
		90%	10%	0.659	0.580	0.350
Photographing	MLR	–	–	–	–	0.160
	RBF	70%	30%	0.914	0.926	0.072
		80%	20%	0.923	0.895	0.087
		90%	10%	0.919	0.951	0.074
	MLP	70%	30%	0.864	0.887	0.132
		80%	20%	0.827	0.823	0.179
		90%	10%	0.688	0.597	0.319
Strolling	MLR	–	–	–	–	0.431
	RBF	70%	30%	0.707	0.796	0.260
		80%	20%	0.786	0.791	0.213
		90%	10%	0.750	0.703	0.260
	MLP	70%	30%	0.319	0.425	0.657
		80%	20%	0.361	0.435	0.630
		90%	10%	0.286	0.386	0.703
Sitting and resting	MLR	–	–	–	–	0.513
	RBF	70%	30%	0.717	0.721	0.283
		80%	20%	0.781	0.817	0.215
		90%	10%	0.745	0.885	0.250
	MLP	70%	30%	0.160	0.250	0.811
		80%	20%	0.225	0.219	0.779
		90%	10%	0.160	0.134	0.844
Standing and talking	MLR	–	–	–	–	0.231
	RBF	70%	30%	0.884	0.900	0.112
		80%	20%	0.893	0.892	0.108
		90%	10%	0.860	0.646	0.161
	MLP	70%	30%	0.568	0.885	0.320
		80%	20%	0.800	0.811	0.216
		90%	10%	0.617	0.569	0.387
Playing	MLR	–	–	–	–	0.226
	RBF	70%	30%	0.899	0.843	0.119
		80%	20%	0.893	0.885	0.110
		90%	10%	0.906	0.881	0.096
	MLP	70%	30%	0.772	0.825	0.217
		80%	20%	0.507	0.588	0.472
		90%	10%	0.898	0.770	0.127
Jogging	MLR	–	–	–	–	0.120
	RBF	70%	30%	0.897	0.968	0.085
		80%	20%	0.907	0.909	0.093
		90%	10%	0.949	0.876	0.119
	MLP	70%	30%	0.926	0.976	0.076
		80%	20%	0.800	0.838	0.193
		90%	10%	0.872	0.824	0.133
Exercising	MLR	–	–	–	–	0.057
	RBF	70%	30%	0.962	0.949	0.046
		80%	20%	0.989	0.979	0.014
		90%	10%	0.998	0.959	0.037
	MLP	70%	30%	0.873	0.963	0.097
		80%	20%	0.817	0.734	0.200
		90%	10%	0.918	0.929	0.081
Fitness dancing in the square	MLR	–	–	–	–	0.164
	RBF	70%	30%	0.961	0.946	0.044
		80%	20%	0.968	0.979	0.031
		90%	10%	0.977	0.953	0.031
	MLP	70%	30%	0.695	0.714	0.302
		80%	20%	0.918	0.900	0.101
		90%	10%	0.848	0.686	0.195

(continued on next page)

Table 6 (*continued*)

Activity type	Analysis model type	Sample proportion		Relative error		R^2
		Training	Validation	Training	Validation	
Dining (outdoor)	MLR	–	–	–	–	0.263
	RBF	70%	30%	0.802	0.869	0.176
		80%	20%	0.813	0.753	0.199
		90%	10%	0.680	0.583	0.331
	MLP	70%	30%	0.554	0.719	0.413
		80%	20%	0.512	0.792	0.450
		90%	10%	0.304	0.315	0.695
Shopping (outdoor)	MLR	–	–	–	–	0.314
	RBF	70%	30%	0.772	0.805	0.227
		80%	20%	0.719	0.987	0.266
		90%	10%	0.967	0.927	0.071
	MLP	70%	30%	0.843	0.827	0.170
		80%	20%	0.586	0.510	0.433
		90%	10%	0.561	0.560	0.439

