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RESEARCH ARTICLE

How site-specific spatial morphology influences healthy activities in urban green spaces: A case study of Lovers' Garden

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Abstract Urban green spaces serve as key places for outdoor activities. Understanding how spatial morphology influences where and how people engage in activities is essential for landscape design and optimization. However, previous studies often neglected 3D characteristics, variability, and complexity of green spaces, limiting analytical depth and quantification. We proposed a fine-grained mapping and correlation analysis framework to explore the relationship between site-specific landscape spatial morphology and on-site healthy (physical and social) activities at a detailed scale. Using Nanjing Lovers' Garden in China as a case, activity patterns were reflected through spatial distribution and attributes of 3191 visitors in 30 spatial units. 3D models and human eye perception simulations were constructed based on point clouds for quantitative analysis and mapping-based visualization. Regression and threshold analysis through ArcGIS linkage reveal that the influence of spatial morphology on people's activities does not follow a single linear pattern, with complex fitting models and certain indicator ranges associated with comfort. Although based on a single representative case, this study proposes a transferable framework and demonstrates the value of applying fine-grained mapping to small-scale spaces by linking 2D and 3D spatial characteristics, contributing to predicting activity distribution and supporting spatial refinement, assessment, and renewal.

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1. Introduction

The spatial design and service functions of urban green spaces directly impact people's spatial perception and healthy activities. High-quality urban green space has a positive effect on improving people's mood (Kong et al., 2022) and health (Fleming et al., 2024; Yuan et al., 2024). Visual engagement with vegetation can support mental health by promoting stress recovery and attention restoration (Jato-Espino et al., 2022). The ecological services of green spaces, as well as facility-assisted recreation and activities, contribute to physical health (Geng et al., 2021). In addition, green spaces serve as places of social communication and promote healthy social interactions (Huang and Lin, 2023). Beyond supporting healthy activities, attractive landscape spaces can help residents overcome subjective barriers and promote healthy behaviors (Li and Lin, 2024; S. Wang et al., 2023). As the basic availability of green space becomes more common (Lu et al., 2023; Ye et al., 2018), how to scientifically recognize the spatial morphology and people's activities and refine the spatial design to meet people's perceived needs and potential desires has become an important research topic.

The distribution of visitors in urban green spaces is often uneven, showing certain spatial preference characteristics. Visitors' behavior in parks is closely related to multisensory environmental perceptions, including visual (Yang, 2023), auditory (Hong et al., 2022), olfactory (Ba and Kang, 2022), thermal, and humidity-related stimuli (Han et al., 2021). Visual perception, as the most direct spatial experience, determines the judgement of safety, attractiveness and comfort in the environment (Kawshalya et al., 2022). For instance, Prospect-Refuge Theory (Kaplan and Kaplan, 1989) and Perceived Sensory Dimensions (Wang and Li, 2024) explain the behavioral choices of crowds. Prospect and refuge are positive predictors of preference and are strongly related to enclosure, transparency, and complexity (Akcelik et al., 2024). Perceived Sensory Dimensions proposes eight significant landscape character indicators, including natural, cultural, open, social, cohesive, diverse, sheltered, and serene (Chen et al., 2019; Grahn and Stigsdotter, 2010), which reflect landscape spatial characteristics and are also the main points to guide refined spatial design. Considering perceptual preference studies and related indicators (Tveit et al., 2006), indicators related to three-dimensional space and morphology can be summarized into five aspects such as prospect, refuge, spatial scale, enclosure, and complexity, which are also the key indicators of landscape spatial preference research (Cai et al., 2022; Chen et al., 2019; Zhang et al., 2023). Three-dimensional spatial morphology affects perception of environmental safety and aesthetics, influencing visitors' willingness to stay in the space (Akcelik et al., 2024). Understanding the relationship between public's activities and landscape space could lead to a evidence-based design that meets the public's needs and contributes to the intensive and efficient use of spatial resources (Jim and Chen, 2006).

Urban green space morphology is complex and varied, and people's activities in space are equally multifaceted. Studies related to Prospect-Refuge Theory show evidence that people's preference for shelter and prospect is not uniform. There are differences in the strength of the correlation and even the positive and negative correlations, and the specific value ranges of spatial morphology characteristics that contribute to greater perceived comfort are still unknown (Dosen and Ostwald, 2016; Stamps, 2014). Activity preferences are influenced by multiple spatial morphological characteristics and the preference mechanisms are complex. Existing studies are limited to qualitative summaries of preference types, such as open landscapes with shaded squares and abundant vegetation (Cai et al., 2022), flat areas with appropriate vegetation (Lis et al., 2024), while lacking quantitative conclusions on specific characteristics.

Research has focused on the relationship between landscape preferences and spatial elements, considering elements such as plants, water, structures, and the spatial characteristics of their composition (Cai et al., 2022; Lis et al., 2024). In order to facilitate analysis and comparison, most studies tend to divide the space and use the central location pattern to represent overall spatial characteristics (El-Metwally et al., 2021; Wang et al., 2020), which overlooks the characteristics of landscape space as a flowing and gradual whole with ambiguity and continuity (Cheng, 2014).

In terms of methodology, previous studies have mostly used photographs for image segmentation and quantitative scoring (Cai et al., 2022; Zhang et al., 2023). However, this method is constrained by the spatiotemporal limitation of photographs, which can only reflect the spatial morphological features of a single location (Akcelik et al., 2024; Fang et al., 2024). Furthermore, 2D images fail to convey 3D attributes and detailed morphological characteristics of green spaces. In addition, although combining images with questionnaires (Talen et al., 2023) or electroencephalography experiments (Ren et al., 2024) can help researchers obtain visitors' preferences for the scene or willingness to enter the space, detailed information about their stay and activity patterns in the space is still missing.

With the development and application of 3D technology, some studies have explored 3D spatial characteristics methods based on tilt photography and point cloud data. 3D modeling can effectively restore the complex morphology of the landscape, and 3D indicators show the visual quality more directly and support the parametric simulation of complex shapes and volumes (Qi et al., 2022). 3D spatial models combined with visual field simulation can depict the real visual landscape in a virtual 3D environment (Zhang et al., 2021), which provides new ideas for landscape spatial morphology analysis. Past studies on human population data acquisition include "big data" technology (Zhou et al., 2022), GIS behavioral maps (Hou et al., 2017; Yang, 2023), and regional activity statistics (Feng and Lin, 2023). In the regional activity analysis process, the population data were partitioned and counted in spatial units, sample plots, or parks, and the detailed location attributes of the population were blurred. This leads to difficulties in exploring and predicting the number and location of the population in green space. Fine-grained mapping captures subtle spatial variations and heterogeneity to realize the high-resolution, spatially detailed representation and analysis of specific features, which has been applied in urban planning (Zhou et al., 2024) and environmental monitoring (Shi et al., 2023).

This study focuses on fine-grained spatial morphological features and the analysis of people's activities, aiming to deepen the understanding of their interrelationship. Green spaces within the built environment encompass a wide variety of forms. Influenced by factors such as type, function, topography, scale, and design features, the spatial design of parks exhibits significant variation (Boulton et al., 2018). Comprehensive parks, with diverse functions, strong attractions, and wide service coverage, are common in cities and play an important role (Cao et al., 2021). As a prominent comprehensive park in the city center, Nanjing Lovers' Park is one of the most representative urban green spaces (Wang et al., 2024a, 2024b), and is popular among visitors for its varied spaces and plants (Zhou, 2020). This study takes Nanjing Lovers' Garden as a case study to explore the following research questions: (1) How can the effects of spatial morphological characteristics on people's activities be explored from a site-specific perspective? (2) What kind of spatial morphological characteristics are more attractive to healthy activities? Based on empirical observations, this study hypothesizes that the relationship between crowd activities and spatial morphology is not simply linear, and that spatial environments can offer comfort and attractiveness only within specific ranges of morphological characteristics.

