Dynamic Visual Assessment of Urban Streetscapes: Hengshan Street in Shanghai as a Case Study

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Abstract

Objectives: By investigating the urban street-human perception nexus under "dynamic" walks, this paper aims to enhance urban streetscapes and optimize pedestrian experiences.
Methods: In this study, a dynamic visual assessment system, encompassing objective, subjective, and interactive components, was developed through a combined application of qualitative and quantitative research methods. The computational foundation of this system was strengthened by Geographic Information System (GIS) spatial analysis, image semantic segmentation algorithms, Partial Least Squares Regression in SPSS, and so forth.
Results: Reduced desire for space and pedestrian flow are caused by an increase in dynamic viewing frequency. The public's impression of street space is enhanced in terms of clarity, transparency, ease of use, and richness when there is a greater range of spatial hues within the field of view, a smaller building area, and more translucent and clear spaces.
Conclusion: The research results are of great significance to street spatial design.

Keywords

dynamic viewing, visual assessment of landscapes, interaction between subjects and objects, urban streetscape

1 Introduction

Urban streets are not only crucial carriers of transportation hubs, but also the most fundamental public product of a city, serving as an important slow-moving traffic system for citizens to carry out their daily activities. It holds significant importance for the physical and mental health of the public (Jacobs, 2006). When individuals traverse urban streets, whether they pause momentarily to observe their surroundings or stride rapidly through, they remain in a state of "dynamic" observation, encompassing even periods of relative stillness (Xiong, 1984). The variations in visual angles and the adaptations in visual behaviors jointly enhance a profound sense of visual artistry within the dynamic urban landscape that is constantly in a "moving" state (Yang, 2019).

In this study, we address the interactive between the observer and the streetscape during the viewing state, specifically termed "dynamic observation," into the landscape visual evaluation index system. This methodology significantly beyond the traditional research, which primarily focused on the static relationship between "observer" and "environment" factors. Instead, it enables a multifaceted, three-dimensional correlation analysis that comprehensively considers the "subjective," the "objective," and the intricate "subject-object interaction." As a result, we derive profound insights into the observer's perception and the salient characteristics of the objective spatial environment, both of which are intimately tied to the dynamic observation state.

There are five sections in this study. A concise overview of the literature on the visual assessment of streetscapes is given in Section 1, which covers three essential aspects: the street's spatial environment, visual perception, and spatial behavior. We create a thorough assessment index system in Section 2 that considering the street spatial context, observer perception, and human behavior. The specific approach for measuring this assessment index system is described in Section 3, with an empirical measurement of Hengshan Road in Shanghai as the study region. A detailed overview of the outcomes of our measurement is given in Section 4. In Section 5, we utilize correlation analysis to derive findings about the complex relationships among the three elements of our assessment index system: behavior, perception, and street environment.

2 Literature review

The current quantitative research on street space predominantly adopts the fundamental logic of constructing an indicator system, which integrates technologies such as geographic information systems (GIS) and 3D software to visualize the morphological measurements of the street environment. In a comprehensive view, the objective index in urban street research generally encompass the urban skyline morphology (Zhang, 2001), degree of visual depth in urban space (NIU, 2013), Hierarchical levels of space (Peng, 2015), vision and spatial openness (Liu, 2009), comprehensive study of vision and space (Wang, 2013)， as well as visual perception with other factor (Cheng, 2017). The foundational data and their sources include: OpenStreetMap data, POI data, streetscape images, positioning system trajectory data, and elevation data (building heights, ground elevations). Specifically, we utilized machine learning algorithms and street-view data to measure the impact of street green view index (GVI) on walking time, and established quantitative evaluation metrics. The comprehensive study incorporated various data sources to gain a deeper understanding of the relationship between urban visual landscapes and pedestrian mobility (KI D, 2002). Utilize the theory of space syntax to delve into the effects of spatial openness on social interactions, and subsequently establish a comprehensive analysis model that incorporates both two-dimensional and three-dimensional visual (NIU, 2019).

The research on subjective components mainly focuses on aspects such as street spatial safety and perceived scenic beauty, proposing factors such as accessibility, ease of reach, safety, comfort, pleasure, aesthetic appeal, imagery, enclosure, permeability, human-scale design, and cleanliness. Using methods such as questionnaires, data is collected on the public's satisfaction ratings of streetscape images. This data is then combined with the results of objective index of the images to evaluate the public's perception of landscape aesthetics (Shao, 2017).

In the study of the interaction between environments and perception, there is a diversity in data sources, technical approaches, and research focuses. Some scholars have employed qualitative "cognition" analysis, along with quantitative measures of building density and ratio of wall (Zhou, 2012). The research examines the correlation between the subjective and objective factors, focusing on the relationship between street environments and the duration of people's stay as well as their subjective perceptual experiences (Hu, 2009). Wilson et al. (2016) argue that the index of "safety" and "pedestrian-friendliness" play a decisive role in the perception of urban streets. Pyo et al. (2015) discovered that pedestrians on street sidewalks have a higher degree of perception of spatial environmental elements, leading to a corresponding higher level of walking satisfaction. Elements such as the space outside shops, the density of street trees, enclosed spaces, the travers ability of the street space, and space utilization can all affect subjective preferences and feelings. Li Yajuan et al. (2018) used GIS analysis to explore the spatial structural characteristics and external transportation connectivity of historical districts, as well as tourists' perception of the district's image and location. [19] The forementioned studies primarily integrate the derivative terms of perception and sentiment with existing big data, utilizing various scientific software technologies to qualitatively describe relevant index and quantitatively analyze spatial numerical values, ultimately leading to corresponding conclusions.

As individuals continuously move and change their behavior in objective environments, buildings and landscapes emerge or recede in a continuous manner within one's visual field. [20] Some scholars have explored the spatial environmental characteristics in a "dynamic observation" state from the perspectives of behavioral activities, preferences, and spatial vitality. Author Cheng Shi (2021), building on the concept of "landscape," has integrated new technological means and proposed a new method of "dynamic observation evaluation" that aligns with the characteristics of crowd viewing behaviors. Do N (2019) utilized various methods such as questionnaires, scientific observations, and spatial analysis to collect and analyze data, exploring people's activities, preferences, and behavioral patterns within these parks. Fard H R (2014) studied the relationship between the physical characteristics of plazas and behavioral patterns and specific activities through questionnaires and scientific observations. Carmon (2003) employed case studies and theoretical frameworks to explore the influencing factors of street spatial vitality, including buildings, sidewalks, amenities, and other elements. Ewing R et al. (2014) examined the physical characteristics of urban streets and their edge spaces, focusing on objective index such as window ratios, street frontage ratios, and the number of street furnishings, to explore their impact on pedestrian traffic volumes. Li Y et al. employed a semantic segmentation method to explore the relationship between street width, transparency, and street vitality. Carmelino G et al. (2019) delved into the impact of the built environment on pedestrian vitality, considering key visual characteristics such as architectural form and proportion, streetscapes, materials and colors, spatial layouts and flow, as well as building façades and their elements.