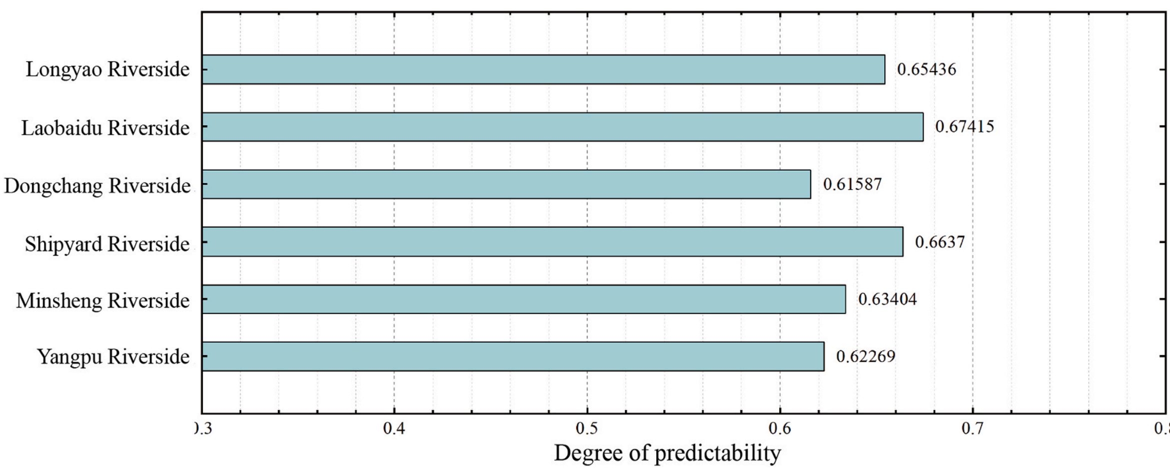


Fig. 14. Comparison of prediction performance (R^2) for different sites.