2. Materials and methods

2.1. Research framework

This study focuses on the relationship between visitors' activities and landscape spatial characteristics. Using Lovers' Garden as an example, it conducts a refined analysis of how different spatial characteristics influence the spatiotemporal distribution of healthy activities. The research framework is shown in Fig. 1, which contains three main parts: (a) projecting the objective landscape environment, quantifying and mapping typical spatial feature indicators from human perception using 3D point cloud data; (b) quantifying the spatiotemporal distribution and behavioral characteristics of visitors in the park by combining field research, observation visits and panoramic photographs under sunny weather in September−October 2024; (c) digitally analyzing the relationship between landscape spatial morphology and visitors' activity patterns based on correlation, regression and descriptive statistics.

2.2. Study area and data processing

The Lovers' Garden is in the main city area on the east side of Xuanwu Lake, conveniently reached via multiple modes of transportation, such as bus, subway, and car. This comprehensive park covers an area of about 30 ha, with a natural layout in the north-south direction, divided into three parts. In the south and center of the park are the Couple's Garden and the Flower Garden, which have a more spacious and flexible layout, while in the north is the Medicine Garden with a wide variety of plants and relatively narrow and dense spaces. The water surface in the park occupies about 10 ha, with free forms and interconnections. The park is free of charge throughout the year and is easily accessible to the public.

2.2.1. Point cloud classification and 3D modelling

In this study, the overall spatial data of the park was acquired by UAV (Unmanned Aerial Vehicle) tilt photography, converted into a 3D point cloud model, and further refined through on-site research to remove anomalies from the model (such as noise points, edge burrs, and ground penetration errors), which served as the basic data for subsequent spatial characteristics research. The point cloud model was classified into five categories: water bodies, buildings, trees and shrubs, grass, plazas and other hard surfaces, and the classification was corrected by manual editing to support the subsequent analysis and quantification (Fig. 2(a)).

The 3D model was constructed according to the feature grouping of different elements. With the help of Rhino8 software, the ShrinkWrap algorithm was applied on the simplified point cloud (Fig. 2(b)), which created a mesh wrapping around the selected geometry including NURBS (Non-Uniform Rational B-Splines) surfaces, Subdivision Surface Modelling, meshes, point clouds, and point objects, to obtain a multi-mesh model. And then the mesh-based model was converted to NURBS surfaces to achieve 3D model solid modelling (Pepe et al., 2024).

2.2.2. Spaces selection

This study focused on open spaces in parks, with spaces that can accommodate people to stay and be active freely as the main object of study. Therefore, this paper defined the target spaces, which need to meet the following conditions: meeting the minimum external spatial scale modulus, exhibiting a sense of enclosure, being accessible via park paths, and allowing free activities in the space without interference from facilities and pavement materials. Based on the above principles, the study identified the overall model of the Lovers' Garden with the help of ArcGIS, resulting in the identification of 30 major spatial units (Fig. 2(c)). These units were used as research objects for the subsequent spatial characteristics analysis and the investigation of visitors' behaviors. Spatial boundaries and vertical enclosures distinguish specific areas from the background environment. To ensure the accuracy of morphological features at the spatial edges, the spatial contour was extracted and expanded outward by 10 m as the study boundary (Wang et al., 2020).

2.3. Quantification of spatial morphological characteristics

With reference to the previous quantitative methods of spatial morphological characteristics, this study relied on the 3D spatial model and the Grasshopper platform to simulate the indicators calculation (Fig. 3(f)). Firstly, the 3D spatial model was loaded in Rhino8 software, and the points were evenly distributed in the 3D space using Grasshopper. After projecting the sample points on the ground, the points were translated upwards by 1.6 m to obtain the viewpoints that conform to the height of the human eye (Fig. 3(a) and (b)). Taking each viewpoint as the

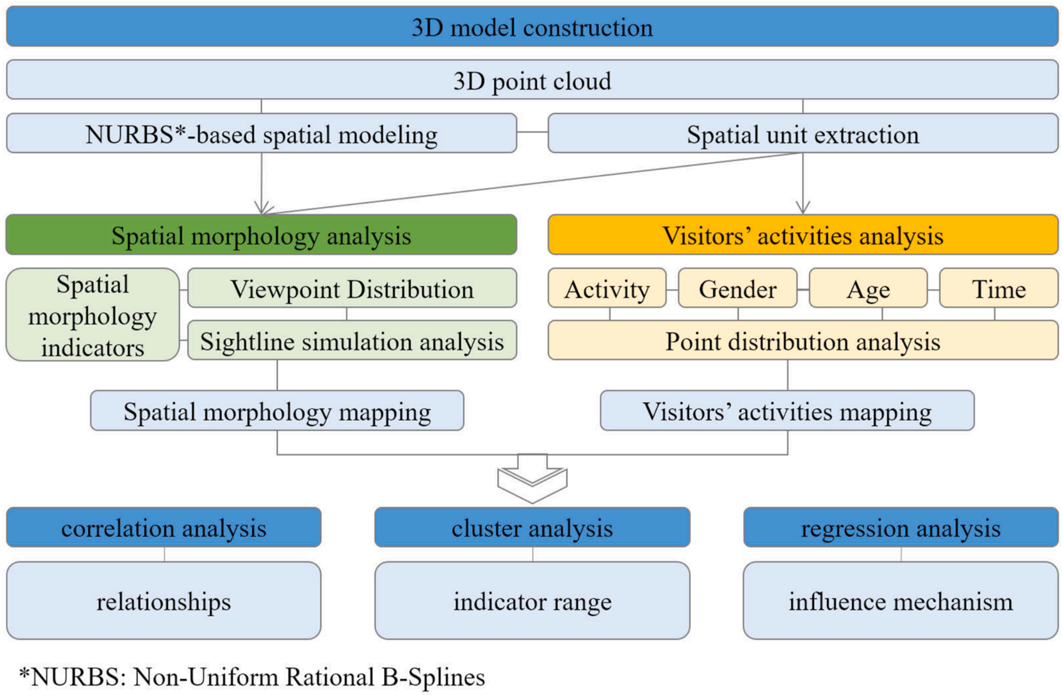


Fig. 1 Research framework.

