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Spatial Quality Measurement and Characterization of Daily High-Frequency Pedestrian Streets in Xi'an City

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Abstract: Street space plays a crucial role in human activity and social life, forming an essential component of a livable and sustainable built environment. Consequently, its quality has garnered significant attention from researchers, designers, and policymakers who aim to achieve precise assessments of street infrastructure and conditions. This study presents a multi-dimensional framework for evaluating street space, considering factors such as access frequency, environmental quality, and amenity richness. By utilizing city-level path planning data, street view imagery, point of interest data, and social media check-in data, this framework assesses each street and assigns scores across these dimensions. These scores facilitate a human-centered analysis of the disparities in street usage and quality. The aggregation of results by administrative regions supports effective policy formulation and implementation. Application of this framework in Xi'an, China, reveals that only 6.95% of frequently visited streets exhibit high environmental quality and functional richness. This study underscores the potential of leveraging public data for detailed street space assessments to inform urban renewal policies.

Keywords: high-frequency pedestrian streets; spatial quality; facility function; streetscape image

Citation: Liu, L.; Tu, Y.; Sun, M.; Lyu, H.; Wang, P.; He, J. Spatial Quality Measurement and Characterization of Daily High-Frequency Pedestrian Streets in Xi'an City. *Land* **2024**, *13*, 885. https://doi.org/10.3390/land13060885

Academic Editors: Yangyi Wu and Monika Kopecká

Received: 4 May 2024
Revised: 9 June 2024
Accepted: 14 June 2024
Published: 19 June 2024

1. Introduction

In urban stock planning, accurately and effectively improving the quality of urban public space is becoming one of the focuses of urban design work in the new era [1–3]. Improving the quality of urban public space plays a crucial role in promoting sustainable urban development [4]. Streets, as the main space for urban functional connection and urban daily life, are not only an important type of urban public space but also a carrier for urban residents to recognize the city and feel the urban life [5] and their spatial quality has been increasingly emphasized. In order to improve the livability and vitality of cities, many cities around the world have successively put forward the strategy of building friendly street spaces, Such as the Better Streets in London, UK, the Urban Street Design Guide in the USA, and the Street Design Guidelines in Shanghai, China (Table 1). However, identifying street space quality problems and implementing street renewal planning and management are becoming new challenges in urban renewal and renovation.

Since the 1960s, urban planning scholars have debated the link between street quality and street social activities. Street quality not only encompasses the visual environmental aspects but also involves green spaces and air quality [6,7]. Lynch, Whyte, Jacobs, and Gehl have emphasized the value of streets in terms of their physical characteristics [8–11], pointing out that better visual perceptions of streets enhance street walking activities. In the past, methods for measuring the quality of streets have relied mainly on subjective and objective evaluations from designer team surveys. Representative studies such as Gehl's PLPS [12] survey method measure pedestrian flow, stopping activities in public spaces, the quality of public spaces, and the quality of street façades, mainly by means of field surveys. Ewing and Clemente [13] analyze the street image by analyzing the respondents' by analyzing the respondents' ratings of street images and quantitatively evaluating them in terms of five dimensions: enclosure, human scale, transparency, tidiness, and imageability. Tang and Long [1] further quantified the spatial quality according to the five dimensions proposed by Ewing and Clemente for decomposition and then manual scoring. In recent years, the filed has gradually introduced quantitative research methods [3,14,15]. However, traditional questionnaires, interviews, and field research methods are usually suitable for measuring small plots, which is inefficient and heavy workload. It is difficult for researchers to obtain large-scale street space feature data through field research, mainly due to time-consuming field research, diverse street types, difficulty in ensuring data continuity and consistency, and rapid changes in urban development. Therefore, Comprehensive and systematic acquisition of large-scale street spatial feature data is still a major challenge in research, so the overall and large-scale measurement of street spatial quality has not been realized.

Table 1. Global Typical Street Space Design Guidelines.