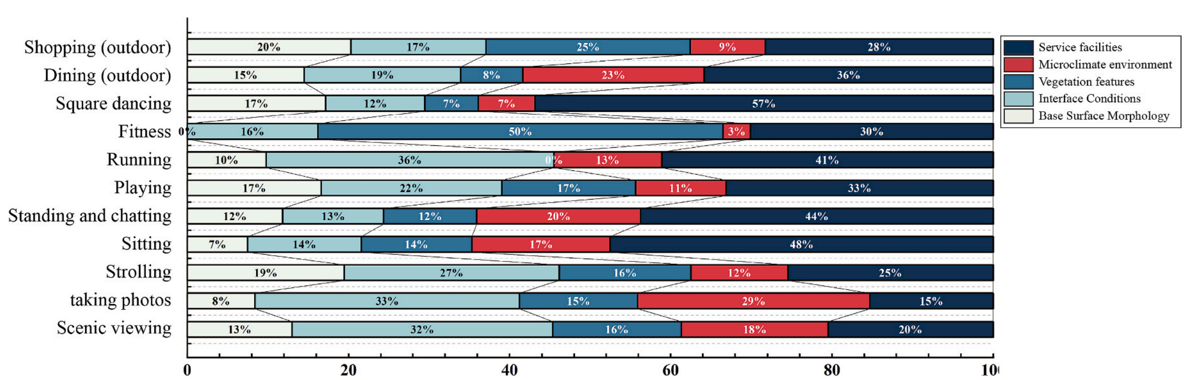


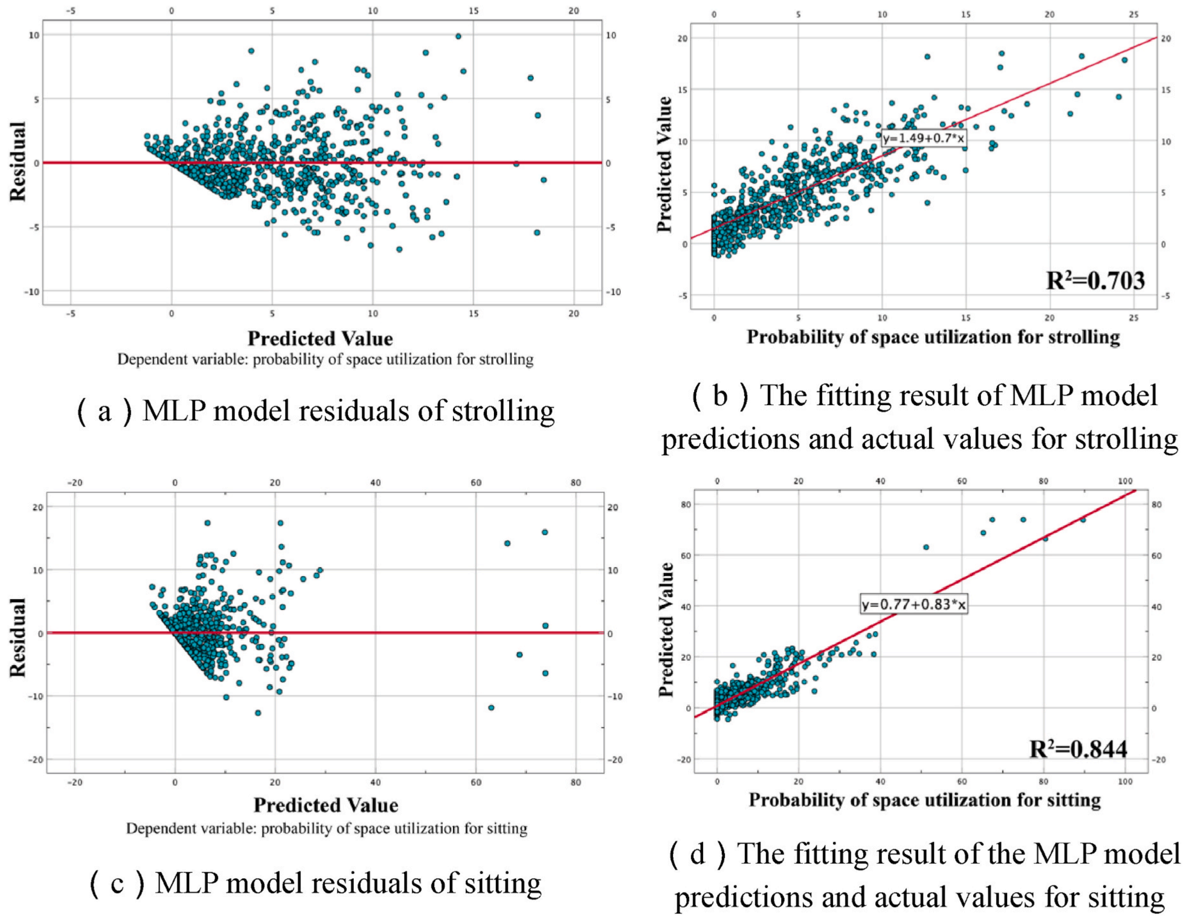
Fig. 15. Weights comparison of POSIM indicators on different types of activities.

especially in predicting the distribution of middle-aged pedestrians' activities. Fig. 19 reveals that most POSIM preferences across age groups did not exhibit significant differences (weight ≤0.05). The only notable difference was the variation in the influence weights of service facilities on the elderly and the youth (0.06), indicating a higher dependency of the elderly on service facilities.

Additionally, previous studies have shown that tourists' activity are often not affected by outdoor environments [54], which is similar to the high randomness of sightseeing activities found in this study. Generally, pedestrians for sightseeing purposes usually have a stronger tolerance to the thermal environment but have higher requirements for the quality of the landscape, which can also be attributed to differences in the purposes of their activities [55].

5.3. *Necessity of nonlinear analysis models*

Currently, the influence of spatial and physical environmental factors on human activity is mainly focused on indoor environment of multiple building types such as residential buildings [27,56], offices [57, 58]and schools [59–61], in order to accurately predict occupant



(a) MLP model residuals of strolling

(b) The fitting result of MLP model predictions and actual values for strolling

(c) MLP model residuals of sitting

(d) The fitting result of the MLP model predictions and actual values for sitting

Fig. 16. MLP prediction model residuals and fitting results for strolling and sitting activities.