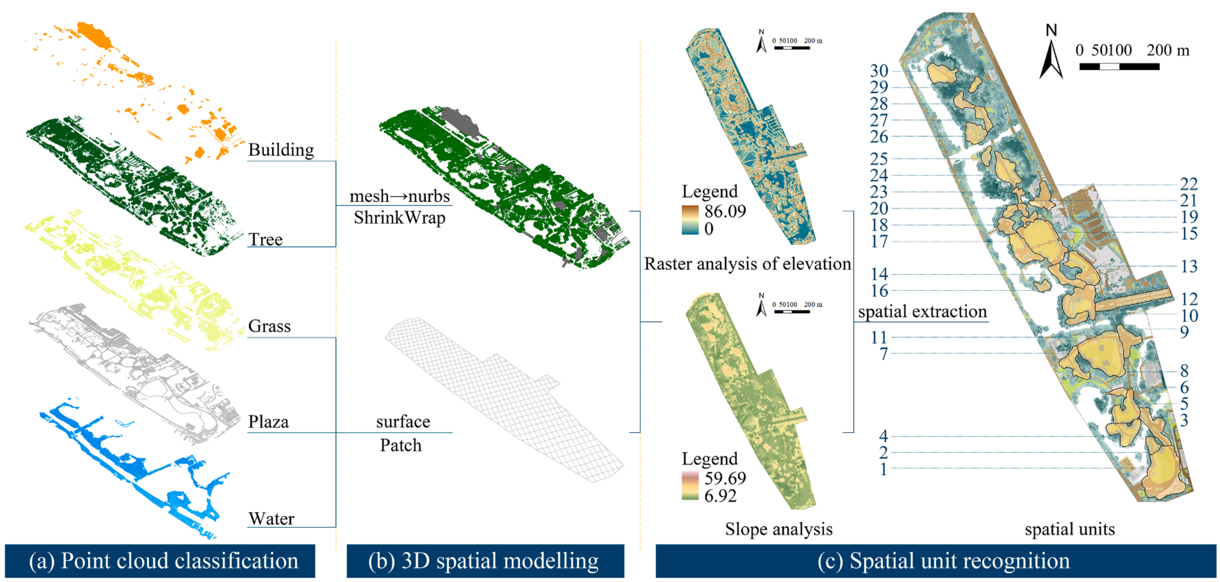
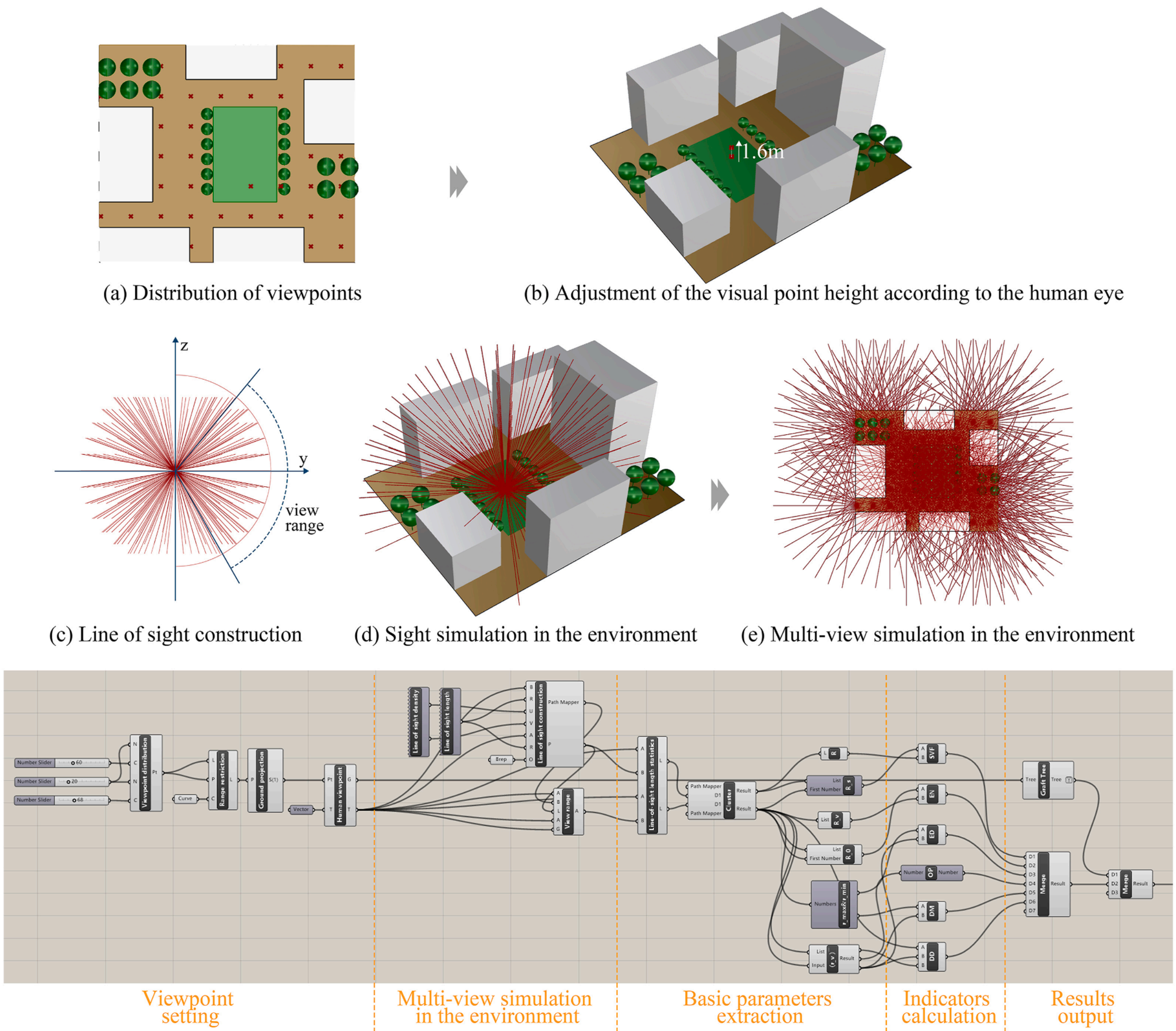


Fig. 2 3D model construction and spatial recognition. This figure illustrates the workflow used for the recognition of 30 spatial units in the study area.

starting point, 100 m long simulated lines of sight with a 10° angle were launched in all directions. 100 m is the boundary of the visual socialization range in urban planning environments, and above 100 m is a distant view that gradually blurs (Gehl, 2013). The 3D visual analysis study based on viewpoints also used 100 m as the visual radius parameter (Cimburova and Blumentrath, 2022; Zhao et al., 2020). The smaller the angle of line of sight, the higher the accuracy of results obtained from the simulation, which brings a significant increase in calculation time. Due to the large number of viewpoints selected for this study and the large amount of calculation, 10° was chosen as the input parameter due to the limitation of the equipment's calculation capability. According to the normal range of human visual field, the lines of sight within 360° horizontally and 120° vertically were extracted from each viewpoint to simulate the real feeling of the human eye (Fig. 3(c)).

The visible lines of sight for each viewpoint are 468, with a total of 352 viewpoints in 30 spaces, and a total of 164,736 lines were constructed. The lines of sight were



(a) Distribution of viewpoints (b) Adjustment of the visual point height according to the human eye

(c) Line of sight construction (d) Sight simulation in the environment (e) Multi-view simulation in the environment

(f) Grasshopper-based indicator calculation model

Fig. 3 Spatial morphology analysis based on line-of-sight simulation.

intersected with the 3D solid model to obtain the length of each line of sight and the attributes of the corresponding view field, thus simulating the spatial state perceived by the human eye (Fig. 3(d) and (e)).

Previous studies have shown that spatial visual characteristics related to morphology include dimensions such as visual scale, complexity, and naturalness (Tveit et al., 2006), of which openness, enclosure, diversity, prospect, refuge, and other indicators (Akcelik et al., 2024; Wang and Li, 2024; Zhang et al., 2023) have an important impact on people's activity patterns.

In this paper, six indicators of Sky View Factor (SVF), Enclosure (EN), Edge Degree (ED), Openness (OP), Maximum Depth (DM), and Depth Diversity (DD) were selected to describe the selected 30 spatial units' spatial morphology from the dimensions of enclosure, refuge, visual scale, prospect, and complexity characteristics (Table 1). SVF and EN describe the degree of enclosure at the top and side interfaces of a space, respectively (Akcelik et al., 2024; Qi et al., 2022). SVF characterizes the proportion of sky in the overall field of view at a certain viewpoint. The higher the proportion, the higher the sky visibility (Zeng et al., 2018). The larger the value of the indicator, the less occlusion above the visitor's location. EN refers to the sum of the proportion of buildings, walls and plants in the visual envelope. A good sense of enclosure gives a feeling of comfort and security (Jia et al., 2023). Ashihara (1975) identified a D/H ratio of 4 as the critical value beyond which the sense of enclosure is significantly diminished, where D refers to the width of the open space and H to the height of the surrounding buildings. The vegetation height in Lovers' Garden is more than 5 m, and the corresponding maximum distance that can still produce a sense of enclosure is approximately 20 m. This implies that the distance from the center to the boundary should be less than 10 m to achieve a sense of privacy and enclosure. Previous studies on enclosure also mentioned that the appropriate visual quality requires that the width of the street should not exceed 10 m (Akbarishahabi, 2021; Ewing and Handy, 2009). Therefore, we proposed in this paper, based on the line-of-

Table 1 Quantitative indicators of spatial morphological characteristics.