Country	City	Guide Name	Compilation Time	Goal Orientation
UK	London	Streetscape Guidance	2004, revised in 2009	Create 'the best street in the world'
USA	New York	NYC Street Design Manual	2009	Provide residents with a safe and beautiful city
United Arab Emirates	Abu Dhabi	Abu Dhabi Urban Street Design Guidelines	2010	Provide a safe, convenient, and comfortable walking environment for residents and promote sustainable urban development
India	New Delhi	New Delhi Street Design Guidelines	2010	Explore reasonable street layouts and solve street space quality problems
China	Shanghai	Shanghai Street Design Guidelines	2009	Promote the transformation of urban development mode, improve the quality of transportation space, and create a new space for sustainable urban development
China	Shenzhen	Shenzhen Urban Street Design Manual	2016	Promote the humanization, artistry, and characteristic transformation of urban street facilities

The emergence and development of new technologies and data provide opportunities for large-scale and refined quantitative spatial analysis. For example, the street view image (SVI) acts as an important data source for street research with human perspective and 360-degree panoramic information of the street. It is easily accessible through the interface provided by the map supplier and the web crawler technology. It allows automated and large-scale street quality research [3,14–16]. The emergence of high-precision open data such as road networks [17], points of interest [18], and three-dimensional (3D) buildings [19,20] also provides new methods for quantitative analysis of street quality. In addition, the development of machine learning, deep learning and other technologies in the computer science field further provides the possibility for quantitative study of street space. For example, datasets such as Cityscapes [21], ADE20K [22], and PASCAL VOC [23] provide researchers with large-scale benchmark datasets. Deep learning models (e.g., SegNet [24], U-Net [25], DeconvNet [26], and DeepLab [27]) pre-trained on these datasets can perform accurate spatial feature measurements of streets. Therefore, the combination of machine learning and multi-source urban data provide refined data for spatial quality measurement, and quickly process large-scale data in fine grain.

Due to the vast street space, maintenance, renovation, and restoration work becomes especially difficult for cities with limited resources and insufficient budgets. It is estimated that streets occupy 10–20% of the urban area [5]. Therefore, identifying street areas in urgent need of renovation or maintenance and rationally allocating resources to them is crucial to improving the efficiency of urban renewal. In recent years, scholars have paid attention to the matching relationship between the spatial quality of streets and the demand for their use. They point out that streets with mismatched street quality supply and visitation demand should be prioritized for rehabilitation in urban renewal. For example, Wang et al. [28] evaluated spatial accessibility by calculating the integration degree of the road network and analyzed the subjective perception evaluation of residents to identify the streets that need to be prioritized for renovation. Zhang et al. [29] combined the quality of the streets with the spatial network accessibility analysis of sDNA to establish an evaluation matrix to identify the streets that have the potential for renewal. However, these studies usually utilize the road network model to measure the accessibility level of streets from the "top down" and as an evaluation index of the demand for use. The targeted discussion of the current quality of high-frequency pedestrian streets needs to be included. Therefore, it is necessary to explore high-frequency pedestrian streets and evaluate their quality from a humanistic perspective. Guo Xin et al. [30] constructed a bottom-up screening mechanism for residents' daily high-frequency use of streets from the perspective of crowd use. In the selection of street spatial quality evaluation indexes, only the level of street greening was considered. Such a single perspective may lead to one-sidedness of the evaluation results and fail to fully reflect the comprehensive quality of street space.

To compensate for the deficiency of existing research, this paper proposes a comprehensive framework for street quality evaluation. Our framework constructs a screening mechanism for high-frequency pedestrian streets based on the daily travel patterns of Xi'an urban residents from the bottom-up. We use street view image data and geographic information data to evaluate street spatial quality. Additionally, an evaluation matrix is established to assess the relationship between street quality and usage demand from a multi-dimensional perspective, providing critical, argumentative support for current urban regeneration. We preliminarily validated the operability and rationality of the framework via empirical analysis in the central area of Xi'an.