From the perspective of research approaches, current studies have yielded numerous achievements in both objective quantification and subjective perception, and some have begun to explore the correlation between subjective and objective factors. Nevertheless, a thorough investigation that incorporates subjective, objective, and subjective-objective interactions is still absent in the research on index under the interaction between subject and object, which is still limited to the analysis of single-faceted features like human traffic aggregate. Research-wise, most of the studies that have already been done focus on "off-scene" static observations, ignoring the dynamic "in-scene" perception of the three-dimensional "space" that functions as the overall framework. In order to build a multi-dimensional study, they rarely consider the dynamic walking state of persons, such as walking routes and the vitality of walking places. In light of the research topic, this paper intends to investigate the relationship that exists between human perception, walking behavior, and urban streetscapes by means of an interactive study that includes three dimensions: "subjective," "objective," and " interactive components."

3 Establishing of the evaluation index system

Clustering analysis of premier research fields, we screened out the evaluation index of environment-perception that have relevant relationships and compiled an interactive relationship table of subjective and objective evaluation index (Tables 1).

Table 1. Relationship expressions of subjective and objective evaluation index (Liu, 2022)

Objective	The formula for calculating the correlation	R^2
Clarity	2.336 + 0.002×mean horizontal visual depth + 0.045×color richness	0.546
Transparency	2.574 - 1.677×architectural visual proportion + 2.250×sky view factor + 0.001×mean horizontal visual depth + 0.025×color richness	0.775
Relaxation	1.072 + 0.091×color richness + 6.663×green view index	0.641
Richness	0.929 + 0.089×color richness + 6.947×green view index	0.557

3.1 Establishing Objective Indicator System

Based on the analysis, three indexes are established for the objective index system, including spatial elements, spatial structure, and spatial vision. Specifically, spatial elements correspond to the openness of the sky, the visual proportion of buildings, and the green view index. Spatial structure corresponds to the horizontal visibility distance, while spatial vision corresponds to the color richness.

Table 2. Objective index and measurement methods (Huang, 2019. NIU, 2013. Dan, 2008. Li,2020)

Objective	Factor	Concept and formula interpretation	Formula
Spatial elements（B）	sky view factor （B_1）	Refers to the degree of the sky within the human visual field, which is the proportion of the sky within the "sphere of vision." B_1 represents the openness of the sky in a streetscape image, S_1 is the proportion of pixels identified as sky and S_0 represents the total number of pixels in each streetscape image.	$B_1 = S_1/ S_0$
	architectural visual proportion（B_2）	The building proportion of building area within the visual field, primarily including the building facade as well as its affiliated gray infrastructure. B_2 represents the visual proportion of buildings, S_2 is the number of pixels occupied by building facades within the visual field, and S_0 is the total number of pixels in the streetscape.	$B_2 = S_2/ S_0$
	green view index （B_3）	Referring to the proportion of green plants within the visual field. B_3 represents the green view index of a streetscape image, S_3 is the number of pixels representing trees, grass, plants, and other greenery in the image, and S_0 represents the total number of pixels in each streetscape image.	$B_3 = S_3/ S_0$
Spatial structure （C）	mean horizontal visual depth （C1）	Taking the observer's position on the street as the centre, 360° horizontal line of sight is projected around, and the maximum distance that the human eye can observe is limited. The average length of sight lines in all horizontal directions is denoted as C_1, and the length of the nth sight line is denoted as C_n	$C_1 = \frac{1}{n}\sum_{i=1}^{n} C_n(i\in N^*$
Spatial vision （D）	color richness （D_1）	It refers to the richness of color factors. Extracting the brightness values of the color components R (red), G (green), and B (blue) from the streetscape images, and calculate the rg and yb values using the formulas: rg = R – G, yb = (R + G)/2 – B. Calculating the standard deviation σ and average values of rg and yb for pixel.	$D_1 = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2} + 0.3\sqrt{\mu_{rg}^2 + \mu_{yb}^2}$

3.2 Establishing subjective index system

Four components of subjective evaluation indexes are selected: clarity (vague-clear), transparency (enclosed-open), richness (monotonous-rich), and relaxation (suppressed-relaxed).

Table 3. Subjective index and measurement methods

Subjective	two-level vocabulary	Concept
Clarity	vague-clear	The degree of sharpness and explicitness that a block's visual environment imparts to people is referred to as clarity. In contrast, pedestrians may need to continuously rotate their line of sight in order to observe and perceive the surrounding spatial structure, which can quickly cause physical and mental fatigue. The better the clarity, the faster pedestrians can perceive the surrounding spatial structure through visual observation.
Transparency	enclosed-open	The phrase refers to the streetscape's power of directional indications and sense of visual permeability. Pedestrians can more easily discern direction and rapidly identify the main forward direction of the roadway and adjacent spaces if the street space has better permeability. On the other hand, disorientation and a loss of orientation can quickly result from uniform obstruction of the field of vision in all directions.
Relaxation	suppressed-relaxed	The phrase describes how at ease pedestrians feel in the streetscape. Pedestrians feel more at peace in a street area the easier it is to navigate. On the other hand, they might feel uneasy.
Richness	monotonous-rich	The phrase describes the level of richness that pedestrians find in the streetscape. Pedestrians are more likely to feel engaged and intrigued about the street and its environs when it is richer, which makes them more receptive to the street. On the other hand, they can experience fatigue and boredom and be unable to enjoy a leisurely stroll down the street.

3.3 Establishing interactive index system

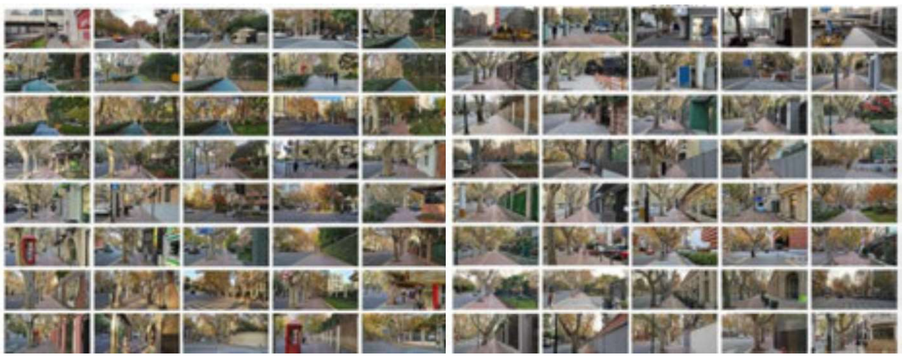
The term "human behaviour based on observation" describes a range of proactive-reactive behavioural patterns that people exhibit when they are in public areas. The spatial nodes that walking traverses are linked together to form a whole observation trail as these behaviours move across the area. The characteristics of spatial human flow distribution, often referred to as spatial vitality, are the dynamic observation states of many people overlapping, converging, and dispersing in the space.