Dimension	Indicator	Formula	Parameter
Enclosure	Sky view factor (SVF)	$SVF = \frac{R_s}{R}$	R = total number of lines of sight emitted on the sphere
	Enclosure (EN)	$EN = \frac{R_0}{R_v}$	R_s = number of lines of sight emitted to the sky
Refuge	Edge degree (ED)	$ED = \frac{r_{min}}{\overline{r_v}}$	R_v = total number of visible lines of sight in the field of view
Visual scale	Openness (OP)	$OP = \overline{r_v}$	R_0 = number of lines of sight with a length of less than 10m
Prospect	Maximum depth (DM)	$DM = \frac{r_{max}}{\overline{r_v}}$	$\overline{r_v}$ = mean length of visible lines of sight in the field of view
Complexity	Depth diversity (DD)	$DD = \sum_{i=1}^{n} \frac{(r_i - \overline{r_v})^2}{R_v}$	r_{max} = maximum length of the line of sight (except the sky portion) at the viewpoint
			r_{min} = minimum length of the line of sight at the viewpoint
			r_i = length of a particular line of sight emitted from the viewpoint

sight simulation method, to characterize EN in terms of the ratio of the number of spatial sightlines with a length of 10m or less to the total number of all visible sightlines from a certain viewpoint. An area is considered fully enclosed when all spatial sightline lengths are less than 10 m. ED is a measure of how close a viewpoint is to the space's edge. The closer it is to the space's edge or obstacles, the better the edge effect is and provides a better sense of sheltered security (Lis et al., 2024; Zhang et al., 2023). Based on the concept of Edge Degree, this paper proposed the ratio of the shortest sight distance to the average sight length as the value of ED. The smaller the ED, the closer the location is to the edge. OP indicator describes the visible space volume. At a certain viewpoint, the larger the volume of visible space, the further away the obstacles that block the view (Niu and Xu, 2011; Tveit, 2009; Zhang, 2019). Based on three-dimensional visual characteristics, the study defined OP in terms of the average length of the visual sightlines. DM reflects the degree of visual extension of a viewpoint in the depth direction (Zhang et al., 2023), and can also be used to characterize the spatial shape extension. In this study, DM is represented by the maximum value of sight length. DD is used to describe the degree of variation in the deep direction of a spatial visual interface. When the visual interface has significant concavity and convexity changes in the deep direction, the spatial depth values are more varied and the interface is more complex and richly layered (Tveit et al., 2006).

After obtaining the spatial morphological characteristics of each viewpoint, the attribute table function in ArcGIS was used to add the corresponding feature data for each point, to situate the morphological characteristics. Then, the area between each viewpoint was interpolated and filled using the Kriging interpolation tool in ArcGIS to generate a raster distribution map of spatial morphological indicators covering the whole area of the 30 spatial units. The spatial morphology mapping provided a database for the subsequent study of the relationship between people's activities and spatial morphology characteristics.

2.4. Analysis of health behaviors and distribution

Spatiotemporal distribution characteristics were used to assess visitor activity patterns, quantified by visitor numbers, point locations, density, etc. Weekday and weekend days of sunny weather were selected, including four time periods: 7:00—10:00, 10:00—13:00, 13:00—16:00, and 16:00—19:00, to obtain the health behaviors and distribution. As a validated direct observation tool, the System for Observing Play and Recreation in Communities (SOPARC) was chosen to analysis public space usage and physical activity patterns. Its structured protocol allows for consistent data collection across different observers and environments (Marquet et al., 2019; McKenzie et al., 2006; Parra et al., 2010), ensuring its reliability, feasibility, and widespread application in diverse settings. Visitor point locations, gender (female and male), age group (children and adolescents, adults, elderly), and activity type were observed on site and recorded manually on a map. According to the SOPARC theory (McKenzie et al., 2006), the type of visitor activity was categorized as sedentary (lying down, sitting, and standing), walking (walking, strengthening exercises, and photographing), and vigorous (running, jumping, climbing, sporting, and chasing), which corresponded to different intensities of health behaviors (Li and Lin, 2024) (Fig. 4).

The study observed and recorded the behavior and spatial distribution of visitors with the help of a panoramic camera. Based on the results of spatial unit extraction, panoramic filming and recording were carried out in the center of each space using GoPro Max equipment at a height of 1.65 m, and additional filming was carried out for obstructed areas. The photos provided support for visitor recording and correction. From September to October 2024, the visitors in 30 spatial units of the Lovers' Garden were observed and recorded. Combining on-site observation visits and panoramic photographs, excluding the influence of special activities on crowd distribution, representative activity records were selected to jointly form the results of health behaviors research covering eight time periods, including weekdays and weekends. With the help of ArcGIS point elements and attribute tables, the park map was marked to describe and analyze visitors' characteristics.

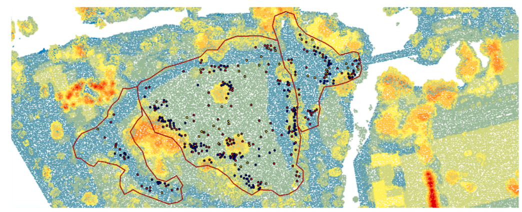
With the help of point density analysis tools in GIS, the study respectively constructed a mapping raster for the overall visitor distribution and different types of visitor distribution in the park to visualize the spatiotemporal distribution of visitors and to prepare data for subsequent correlation analysis.

Crowd recognition

SOPARC Data Collection Form

Person	Gender		Age			Activity			Time	Unit
	Male	Female	Child&Teen	Adult	Old	Sedentary	Walking	Vigorous		
1	1				1	1			1	1
2		1	1			1			1	1
3		1		1		1			2	1
4		1		1			1		6	3
5	1		1					1	8	3
......										

● **Sedentary:** lying down; sitting; standing
● **Walking:** walking; strengthening exercises; photographing
● **Vigorous:** running; jumping; climbing; sporting; chasing



Activity location marker

Fig. 4 Collection and recording of visitor information.

2.5. Exploring relationships between morphological indicators and visitor activities

The study explored the correlation and influence mechanism of spatial morphology and visitor activities with the help of correlation analysis, regression analysis and statistical analysis tools. First, a 5 m × 5 m fishnet was created in ArcGIS, and the mapping raster data of spatial morphology characteristics and visitor density were partitioned and counted by Zonal Statistics. Referring to the "external modulus theory" (Ashihara, 1975), and combining with the spatial units' size of Lovers' Garden, the grid size of 5 m can divide the smallest spatial unit (20 m × 20 m) into edge and inside as well. The average raster data value corresponding to each grid was calculated and connected to the grid attributes. Through the grid attribute table, the values of 6 spatial morphology characteristic indicators and the distribution density of different activity types of visitors were all aligned and correlated. Then, Spearman correlation analysis was carried out with the help of Origin software. The associations between spatial morphological characteristics and visitor activities were explored in 30 spatial units and in a fishnet of the overall park, respectively. After that, the study used the spatial morphological characteristics as the independent variable and the population distribution as the dependent variable, and multiple linear regression analysis was conducted by SPSS in order to explore the association mechanism. To explore correlations, the study constructed scatter plots and violin plots to further clarify the numerical intervals of the spatial morphological characteristics of healthy activities.

3. Results

3.1. Characteristics of visitors

The results of the visitor analysis are shown in Fig. 5, including the selected representative eight time periods (weekday and weekend), with a total of 3191 visitors. Overall, female visitors (57.5%) outnumbered male visitors (42.5%). In terms of activity time, the number of visitors on weekends accounted for 66.4% of all, twice as many as the number on weekdays. Afternoon and evening were the peak periods of visitors in a day, of which the number of visitors in the evening (16:00—19:00) on weekdays and weekends accounted for 12.9% and 18.6% respectively, and the number of visitors in the afternoon (13:00—16:00) on weekends was the highest, reaching 32.5%. In terms of age distribution, it was mainly dominated by young people, accounting for 50.2%. Visitors to the park mainly engaged in sedentary and walking activities, and less in vigorous activities.

Further analysis reveals that males and females were similarly active in the park on weekdays, but the proportion of female visitors was higher on weekends, especially during 13:00—19:00. The Child, Teen, and Adult groups tended to be active on weekends, while there was not much difference between weekends and weekdays for the Old group. In addition, in terms of activity intensity, Child and Teen groups were more active compared to the other two age groups, while Adult and Old groups tended to be more sedentary and walking with relatively calm activities.

3.2. Characteristics of visitors' spatial distribution

As shown in the points and density distribution of visitors in Fig. 6(a) and (b), the densest distribution of visitors was found within spaces 8, 12, 15, and 17, followed by spaces 1, 9, 10, 14, 22, and 24. Spaces 3, 7, 20, 18, 25, and 29 had the sparsest distribution of visitors. Overall, the distribution of visitors south of space 24 was densely higher, and the density of visitors in the north was lower except for space 28. Analysis of the distribution ratio of people in each space showed that spaces 1, 8, 12, 13, and 15 were the main activity areas, and space 15 had the largest number of visitors, accounting for 19.1%; spaces 3, 11, 20, 24, 26, and 29 had the smallest number of visitors, which all accounted for less than 1%. In general, the center of the park in the space unit 10—20 had the largest proportion of people and active activities, while the north side, especially in the space unit 25—30, had a lower proportion of people and a relatively calm type of activity, mainly sedentary.