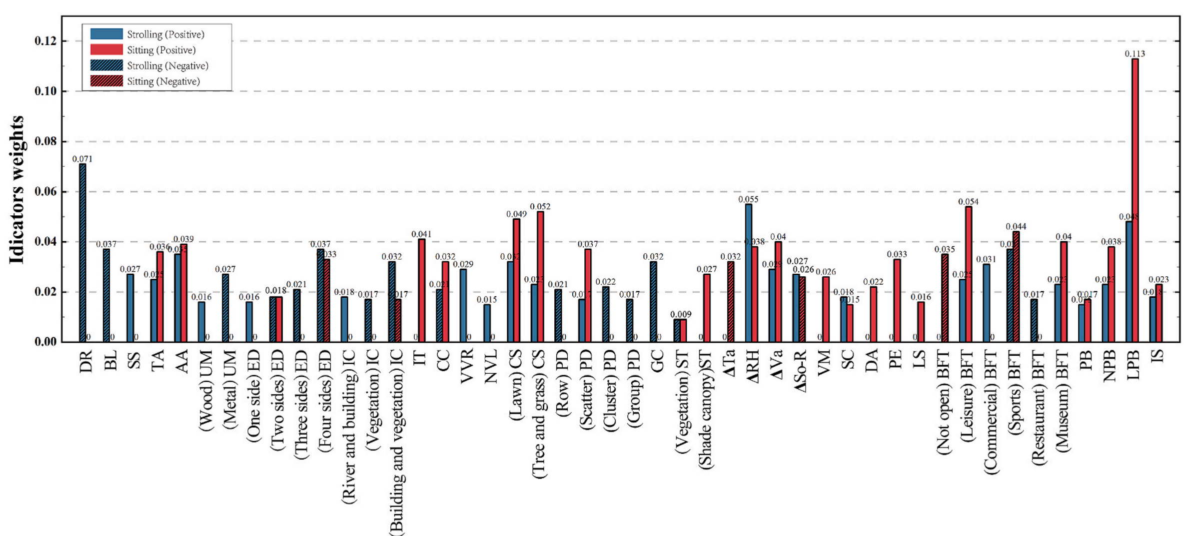


Fig. 17. Weights of POSIM indicators for strolling and sitting.

comfort, behavior patterns, and energy consumption. There are relatively few studies on outdoor POSIM and pedestrian activity, which may be due to the following reasons. First, the activities of pedestrians in outdoor public open spaces are diverse and complex, and many activities have no purpose, requiring a large amount of experimental data to support the reliability of the results. Second, human activity in outdoor public spaces is often influenced by multiple factors (spatial form, greening, facilities, thermal comfort, noise level, visual comfort, etc.) simultaneously to form a typical complex system, which requires multi-factor collaborative evaluation to better describe the characteristics of association mechanism.

In addition, based on previous studies, the goodness of fit (R^2) of linear models has shown limited performance. Li et al.'s related research demonstrated that in summer and winter, there was a good linear

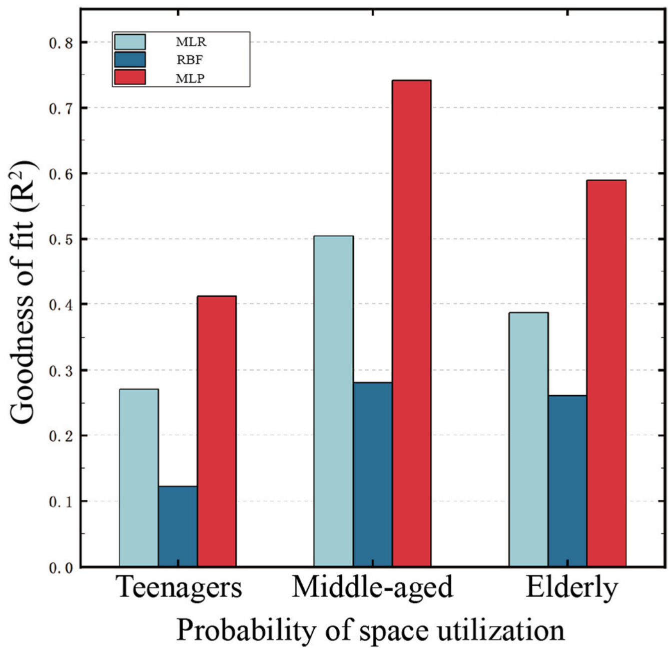


Fig. 18. Comparison of model prediction performance (R^2).

relationship between PET and pedestrians' attendance (R^2 of 0.666 and 0.698, respectively). However, in spring, a second-order polynomial relationship was observed [44]. This finding aligns with the results of this study, which achieved higher predictive accuracy using non-linear models. Furthermore, Huang et al. predicted the influence of UTCI on hourly, daily, weekly, and monthly attendance rates using a linear regression model, with R^2 ranging from 0.03 to 0.583 [62]. Besides, it was found that in linear regression analysis, the influence of microclimate factors is not significant enough, which prevents this study from further exploring pedestrian preferences for microclimate factors. Therefore, a neural network model using nonlinear functions was introduced to investigate the influence mechanism of the POSIM indicators on pedestrian activities and obtain a higher fitting prediction model. This shows that the nonlinear model has more advantages and reliability in the field of outdoor activity prediction under the influence of POSIM.