We suggest the objective-subjective interaction index, which includes two indicator levels: the spatial vitality index and the frequency of dynamic observation of subjects in the guest space environment. This indicator serves as an evaluation metric for the dynamic observation of subjects.

When people watch landscapes in a space, their bodies and eyes follow certain trajectories, which are referred to as observation routes. The frequency of dynamic observation paths is defined as the ratio of the total number of observation paths in the neighbourhood to the overlapping times of different users' paths in the same location. The following are the precise steps in measurement: Gather walking trajectory data for the research area from a website (e.g., two-step path trajectory data), import it into a geographic information system (GIS), and overlay it with the spatial locations of observation points. Next, compute the ratio between the frequency of each sample point's path and the total number of paths using inductive statistical methods.

The spatial vitality index refers to the distribution state of spatial human flow formed by the aggregation and dispersion of people due to social, cultural, economic, and environmental activities. It is calculated by averaging the heat values of the same sample point at different time periods, resulting in the spatial vitality value of the sample point.

4 Method



4.1 Study area and sample collection

This study focuses on Hengshan Street in Shanghai as the research area. To ensure the accuracy, operability, and comprehensiveness of the evaluation results, a quasi-experimental simulation was conducted based on real-world conditions. Comprehensive consideration was given to factors such as street spatial elements, spatial structure, and visibility distance. The evaluation was conducted with 50m as a research unit, and the central line of the roadway was used as the dividing line to divide the west and east sidewalks of the block. Combining with the Chinese people's long-standing consciousness of "walking on the right side," we simulated the walking process and collected corresponding streetscape samples. Specifically, the east sidewalk adopted a walking route from south to north, while the west sidewalk adopted a walking route from north to south, simulating the way pedestrians walk in the street. The photos were taken at eye level, approximately 1.6 meters high, with a mobile phone's camera function in 1X zoom mode and full-screen photo ratio, every 50 meters apart[32]. At the same time, the positioning function of the two-step path APP was activated, and a field photo was taken at each sample point as a reference for observation point location. The observation path files were also preserved, resulting in a total of 80 sample images (Figure 1), two kml file paths, and 80 points.

Figure 1. Schematic Diagram of Sample Images

4.2 Measurement methods for objective index

The calculation methods for objective index include streetscape image semantic segmentation, GIS spatial operation, and Colorimpact color analysis. Semantic segmentation is used to measure three objective indexes of spatial elements: sky view factor, architectural visual proportion and green view index. GIS is used to determine mean horizontal visual depth of the sample spatial structure, while the Colorimpact software is used to analyze the RGB color values in the sample images.

4.2.1 Semantic Segmentation of Streetscape Images

To begin preprocessing, the gathered streetscape image dataset is first imported into Adobe Photoshop. To prevent any potential segmentation errors caused by extremely large image resolutions, the image size is lowered to 1000 x 462 pixels. The processed images are next subjected to analysis using a visual image semantic segmentation, namely the CUG.HPSCIL image recognition tool. To determine the sample image's sky view factor, we segment the spatial elements and then extract the "03_Sky" from the segmentation results. In order to determine the visual percentage of building façades in the sample image, we additionally extract the "02_Buildings". Furthermore, the "05_rees," "10_Grass," and "18_Plants" from the segmentation results were added together.

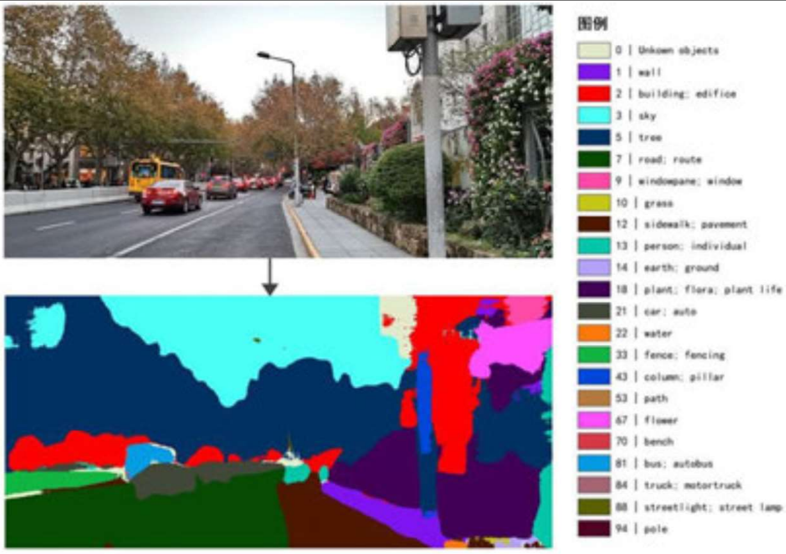
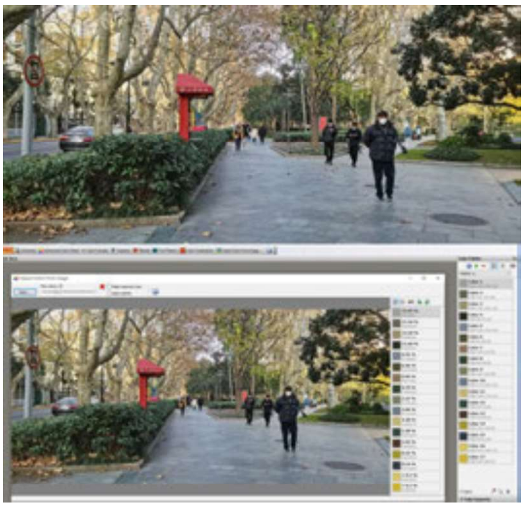


Figure 2. Image and semantic segmentation results for sample point East_02

4.2.2 Colorimpact color analysis

Sample images are imported into Colorimpact, and the RGB color values that account for more than 0.1% of image are exported (Figure 3). These values are then recorded in an Excel document, and the final result is calculated based on the formula for color richness.