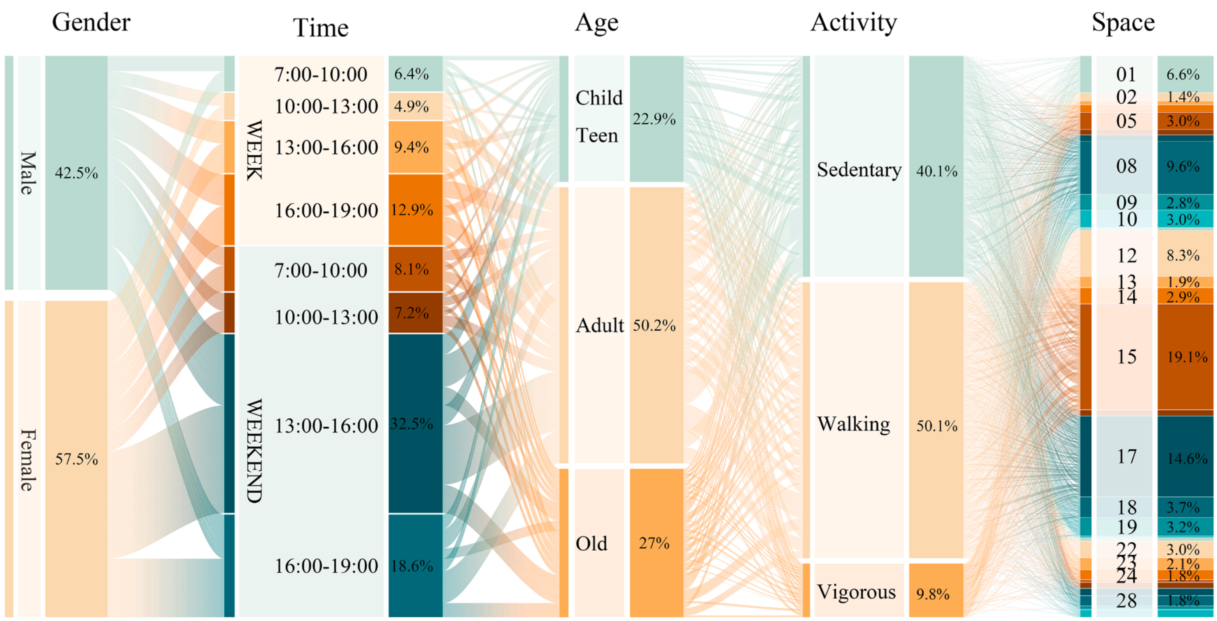
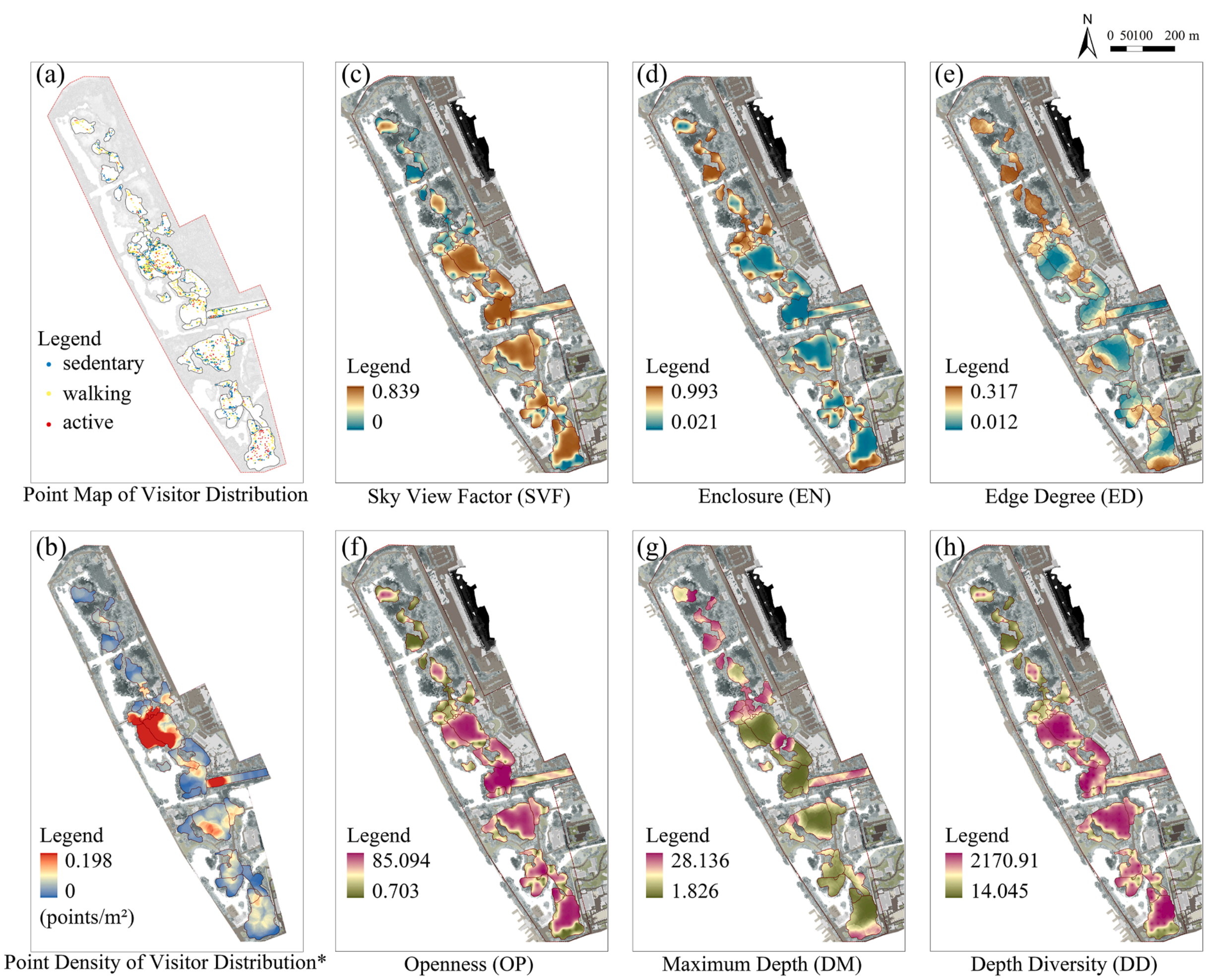


Fig. 5 Health behaviors and distribution characteristics.



* pdensOut = PointDensity("points.shp", "NONE", 1, NbrCircle(25, "MAP"))

Fig. 6 Mapping of visitors' distribution and spatial morphological characteristics.

3.3. Characteristics of spatial morphology

The mapping results of the 6 spatial morphology feature indicators are shown in Fig. 6(c−h). From the mapping diagrams, there are significant differences in the spatial morphological characteristics of visual perception in various locations. Taking SVF as an example, the theoretical value range of the formula was [0, 1], and the actual analysis result value of the park was [0, 0.839], and the theoretical value range of the formula for OP indicator was [0, 100], and the actual analysis result value of the park was [0.703, 85.094]. From the overall scope of the park, the 6 indicators had spatial distribution differences in the south, center, and north of the park. Taking SVF and OP as an example, the values of the indicators were generally larger in the south and center, while lower in the north, which may be related to the fact that the north area is more vegetated. The shading effect on space caused by vegetation was obvious. In addition, the higher EN and lower DM in the north area may be related to the higher number of shrubs and herbs, with a large number of low-growing plants filling the understory space and creating a sight barrier.

Morphological characteristics within the space were not homogeneous and had a high degree of variability. The distribution pattern of morphological characteristics in the spatial units was not obvious, for example, in space 8 and 24, the SVF values generally showed a trend of high in the middle and low in the surroundings. The ED values of space 8 were homogeneous, and those of space 24 decreased from southwest to northeast, which may be related to the composition of the spatial interface. In addition, the SVF values of space 1 were generally lower in the west and south and higher in the east, while those of space 9 were higher in the west and lower in the east.