5.4. Limitations and significance

This research focuses specifically on the waterfront public spaces in Shanghai, which exhibit significant regional specificity, climate characteristics, and limited variation in environmental and design factors. In future research, we aim to expand the scope of this research to include urban public spaces in different regions with distinct climatic features, in order to explore a wider range of factors and compare their influence mechanisms.

Through extensive data collection and statistical analysis, this research integrates POSIM factors to construct models that assess their influence on various types of activities. The findings can provide valuable guidance to designers and decision-makers by highlighting pedestrians' usage patterns and environmental preferences in public spaces. This information can be utilized to enhance the efficiency of public space utilization, creating more comfortable and practical public spaces.

6. Conclusion

This study collected POSIM data and activity data from six typical urban waterfront public spaces in Shanghai, and established a predictive model to analyze the influence of POSIM indicators on pedestrian activities. The main conclusions are as follows.

(1) In terms of the influence of POSIM indicators on pedestrian activity preferences and distribution, the MLP neural network model had the best prediction performance. Compared with linear models, MLP improved the predictability (R^2) by up to 0.331.
(2) MLP achieved a higher level of prediction for walking and sitting activities in public spaces, with R^2 values of 0.704 and 0.844, respectively. However, the predictive performance for other activities, such as sightseeing, photography, playing, and exercising, was lower, with R^2 values less than 0.5. This indicates that these activities have significant randomness and are less sensitive to the perception of space and microclimate.
(3) The dynamic activity trajectory represented by strolling is limited by the linear spatial form of the waterfront area, mainly affected by the visual interface and service facility. Therefore, strolling activities tend to occur in open and bright sites with low CC and relatively high ΔSo-R. Conversely, static activities such as sitting and dining, which have longer activity times and lower metabolic rates, tend to prefer spaces with shading and cooling, high ΔV_a, high CC, and relatively low ΔSo-R.

This study explored the influence of POSIM indicators on the preferences of outdoor activities in waterfront areas, emphasizing the utility of microclimate environment in decision-making of site selection for pedestrian outdoor activities. Focus on the requirements of space occupants, this study analyzed the intervention mechanism of public space environment on pedestrian activities from the bottom up, providing a decision-making reference for human-centered design and refined optimization of urban waterfront space.

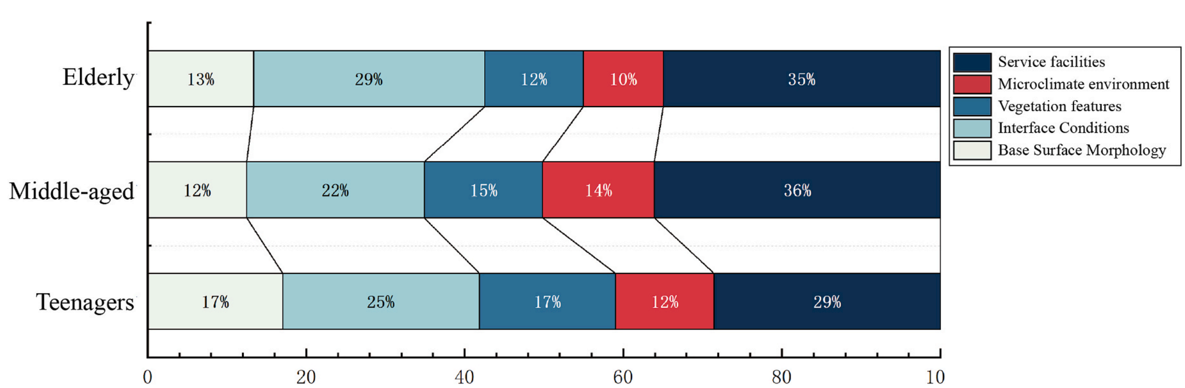


Fig. 19. Weight comparison of POSIM indicators on different age groups.

CRediT authorship contribution statement

Mengxuan Liu: Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Data curation, Conceptualization. **Chunxia Yang:** Writing – review & editing, Supervision, Investigation, Funding acquisition. **Zhaoxiang Fan:** Writing – review & editing, Visualization, Supervision, Resources, Investigation. **Chao Yuan:** Writing – review & editing, Supervision, Software.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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