Figure 3. Color analysis results by Colorimpact



4.3 Measurement Methods for Interaction Index

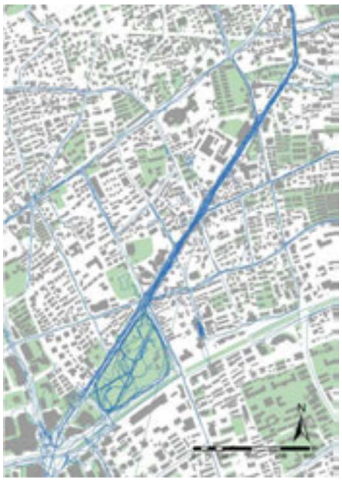
4.3.1 Calculation of dynamic observation frequency based on pedestrian trajectories

Pedestrian trajectory data of the street is obtained from the official website of a walking app, and the data is preprocessed and cleaned to filter out valid user walking trajectories. The data is then imported into a GIS system, where it is overlaid with the spatial layout of buildings and other structures in the observed street for data visualization analysis, specifically the visualization of observation paths in the street space (Figure 4). By integrating the spatial data of observation points, the road is divided into two parts, and a buffer zone of 80 sample points is constructed with a buffer radius of half the road width, which is 8 meters. The number of observation paths within each sample point's buffer zone is then calculated and divided by the total number of observation paths in Hengshan Road, resulting in the dynamic observation frequency for that sample point. The relevant expression is:

$$Rx=n_x/N*100\% \quad (1)$$

Rx represents the frequency of observation paths for sample point x. Taking the eastern sample point 1 as an example, where the sample point number x is East_01, nx represents the number of paths passing through that sample point, and N is the total number of paths collected.

Figure 4. Visualization of two-step path trajectory data



4.3.2 Calculation of spatial vitality index based on Baidu heatmap

Based on the principles of randomness and pedestrian crowding degree, a random weekend day (February 12, 2023) and a weekday (February 13, 2023) were selected. The Baidu heatmap data was captured hourly from 8:00 am to 8:00 pm, resulting in a total of 26 heatmaps. Subsequently, the ArcGIS tool was utilized to define the projection and perform georeferencing. Multi-ring buffer zones were processed using half of the road width, which is eight meters, as the buffer radius. Heatmap areas within these buffers were then extracted to generate "street heatmaps."

The heat values were categorized into seven levels from zero to seven, quantized as zero, one, two, three, four, five, and six, with higher values indicating greater vitality in the sample space. The average heat values for different observation points on weekends were then calculated:

$$T_1=\sum_{i=1}^{n} T_n/N \quad (i \in N^*) \qquad (2)$$

Among them, N represents the total number of heatmaps collected on weekends, which is 13, and Tn represents the heat value collected at different time periods on weekends. The average heat value for weekdays is calculated as follows:

$$T_2=\sum_{i=1}^{n} T_n/N \quad (i \in N^*) \qquad (3)$$

N represents the total number of heatmaps collected on weekdays, which is 13, and Tn represents the heat value collected at different time periods on weekdays. Taking a week (5 weekdays and 2 weekends) as a cycle, the average heat value of the sample points is calculated as:

$$T=(T_1*2+T_2*5)/7 \qquad (4)$$

Through the analysis of the heat values of the sample, the spatial distribution patterns and characteristics of street vitality are finally calculated. A higher average heat value of the street indicates greater pedestrian flow and more vitality.

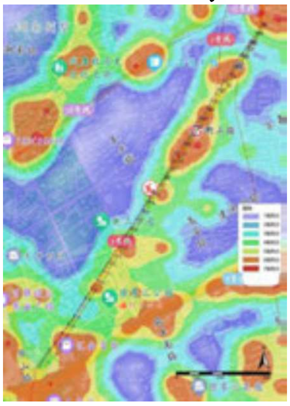


Figure 5 Weekend_13 , 20:00 Baidu heatmap data

5 Results

5.1 The result of objective measurement in Henshan Street

The quantitative results of objective index (Tables 4) show that the spaces with the best sky view are sample point _17 on the east side with view of 23 percent, and sample point _31 on the west side with view of 22 percent. The view of sample point _05 and point_12 on the east side and sample point _20 on the west side are all 17 percent, indicating that these two sample points have the largest area of visible sky.

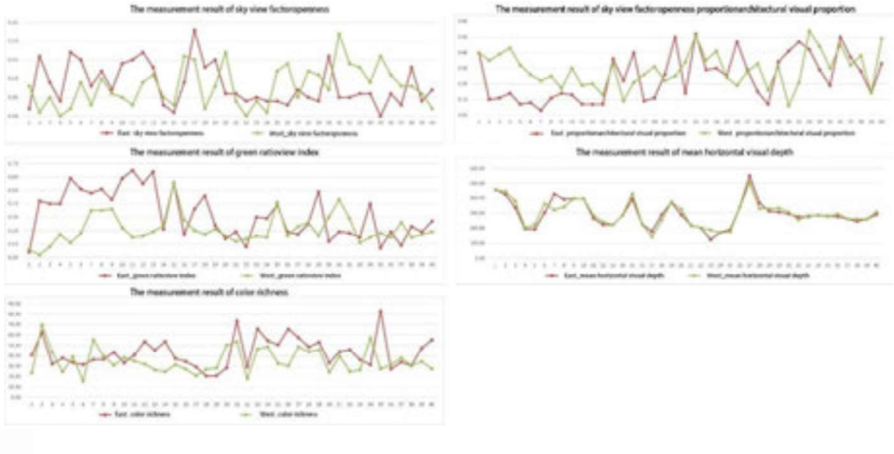
Compared with the visual proportion of buildings, it is found that the overall visual proportion of the sky in Hengshan Road is far lower than that of buildings, indicating that the building density in this area is greater than the sky area. The spaces with the smallest openness are sample point _35 on the east side, sample point _04 on the west side, and sample point _22 on the west side, with a sky visibility area tending to zero, indicating that the spatial closure of these three sample points is too high, and the spatial vision is seriously obstructed.

The fluctuation of horizontal visibility distances on both sides are similar, which may be due to the straightness of Hengshan Street and the similar ground elevations. Among them, the samples with the largest horizontal visibility distances are sample point _27 on the east side with a value of 550.21, and sample point _27 on the west side with a value of 504.82. The smallest ones are sample point _17 on the west side with a value of 141.11, and sample point _23 on the east side with a value of 123.29, showing a significant difference, indicating that the visual length of the studied street varies significantly.

The three points with the highest visual proportion of buildings are sample point _31 on the west side with a visual proportion of up to 58 percent, sample point _22 on the east side with a visual proportion of 52 percent, and sample point _22 on the west side with a visual proportion of buildings at 51 percent. The maximum building area is far higher than the maximum sky area of 23 percent. The lowest building density is sample point _07 on the east side with a value of 3 percent, sample point _31 on the west side with a value of 6 percent, and sample points _05, 11, 12, 13 on the east side, with a visual area proportion of buildings at seven percent.