As a whole, the morphological characteristics of landscape space showed a continuous gradual change trend. There were not only regional but also inner spatial differences in the indicator values. There was no obvious numerical correlation between the morphological characteristics of the spatial center and the overall.

3.4. Relationship between spatial morphological characteristics and visitor activities

3.4.1. Overall spatial characteristics and visitor activities

Figure 7(a) demonstrates the correlation between the distribution of visitors and the average level of morphological characteristics within each spatial unit. According to the results of Spearman correlation analysis, area, EN, ED, and DD indicators of the spatial unit had a significant effect on the activity patterns of people. In terms of age distribution, child and teen groups were more likely to be affected by SVF (0.52), ED (−0.58), and DD (0.58), the old group was more likely to be affected by EN (0.53), OP (0.52), and DD (0.55). Adults showed relatively weak associations with spatial morphology, suggesting a more neutral or tolerant spatial response. In terms of gender distribution, the correlation between the distribution of female visitors and the various morphological indicators was generally higher than that of male visitors, implying a greater sensitivity to spatial characteristics in space selection. In contrast, the most significant differences in associations between people's distribution and spatial morphology were found for different health behaviors, and people walking had generally higher correlation with various morphological indicators than those either sedentary or performing vigorous activity.

3.4.2. Site-specific spatial characteristics and activities

Figure 7(b) shows the correlation analysis results between the distribution of different activity types and the 6 spatial morphology indicators mapping based on fishnet grid. Overall, the correlation trend of each indicator with different healthy activities' distribution is consistent with Fig. 7(a), with stronger significance, but the correlation coefficients are reduced. SVF, OP, and DD had a positive effect on activity distribution, indicating that healthy activities preferred places where the sky was visible, the space was open, and the spatial layers were rich. EN, ED, and DM had negative influence on activity distribution, indicating that people tended to be active in places with lower enclosure, close to the edge, and lower spatial extension. ED, DM, and DD showed the strongest correlations with healthy activity distribution density among 6 spatial indicators, indicating that people were most influenced by edge, extension and richness when choosing activity space. In terms of different activity types, sedentary activities were more affected by ED (0.31), suggesting that people cared more about being at spatial edges; walking activities were most strongly affected by the association of DM (0.31), and vigorous activities were most strongly affected by the associations of SVF, DM, and DD. In general, the vigorous activities were most strongly affected by spatial morphology, with the strongest correlational effects for all morphometric indicators except ED (SVF:0.32, EN: 0.29, OP:0.31, DM:0.33, DD:0.34), ED had a large effect on the sedentary activities, and the strength of correlations between walking activities and the characteristics was intermediate. Sedentary people seemed more concerned about the relationship between location and spatial boundaries, while vigorous people were more concerned about the openness and richness of the space, and walking people had relatively weaker requirements for spatial morphology because they might be moving all around.

The SVF, EN, ED, OP, DM, and DD indicators were used as independent variables and the healthy activity distribution as the dependent variable in a multiple linear regression analysis. To meet the assumptions of normality and homoscedasticity in regression analysis, the dependent variables were log-transformed prior to modeling. The residual diagnostics results indicated an acceptable fit to the assumptions of linear regression, as shown in the Appendices. The P—P plot confirmed the normality of residuals, and the plot of standardized residuals versus predicted values did not indicate strong heteroscedasticity or nonlinear patterns. The fitting results are shown in Table 2. VIFs (Variance Inflation Factor) for all models were <10, which meant that there was no multicollinearity in the multiple linear regression equations; and the Durbin-Waston values ranged from 1.83 to 1.95, close to 2, indicating that the residuals were approximately independent. The model for sedentary behavior had an R^2 of 0.124, indicating that

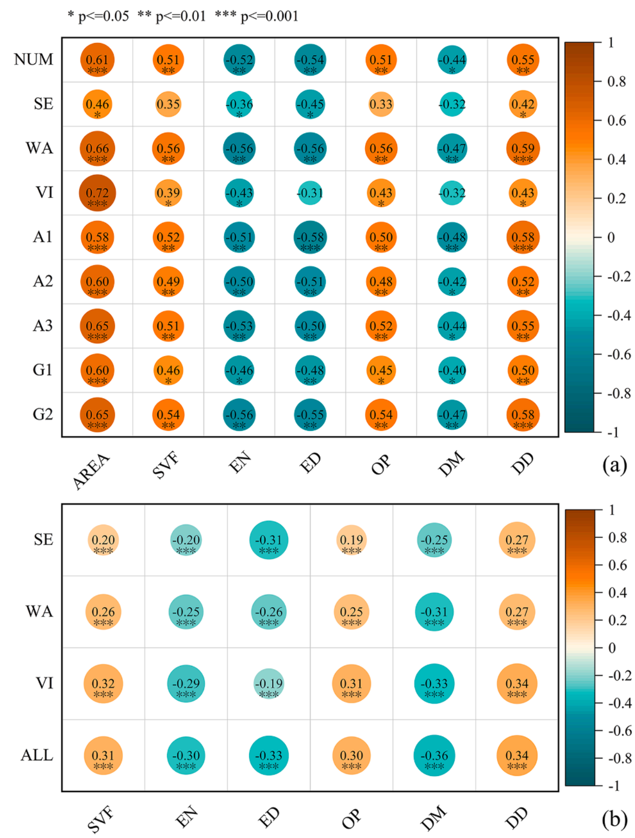


Fig. 7 Correlation analysis between morphological characteristics and people's distribution in 30 spatial units (NUM = Total number of people in each space; SE = Density of sedentary people; WA = Density of walking people; VI = Density of vigorous people; A1 = Density of child & teen people; A2 = Density of adult people; A3 = Density of old people; G1 = Density of male; G2 = Density of female; ALL = Density of people).

12.4% of the variance in sedentary time could be explained by the independent variables. Among them, ED ($B = 0.157$, $p = 0.000$) and DD ($B = 0.238$, $p = 0.000$) showed positive effect on sedentary people; while SVF ($B = -0.238$, $p = 0.000$) had a negative effect. For walking behavior, the model explained 10.4% of the variance ($R^2 = 0.104$). OP showed a significant negative association ($B = -0.124$, $p = 0.027 < 0.05$), while ED ($B = 0.135$, $p = 0.002 < 0.01$), DM ($B = 0.136$, $p = 0.017 < 0.05$), and DD ($B = 0.133$, $p = 0.007 < 0.01$) were positively associated. The model for vigorous activity explained 17.0% of the variance ($R^2 = 0.170$). ED showed a significant negative association ($B = -0.095$, $p = 0.047 < 0.05$), while DD ($B = 0.347$, $p = 0.000$) was positively associated.

Based on fishnet construction and data linkages, the grids and corresponding data within the study spaces were extracted, and a total of 3371 sets of data were obtained and statistically analyzed. Figure 8(a) illustrates the scatterplot of 3371 sets of data, with interval differences for all 6 morphometric indicators. The distribution of people was more concentrated within a certain interval of morphometric indicator values. Taking SVF as an example, the highest people density corresponded to an SVF of about 0.3, and there were more people in the interval of [0, 0.45]. After the SVF exceeded 0.45, the people density dropped below 0.05, and there was no longer high-density distribution. People were more likely to concentrate in spaces with SVF below 0.45, with only a small number of people in spaces with SVF above 0.45. Similarly, people were more likely to be concentrated in the EN of [0.45, 0.95], and the highest density corresponded to an EN of 0.6. For the area with a high density of people, the OP was in the interval of [0, 50], and the OP corresponding to the highest density was 35. The DM was mainly in the interval of [2, 12], and the DM corresponding to the highest density was 7. As the DM value increased, the density of people decreased, and the density of people tended to be zero after exceeding 17.5. When the ED was below 0.03, the people density tended to be close to 0. People were concentrated at an ED of [0.03, 0.16], the highest density corresponded to an ED of 0.05, and the density of people was below the mean and gradually decreased when the ED exceeded 0.20. This suggests that people tend to stay within areas near spatial boundaries, with a decreasing concentration observed from the boundary to the center. The highest density of people corresponded to a DD value of 1700. People were active in the DD interval [100, 2000].

Categorized by type of healthy activities, the 6 spatial indicators of locations where 3191 visits were placed were statistically analyzed, and the data distribution is shown in Fig. 8(b). In general, the spatial distribution range of sedentary activity locations was relatively narrow. Taking SVF as an example, the interval of sedentary activity locations was [0.1026, 0.2097], the interval of walking activity locations was [0.1123, 0.2775], and the interval of vigorous activity locations was [0.1356, 0.3584], the range of the interval was gradually expanding, and the mean of the interval was on an upward trend. This suggests that of the three activities, vigorous has the lowest requirement for sky visibility and is most favored in areas where the sky can be seen and the view is open. Similarly, sedentary preferred to occur in spaces with higher EN [0.6715, 0.7051], lower OP [14.8636, 25.0527]. Correspondingly, vigorous activities were noted on spaces with lower enclosure [0.5470, 0.7482] and higher openness [17.4079, 39.2719] and was more inclusive of spatial morphological characteristics. Vigorous preferred the space of DM at [3.0079, 5.8273], suggesting that clumped spaces with less extension are more suitable for vigorous activity and provide more spacious space. Meanwhile, spaces with more hierarchical variations [886.4701, 1636.9367] attracted vigorous activities, allowing for a more varied visual experience. The three activity types exhibited similar spatial distributions within the ED range of [0.6011, 0.1210].

4. Discussion

4.1. Relationships and mechanisms between spatial morphology characteristics and people's activities

The study realized an exploration of the effects of landscape site-specific spatial morphology characteristics on

Table 2 Multiple linear regression results of spatial morphological characteristics and people distribution density.

Dependent variable	Independent variable	Unstandardized coefficient		Standardized coefficient	*p*-value	VIF	R^2	Durdin-Waston (U)
		B	Standard error	Beta				
Sedentary	Constant	−0.090	0.037	–	–	–	0.124	1.875
	SVF	−0.238	0.050	−0.292	0.000	3.561		
	ED	0.157	0.041	0.183	0.000	2.181		
	DD	0.238	0.044	0.394	0.000	5.185		
Walking	Constant	−0.081	0.39	–	–	–	0.104	1.954
	OP	−0.124	0.056	−0.144	0.027	3.921		
	ED	0.135	0.043	0.154	0.002	2.199		
	DM	0.136	0.057	0.114	0.017	2.130		
	DD	0.133	0.049	0.213	0.007	5.791		
Vigorous	Constant	0.009	0.022	–	–	–	0.170	1.832
	ED	−0.095	0.048	−0.091	0.047	2.138		
	DD	0.347	0.034	0.474	0.000	2.138		

people's activities from a site-specific perspective. In this study, the average value of all viewpoints in a space unit was used as the overall morphology value, reflecting the overall visual morphology of the space unit more comprehensively. The study corroborated that the morphological characteristics of space center do not represent those of all viewpoints in the space (Zhang et al., 2024). Compared to mapping in terms of points (Zhang et al., 2021) or areas (Korpilo et al., 2018), the mapping results in this study show the difference and change trend of spatial morphology in the park more intuitively and in detail. Meanwhile, line-of-sight simulation can reflect people's visual perception of spatial morphology, which is more convenient and efficient than the traditional method of taking photographs without interference from space-time factors (Shi et al., 2023), and avoids the randomness due to the photo shooting angle to a certain extent. Compared with the two-dimensional spatial morphology quantification methods based on photos and drawings, the three-dimensional spatial modeling supported by point cloud data can refine the landscape environment and improve the accuracy of data analysis, as pointed out by Qi et al. (2022). In addition, this study constructed a multi-indicator computing model through Grasshopper, which improved computational efficiency (Ibrahim et al., 2021; Xia and Li, 2021).

The study revealed the complex relationship between spatial morphological characteristics and people's activities, thereby confirming the research hypotheses. Mapping revealed the uneven distribution of spatial morphological features and people in green space. Visitors were more likely to be located near the edge of space rather than in the center, which is consistent with previous research that people tend to stay and act in areas with sheltered areas and better visibility (Dosen and Ostwald, 2016).

In general, the spatial morphology indicators based on health behaviors are mostly moderate indicators, and there are interrelated constraints between them. In the scatter plot (Fig. 8(a)), there is a nonlinear relationship between the two variables, with abrupt changes in the distribution of dependent variable values when the independent variable is at a specific value. This explains the weak correlation coefficients to some extent; the variable relationships do not satisfy linear correlation, but there are clearer inter-area differences (Reshef et al., 2011). Analysis of spatial morphology characteristics of visitor location also revealed a tendency for values to concentrate in a certain interval (Fig. 8(b)), indicating that the influence of spatial morphology on health behaviors in the park is not purely positive or negative. There exists a certain moderate interval, (especially SVF, EN, OP, and DM), which can explain the conflicting and inconsistent findings regarding spatial preferences in previous research (Dosen and Ostwald, 2016), and answers the question of "which degree of prospect and refuge would be perceived as comfortable in a natural or an urban context". SVF and OP have positive correlations with people's activities, but completely open and unshaded spaces do not attract visitors to stay, which may be related to Agoraphobia (Westphal, 1872), where the lack of shelter for individuals in wide spaces predisposes them to feelings of being exposed and observed, leading to insecurity (Mehrabian and Russell, 1974). Visitors tend to prefer a certain degree of spatial enclosure. Completely enclosed spaces may bring a sense of pressure and tension, while those with moderately enclosed and richly layered boundaries offer a more comfortable experience (El-Metwally et al., 2021), especially for vigorous visitors.

The fitted regression results show that the effects of spatial morphology on people's activities are comprehensive. ED and DD have important effects on people's distribution, and ED has the most obvious effect on sedentary people. Space edges can provide visitors with a greater sense of shelter and quietness, which is consistent with the nature of healthy activities such as sitting and stopping. DM and OP are key factors affecting walking. DM can reflect the extension and directionality of the space, and spaces with higher DM are mostly connected spaces, which may be one of the factors contributing to the higher number of walking people.

In addition, there are significant differences in people density between park areas, with the southern and central spaces being popular areas, while the northern areas are