The three points with the highest green view index are sample point _5, point _11, point _12 on the east side, with green view indexes of 59 percent, 65 percent, and 64 percent in order. The green view index exceeds half of the overall visual proportion of 50 percent, indicating a very high green view index. The lowest green view index is sample point _01 on the east side with a value of four percent, sample point _01 on the west side with a value of 8 percent, and sample point _02 on the west side with a value of 1 percent. The three points with the highest color richness are sample point _35 and 21 on the east side and sample point _2 on the west side, with color richness values of 83.09, 73.21, and 69.51 in order. The lowest color richness is sample point _06 and 22 on the west side, with values of 15.84 and 18.00 respectively.

Tables 4. Objective index calculation results for each sample point on Hengshan Street



Using GIS to visualize the spatial results of the objective evaluation, as shown in Figure 6, the deeper the color, the higher the proportion of the skyline visual area, indicating a more open space. The maximum visual proportion of the skyline is 23 percent, while in some local areas, the skyline area is almost zero. The main reasons for this are two points: firstly, the street has a long history with rows of plane trees, covering most of the street space; secondly, the width of the motor vehicle lane on this street is approximately 16 meters, with buildings standing on both sides, resulting in limited public space and a relatively crowded environment.

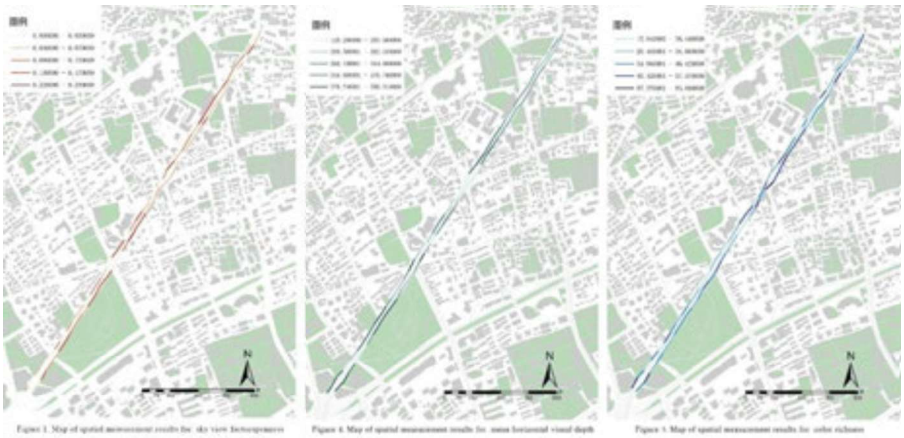


Figure 6. Spatial location map of objective index measurement results

The location of the building visual proportion in the street space shows that the maximum building visual proportion is up to 54 percent, mainly concentrated in the northern area. The southern part is a large commercial district with taller buildings, but they are a certain distance from the street. Additionally, the southeastern part is Xu Jiahui Park, where buildings are sparse.

Therefore, the distribution characteristics of the building visual area in the space are obvious.

The spatial location map of the average horizontal line of sight distance. Since the street is straight and has good permeability, the overall average line of sight distance value is relatively large.

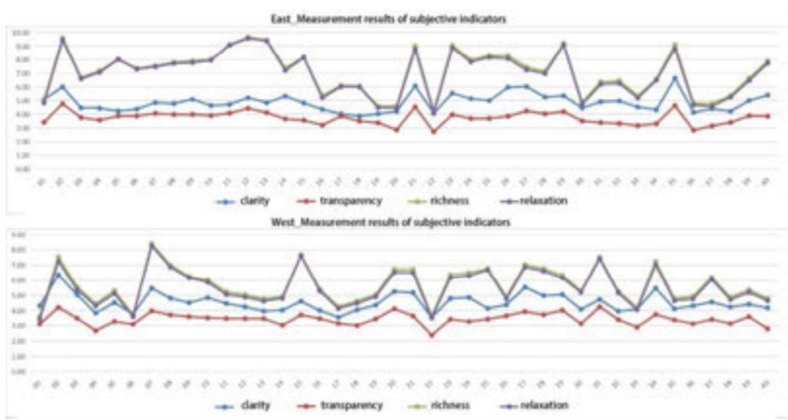
In terms of spatial distribution, it reveals that the green view index is dense in the south and gradually decreases from south to north. Especially along the border of Xu Jiahui Park, the green view index reaches 65 percent. This is because the pedestrian walkway in this area differs from the unilateral planting characteristics of other areas, featuring low hedges and tall plane trees, camphor trees, and other species on both sides. This section of the pedestrian walkway cleverly combines walking and jogging paths, attracting runners and greatly enhancing the spatial vitality of the pedestrian walkway. Furthermore, the hedges separate the pedestrian walkway from the roadway, making human activities less vulnerable and safer.

It expresses the spatial location characteristics of color richness, and the proportion of high-color areas in the entire street space exceeds half. The street district is rich in color variety and locally unified, creating a sense of integrity in the changing spatial vision.

5.2 The result of subjective measurement in Henshan Street

In terms of the correlation equations between environment and perception evaluation index from existing literature research, as well as the analytical results of the spatial environmental index of the sample points, we calculated the subjective index of clarity, transparency, relaxation, and richness. The findings indicate that the values of relaxation and richness in the Hengshan Road district are similar, but there are significant fluctuations in different spaces, resulting in noticeable differences in perception. In contrast, the differences in clarity and transparency are relatively small, resulting in a more homogeneous spatial experience.

Table 5. Subjective Index Calculation Results

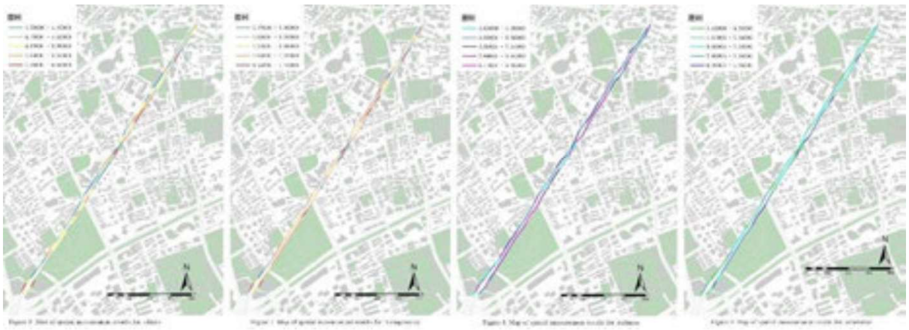


Using GIS to visualization the subjective index results, as shown in Figure 7, the distribution of clarity in the space reveals that areas that tend to create a sense of brightness are relatively scattered. The pedestrian walkway next to Xu Jiahui Park has a lower sense of brightness.

As shown, the darker the color, the better the spatial sense of transparency. The area next to Xu Jiahui Park has a higher sense of transparency, while the transparency of other streets in the area is also good, with few areas having low values.

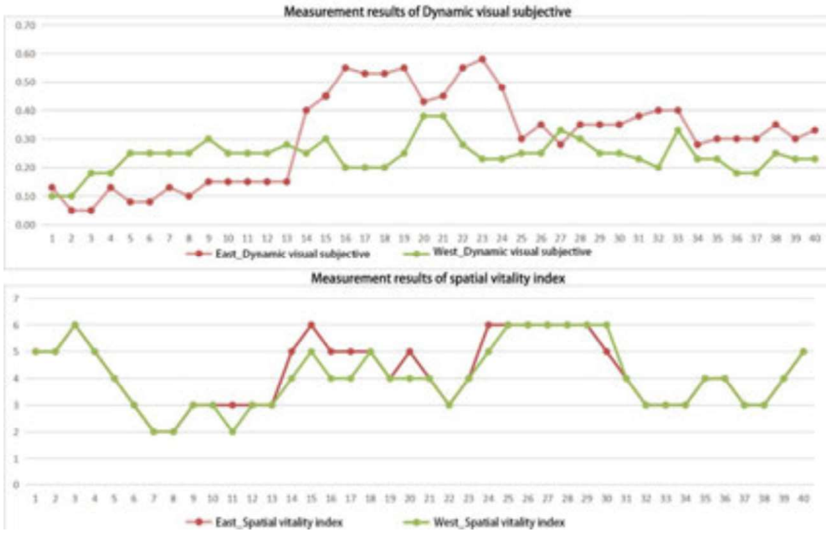
It represents the location maps of the sense of relaxation and richness. The pedestrian spaces close to Xu Jiahui Park tend to evoke a sense of relaxation and have a high spatial richness, indicating that spaces with high vegetation coverage, such as slow-moving pedestrian walkways, provide a positive perceptual experience for people.

Figure 7 Spatial location map of subjective index



5.3 The result of interactive index measurement in Henshan Street

Table 6. Interactive Index Calculation Results

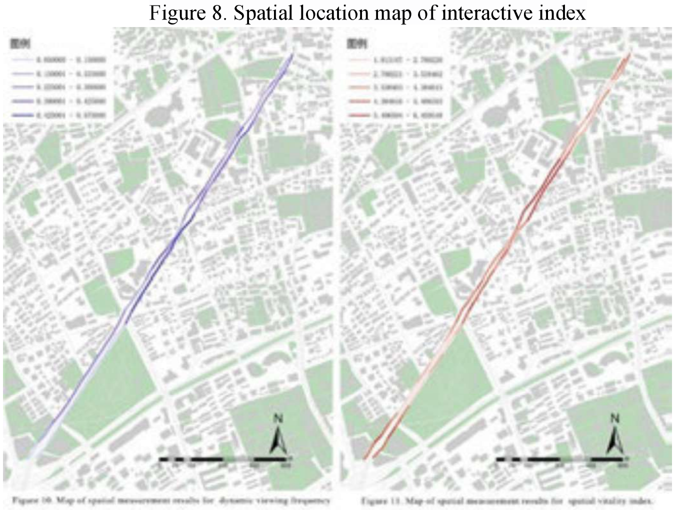


Based on the sample point calculation results, a statistical table of the dynamic viewing frequency for samples on both the east and west sides (Tables 6) have been compiled. The west side shows a relatively balanced spatial distribution of dynamic viewing frequency, while the observation points on the east side near Xu Jiahui Park have a lower pedestrian viewing frequency. As people approach the middle section of the street, the pedestrian viewing frequency increases. The possible reasons for this are as follows: when pedestrians approach Xu Jiahui Park, they may be attracted by the park's internal landscapes and activities. Additionally, this section serves as a jogging track, so to avoid crowding and collisions with other pedestrians, people may choose to change their route and enter the park to walk around.

According to the results of Baidu heatmap, that the high-activity areas are distributed in a "multi-core" point-like pattern in the streets; only eight points have fluctuating spatial heat values in the observation points on both sides of the same serial number; the highest heat value is six which is a high-activity block, and the lowest heat value is two, which includes three points. The maximum difference in heat values for the entire block is four; the areas with the highest heat values are mainly concentrated in serial numbers 24-29, with an average heat value of six, followed by the spatial heat values of serial numbers one-four. The analysis reason is that this area is connected to the Xuhui business district and is relatively easy to attract traffic.

Importing the frequency data of viewing into GIS for data visualization analysis shows that the darker the color, the higher the frequency of people's walking view of the space. Except for the slow-moving path next to Xuhui Park in the south, the frequency of viewing at other locations is high, indicating good utilization of the space for walking. The reason is that this area is connected to Xuhui Park, with multiple locations that can directly access the park. The public who uses walking to tour the streets prefer to enter parks with beautiful scenery, rich vegetation, and diverse spatial activities, which leads to a low frequency of viewing in this area.

Figure 8. Spatial location map of interactive index

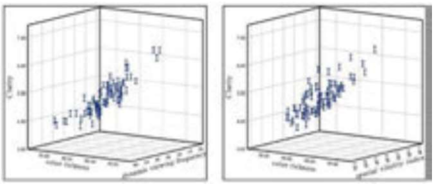


As shown in Figure 8, the darker the color, the higher the spatial vitality index, and the greater the average flow of people in the space. The Hengshan Road block does not have a high density of people throughout the entire route, but there are two distinct low-vitality areas in the middle. The high-vitality area in the middle is mainly due to that it is the entrance and exit of the subway Hengshan Road Station, which has a relatively high flow of people.

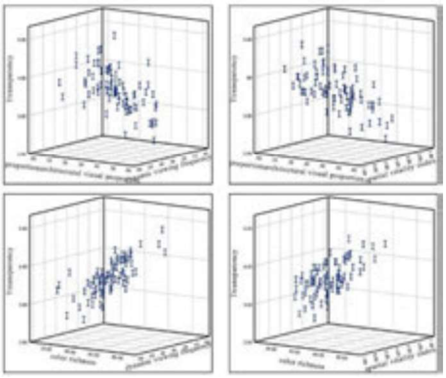
5.4 The Mechanism of Urban Street Dynamic Landscape

One dependent variable and two independent variables were used in a regression study using SPSS's Partial Least Squares Regression (PLSR) method. To be more precise, the first independent variable consisted of five objective evaluation indexes: sky openness, building visual proportion, green view index, average horizontal visibility distance, and colour richness. The other four subjective evaluation indexes were clarity, transparency, openness, and richness. The second independent variable was the spatial vitality index, dynamic viewing frequency, and landscape choice deviation under the interaction between the subjective and objective components. Sample data were used to explore the correlation between subjective, objective, and interaction index, specifically the subjective sensation characteristics under different "dynamic viewing" states and objective environmental characteristics. The indicator equations with a model fit $R^2 \geq 40\%$ were selected and output.