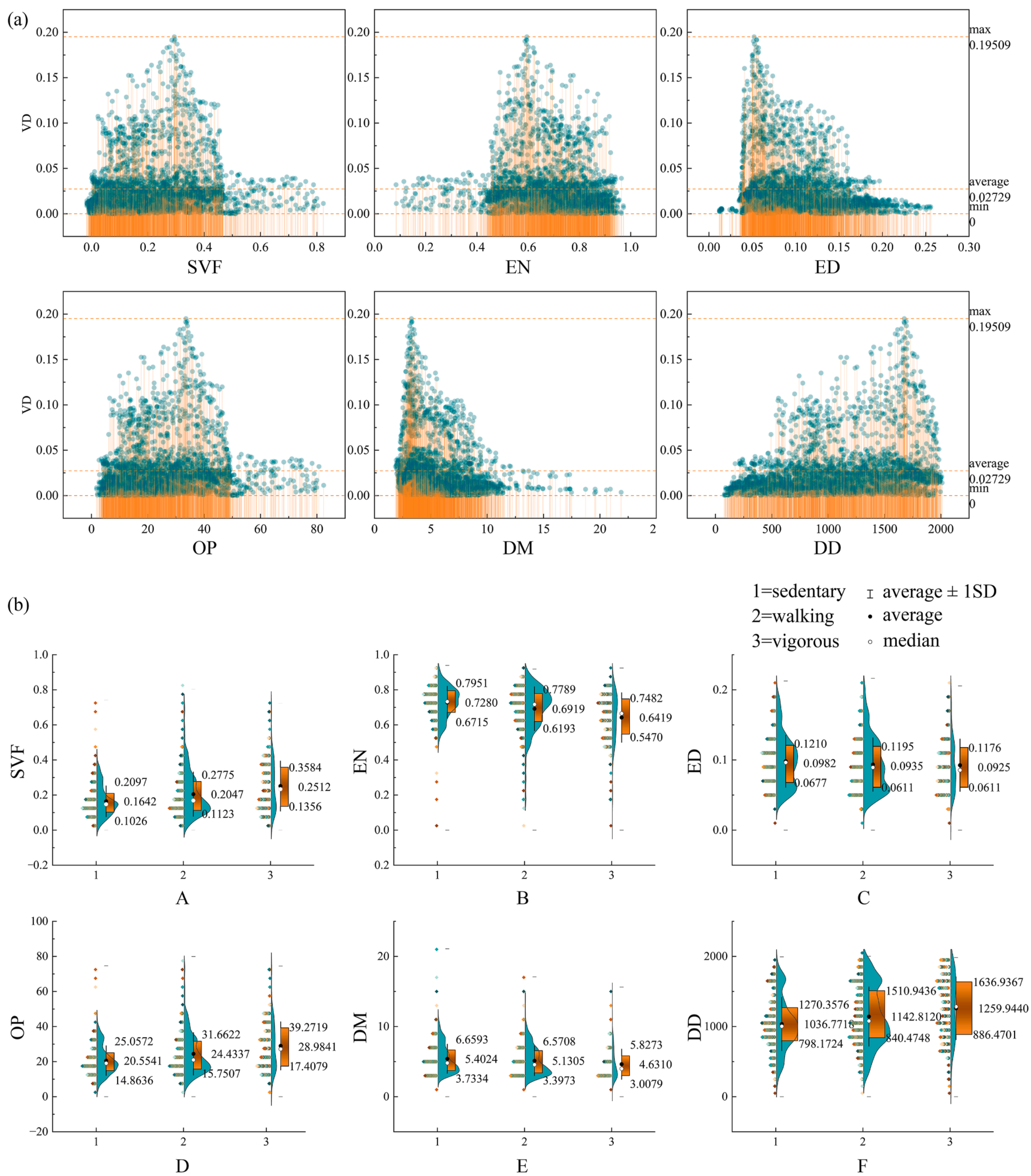


Fig. 8 Scatterplot and violin plot of spatial morphological characteristics and people's distribution.

less visited, which may be related to the spatial enclosure, seclusion, and poor accessibility, further supporting the previous research findings that distance is a major aspect of natural or urban green space accessibility indicators (Ekkel and de Vries, 2017). The area intuitively reflects visitor capacity of the space, and the spaces with higher flow of people (1, 8, 12, 15, 17) have an area of over 3000 m^2. Comparative analysis of similar-sized spaces reveals that the entry and stay of people are affected by a combination of spatial morphology indicators. This finding is consistent with previous research on visual scale, which identified it as an important component of landscape perception, though not a dominant factor and insufficient to fully explain public spatial behavior (Tveit, 2009). In terms of activity type, the vigorous people had the most obvious spatial differentiation characteristics, and acted only in spaces of more than 2000 m^2 or in open sites with limited spatial extension. This is related to higher spatial scale and spatial openness required for vigorous activity, which further supports previous research findings that high-intensity exercise favors open and varied spaces (Feng and Lin, 2023; Gravitz-Sela et al., 2025).

Landscape design should be guided not only by aesthetic or designer-driven intentions, but also by functional requirements and user-centered principles. During the design phase, designers can draw upon empirically derived morphological intervals to align spatial configurations with behavioral needs. Prior to project implementation, the regression model and its future extension prediction model can simulate spatial usage scenarios and forecast activity patterns, thereby supporting design optimization and minimizing potential costs associated with post-construction adjustments. During the use and management phases, spatial monitoring and analysis can assist in identifying performance issues and informing evidence-based interventions and spatial updates. The integrated application of these findings enhances the responsiveness, efficiency, and adaptability of landscape design, ultimately contributing to healthier and more user-friendly urban green spaces.

4.2. Limitations

The spatial morphology mapping and people's activity relationship research method based on point cloud and line-of-sight simulation in this study is significant for fine-grained and on-site analysis of green space, but there are some shortcomings.

First, the mapping raster is obtained by uniform point distribution and interpolation calculation, and its accuracy is related to the sampling density. The sampling density of viewpoints and 5 m $\times$ 5 m spatial grid in this study is limited, and the algorithm can be further optimized in the future to increase the sampling points and improve the quantitative accuracy according to the research demand and arithmetic power. The height of line-of-sight emission at each viewpoint is 1.6 m, based on the average height of human observation, which has a gap with the perception of actual users, especially different age groups, and needs to be simulated in a more refined way.

Second, this study selected spaces with flat ground, no obvious restriction on the range of activities, and fewer facilities such as chairs, to realize the observation and recording of people's spontaneous and free activity distribution. However, the actual study only observed people at different times on weekdays and weekends in fall weather without rain. The study period was short, and health behaviors may be affected by external factors such as season, weather, and temperature, as well as by tour routes, and agglomeration effects in the park. In the future, the study scope and recording time of people can be expanded to reduce the influence of accidental behaviors of people and special spaces, environment, climate, vegetation density, etc., on the results, and further explore how people's spatial behavior varies under different circumstances.

Third, this paper used SOPARC to record crowd activities, simplified activities into three types, oversimplified visitors' behaviors in public space, and recorded observations only from objective perspectives, ignoring subjective experiences and intentions. Future research will combine interviews and questionnaires to add qualitative data, incorporate users' subjective experiences, and consider multiple factors such as duration of stay, social interactions, purpose of visit, and subjective experience to uncover more detailed explanations of activity patterns.

Fourth, the study only selected representative morphological features of people's perceptions, and did not comprehensively consider the influencing factors of other dimensions such as pavement type and sitting infrastructure, which is also the reason for the low value of R^2 in the regression results. In addition, this study is limited to multivariate linear regression analysis, which has limitations in the explanatory power of influence mechanisms, and multiple influencing factors and their joint mechanisms can be explored based on non-linear modeling or machine learning in the future.

5. Conclusion

This study observed and quantified the actual distribution of health behaviors in the park through panoramic photography and point recordings in the field, analyzed the spatial morphology characteristics perceived by the human eye through visual simulation based on the 3D point cloud model, visualized the distribution of people and morphology data through mapping, and explored the associations between health behaviors and spatial morphology using correlation analysis and descriptive statistics. Taking Nanjing Lovers' Garden Park as an example, the study investigated and analyzed 30 spaces and 3191 visitor points as samples, and obtained the following discoveries:

(1) With the help of mapping, the correlation between spatial morphology and people's activities at specific sites can be effectively explored. The landscape spatial morphology characteristics are uneven; the overall characteristics of the space cannot be represented by the morphology characteristics of a point location, and the spatial morphology perceived by the visitors during health behaviors varies across locations.

(2) Visitors' activity patterns are affected by a combination of multiple spatial morphology characteristics, of which edge degree, depth and richness show the strongest associations. Open, richly layered spaces are more likely to attract people. Specific intervals of spatial morphology indicators are more likely to correspond with higher user densities, such as people prefer to gather in the interval with ED of [0.45, 0.95], and the ED of 0.6 is most likely to attract high-density activities. It also proves the inference mentioned in the introduction that spatial features are moderate indicators of health activities, and morphological features of a certain interval degree are attractive to people.

In this paper, a fine-grained correlation analysis method was constructed by combining the analysis of on-site health behavior distribution and spatial morphology characteristics, which provides a path for in-depth investigation of the mechanisms influencing people's perception and healthy activity patterns in urban green spaces. 3D spatial indicators contribute theoretical and methodological insights to the 3D attribute field and the precise quantification of spatial morphology. The research provides practical value for urban design and planning by proposing a morphological framework that supports activity-oriented spatial refinement, predictive modeling for design optimization, and diagnostic insights for post-occupancy improvement. However, this study explored the effect of 6 indicators on people's activity through multivariate linear fitting analysis, the fitting results could only partially (10%—17%) explain the differences in people's distribution and influential factors. Non-linear modeling or machine learning methods will be explored in the future to reveal more complex and detailed influence mechanisms. Besides that, influencing factors such as spatial components, facilities arrangement, and spatial functions will also be added into consideration. Multi-site study and mixed-method approaches should be done to validate so that it can be applied in the design practice.

Ethics statement

The authors declare that their Institutional Ethics Committee confirmed that no ethical review was required for this study. Written informed consent for participation was not required because all participants' data were anonymized before the statistical analyses were done.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author contributions

Ziqian Cheng: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing — original draft, Writing — review and editing, Visualization, Validation. **Xiaohan Zhang**: Methodology, Writing — review and editing. **Yuning Cheng**: Supervision, Funding acquisition.

Declaration of competing interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foar.2025.06.005.

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