Figure 9. 3D scatter plot of clarity



The strong correlation results were visualized using a 3D scatter plot in SPSS. As shown in Figure 9, there is a strong correlation between richness, dynamic viewing frequency, landscape preference, and spatial vitality index. The relevant equation expressions are: Clarity = 2.981 + 0.046 * Color Richness - 0.356 * Dynamic Viewing Frequency, Clarity = 2.732 + 0.046 * Color Richness + 5.523 * Landscape Preference, Clarity = 2.834 + 0.046 * Color Richness + 0.017 * Spatial Vitality Index. The results indicate that the more diverse the spatial colors are, the clearer and more easily understood the spatial environment is perceived by people. Clarity has a negative correlation with dynamic viewing frequency, meaning that the higher the frequency of walking in the space, the lower the perception of spatial clarity. At the same time, clarity has a positive correlation with landscape preference deviation and spatial vitality. The more popular the landscape space is, the lower the clarity is, while the higher the spatial vitality index, the

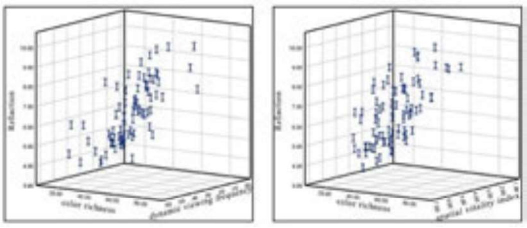


more dynamic and interpretable the space is.

Figure 10. 3D scatter plot of transparency

The sense of transparency has a strong correlation with building visual proportion, color richness, dynamic viewing frequency, landscape preference, and spatial vitality index. The correlation equations are: Transparency = 4.183 - 2.411 * Building Visual Proportion + 0.158 * Dynamic Viewing Frequency, Transparency = 4.208 - 2.370 * Building Visual Proportion + 0.303 * Landscape Preference, and Transparency = 4.018 - 2.406 * Building Visual Proportion + 0.050 * Spatial Vitality Index. These equations suggest that when there is less building volume in the space and a lower proportion of buildings in the visual field, the higher the deviation in people's preference for the spatial landscape, the higher the number of dynamic viewing routes, and the greater the flow of people in the space, indicating a higher sense of transparency and openness.

Figure 11. 3D scatter plot of relaxation



There is a strong correlation between the sense of relaxation and color richness, dynamic viewing frequency, landscape preference, and spatial vitality index. The specific equations are: Ease = 3.369 + 0.090 * Color Richness - 1.791 * Dynamic Viewing Frequency, Ease = 2.323 + 0.091 * Color Richness + 20.765 * Landscape Preference, and Ease = 3.183 + 0.090 * Color Richness - 0.071 * Spatial Vitality Index. These equations suggest that when there is a greater variety of colors in the space, with a decrease in the frequency of walking and viewing, a lower preference for the space, and less foot traffic, people tend to feel more relaxed and focused on the environment and their own experience.

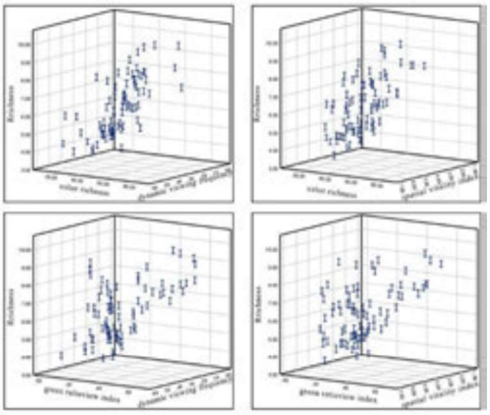


Figure 12. 3D scatter plot of richness

The three-dimensional scatter plot shows that people's sense of richness in spatial environments has a strong correlation with spatial colors, vegetation, walking routes frequency, landscape preference, and spatial vitality index. The specific equations are: Richness = 3.324 + 0.088 * Color Richness - 1.867 * Dynamic Viewing Frequency, Richness = 2.233 + 0.089 * Color Richness + 21.651 * Deviation in Landscape Preference, Richness = 3.130 + 0.088 * Color Richness - 0.074 * Spatial Vitality Index, Richness = 4.223 + 6.829 * Green View Index + 0.789 * Dynamic Viewing Frequency ($R2 = 0.401, 0.412$), Richness = 5.045 + 6.933 * Green View Index - 25.333 * Landscape Preference, and Richness = 3.745 + 6.812 * Green View Index + 0.167 * Spatial Vitality Index. This indicates that with more color variety in the space, fewer walking passages, lower preference for the space, and less foot traffic, people perceive a higher level of richness in the spatial environment and are better able to experience the objective environmental details. As the amount of green vegetation increases and the frequency of viewing also rises, people's preference for the space and spatial vitality increase, leading to a higher perception of spatial richness, indicating an increased ability to perceive the space.

From the comparative analysis of the images, the top three significant linear correlations are: Clarity - Color Richness - Dynamic Viewing Frequency > Clarity - Color Richness - Landscape Preference > Clarity - Color Richness - Spatial Vitality Index. The objective index of sky view proportion and average horizontal visibility distance have low correlation indices with subjective index and subject-objective index, indicating weak correlations. In urban street spaces, green view index mainly affects people's sense of richness, with a lower impact on subjective index. Among the objective index, building area and color richness significantly influence people's perception, and thus should be given priority consideration in planning and design.

6 Conclusions

The study takes objective urban street environmental index such as sky view factor, architectural visual proportion, green view index, mean horizontal visual depth, and color richness, as well as subjective index like clarity, transparency, richness, and relaxation, as independent variables. It also considers the interactive index between the subjective and objective under dynamic viewing conditions, including dynamic viewing frequency, and spatial vitality index, as dependent variables. The study explores the characteristics of streetscape that significantly influence the viewing behavior in urban street environments, as well as their visual perception features. Based on this, design methods are proposed to enhance the frequency of viewing, spatial vitality, and landscape preference in street spaces. The specific conclusions include the following three aspects:

Establishing interactive evaluation index system. Based on the subjective perceptions stimulated by the "dynamic viewing" mode in the objective environment, the study innovates the evaluation index system by adding index such as dynamic viewing frequency based on spatial positioning trajectory data and spatial vitality index based on pedestrian flow distribution status. These indexes are then combined with the subjective and objective index from previous studies to construct regression equations that are closer to realistic viewing conditions.

Qualitative and quantitative evaluation index system. Through data sources such as sample photo collection, spatial positioning data from the "two-step" app, Baidu Heatmap, OpenStreetMap street, building and road data, and GSCloud, methods like image semantic segmentation, GIS analysis, Colorimpact color analysis, and inductive statistics are employed to quantify the index system.

Summary of subjective and objective regression equations. Through partial least squares analysis in SPSS, the study found significant correlations between clarity, relaxation, and color richness, dynamic viewing frequency, and spatial vitality index; as well as between transparency and color richness, visual proportion of buildings, dynamic viewing frequency, and spatial vitality index.

Due to objective reasons such as weather conditions during photography, camera pixel quality, and seasonal changes, the sample images collected may not reflect the true appearance of the streets throughout the four seasons, and the relatively short time span of the samples may introduce certain experimental errors.

Due to the heavy traffic on the streets, the elements in the 360° panoramic photos collected on-site are severely distorted, with an imbalance in visual area proportion. Therefore, a static photography method was adopted as a second-best option, which may lead to incomplete observation point data and have a certain impact on the experimental results. Future research could incorporate behavioral patterns, such as stationary, mobile, and dynamic viewing speed, during the "dynamic viewing" state, employing methods such as eye-tracking experiments, scientific observation, and trajectory tracking to expand the evaluation factors of the subjective-objective evaluation system and improve dynamic viewing evaluation index. The use of 360° panoramic photography can also be adopted to capture more comprehensive spatial environmental elements, improving the sustainability of the experiment. Alternatively, advanced technological means such as GoPro and anti-shake cameras can be utilized to collect spatial image samples of basic units for a more comprehensive perceptual evaluation study.

Conference

Chen, Z., He, X., Yang, W., et al. (2017). Urban Street Landscape Visual Evaluation and Design Supported by Real-Time Realistic Experience. Chinese Urban Forestry, 15(4), 6.

Cheng, S., & Wang, J. (2021). Exploring Visual Landscape Research Based on Dynamic Observation and Evaluation - Taking the Riverside Public Space in Nanjing as an Example. Chinese Landscape Architecture, 37(11), 6.

Carmona, M., Heath, T., OC, T., et al. (2003). Public Places-Urban Spaces: The Dimensions of Urban Design. Public places - urban spaces: the dimensions of urban design.

Carmelion, G., & Hanazato, T. (2019). The built environment of Japanese shopping streets as visual information on pedestrian vibrancy. Frontiers of Architectural Research, 8(2), 261-273.

EWING, R., HAJRASOULIHA, A., NECKERMAN, K., et al. (2014). Streetscape Features Related to Pedestrian Activity. In Proceedings of the Transportation Research Board Meeting.

F, H. R. (2014). Evaluating Spatial Behavior in the Urban Public Space of Kadıköy Square.

HUANG, S., & LIU, B. (2019). Visual Perception and Optimization Strategy of Urban Pedestrian Street Landscape Based on Landscape Theory of "Openness and Enclosure": Taking East Nanjing Road in Shanghai as an Example. In Proceedings of the Annual Conference of Chinese Society of Landscape Architecture (pp. Pages). Shanghai, China.

Jacobs, J. (2006). The Death and Life of Great American Cities. [Translated title: The Death and Life of Great American Cities]. Science & Technology Review, (7), 56-7.

Kallen, L. (1992). Urban Landscape Art.

Jane Jacobs. (2006). The Death and Life of Great American Cities. Science & Technology Review, (7), 56-7.

KI, D., & LEE, S. (2021). Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning. Landscape and Urban Planning, 205.

KARNDACHARUK, A., WILSON, D. J., & DUNN, R. C. M. (2016). Qualitative evaluation study of urban shared spaces in New Zealand. Transportation Research Part D: Transport and Environment, 42(JAN.), 119-134.

Li, Y., Cao, H., Li, C., Wang, R., Zeng, H., & Jia, Y. (2018). Research on Spatial Structure and Spatial Perception of Tourists in Historic Districts of Wuhan City. Resource Development & Market, 34(11), 1599-1603,1622.

Liu, Y. (2009). Urban Mountain Visual Landscape Analysis and Evaluation.

LI, Y., & HUANG, J. (2020). Evaluation of green visual perception in pedestrian environment of historic districts based on green visual decay curve: Taking Tongwen Area of Zhongshan Road, Xiamen as an example. Landscape Architecture Frontiers, 27(11), 110-115.

LI, Y., YABUKI, N., & FUKUDA, T. (2022). Exploring the association between street environment and street vitality using deep learning methods. Sustainable Cities and Society, 79.

LIU, B., & YANG, Y. (2022). Evaluation of Dynamic Visual Openness in Urban Streetscapes. Landscape Architecture Frontiers, 29(08), 64-70.

NIU, X., & LI, K. (2013). Quantitative Analysis Method of Urban Skyline Based on Visual Impact. Urban Planning Forum, (3), 7.

Niu, X., Wu, W., & Li, M. (2019). Research on the Impact of the Built Environment on Street Vitality Based on LBS Positioning Data and Its Temporal and Spatial Characteristics. International Urban Planning, 34(1), 10.

Peng, J., & Xu, Q. (2015). Exploring Quantitative Evaluation of Urban Spatial Environment Based on Multi-dimensional Visual Impact - Taking the Urban Design of the Area around the Moat of Xiangyang Ancient City as an Example. Modern Urban Research, 000(010), 36-46.

Pyo, Kim, et al. (2015). Effects of the Perception of Street Environment Elements and D:H Ratio on the Street Satisfaction on Commercial Streets - Focusing on Garosu Street, Daehakro Street and Jungjadong Café Street. Journal of the Urban Design Institute of Korea Urban Design, 16(2), 77-87.

Shao, Y., & Liu, B. (2017). Research on Visual Aesthetic Evaluation of Urban Street Landscape. Chinese Landscape Architecture, 33(9), 6.

SHAN, L. (2008). Research on Several Key Technologies and Applications of Visual Attention Mechanism (Master's thesis). University of Science and Technology of China.

Xiong, G. (1984). Research and Application of Urban Road Aesthetics - A Discussion on Urban

Road Aesthetics. Journal of Xi'an Highway University, (04), 21-40.

Wang, J., Yang, J., Chen, Y., et al. (2013). Planning Theory and Technical Exploration of the "Landscape-View" Interaction in West Lake City. Urban Planning, (10), 7.

Yang, K. (2019). The Evolution of Urban Planning Theory and Methods in New China Over the Past 70 Years. Management World, 35(12), 11.

YAO, Y., LIANG, Z., YUAN, Z., LIU, P., BIE, Y., ZHANG, J., ... & GUAN, Q. (2019). A human-machine adversarial scoring framework for urban perception assessment using street-view images. International Journal of Geographical Information Science, 33(12), 2363-2384.

Zhang, S. (2001). Introduction to the Science of Historic Urban Conservation.
Niu, X., & Xu, F. (2011). Quantitative Evaluation Method of Spatial Openness of Built Environment Based on Visual Impact. Urban Planning Forum, (1), 7.

Zhou, Y., Zhang, Y., & Yuan, S. (2012). Quantitative Research on the Psychological Cognition of Street Interface. Architectural Journal, (S2), 4.