2. Data and Method

2.1. Analytical Framework

This study is divided into four main phases: the construction of a screening mechanism for high-frequency use streets, data collection, multi-dimensional street spatial quality assessment, and overlay analysis. The research framework of this study is shown in Figure 1.

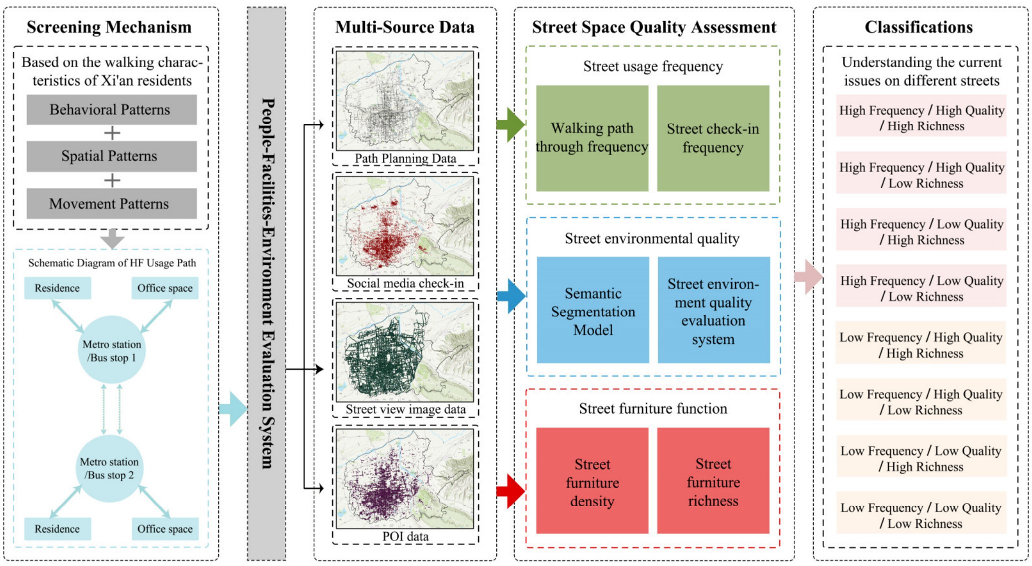

Figure 1. Research framework.

(1) First, this phase constructs the mechanism used to screen high-frequency-use streets based on residents' behavioral patterns, spatial distribution, and movement patterns;
(2) Second, vector road network data were obtained from Open Street Map (OSM) by using Python scripts while accessing Baidu Map (https://lbsyun.baidu.com, accessed on 26 February 2024) for street image data, Gaode Map API (https://lbs.amap.com, accessed on 17 December 2023) for point-of-interest (POI) and path planning data and accessing the Weibo open platform (https://open.weibo.com, accessed on 12 January 2024) for user check-in data;
(3) Again, in the calculation of street usage frequency, we utilize the path planning data to evaluate the frequency of streets that residents walk through and combine it with the Weibo user check-in data to calculate the comprehensive street usage frequency. In the calculation of the environmental quality of streets, we constructed an evaluation system containing multiple environmental indicators and quantified these indicators using Baidu Street View data and deep learning network models. The weights of the indicators were calculated by the Analytical Hierarchy Process (AHP), and then the quantified results were multiplied by the weights to arrive at the environmental quality score of the street. In the calculation of street amenity richness, we use point of interest (POI) data to analyze the density and diversity of street amenities, and the product of these two indicators is used to evaluate the functional richness of street amenities;
(4) Finally, the results of the three indicators of street environment quality, amenity richness, and frequency of use were superimposed and analyzed to form eight street types. Thus, the main problems existing in the street space are identified, the priority areas for improving the quality of urban streets are determined, and the corresponding planning strategies are proposed.

2.2. Study Area

Xi'an is located in the hinterland of Guanzhong Plain and has the reputation as "the ancient capital of 13 dynasties" and "the starting point of the Silk Road". The street space of Xi'an has excellent research value due to its historical and cultural significance. It is one of the first batch of national historical and cultural cities. This study takes Xi'an's central urban area as the study site. The specific scope includes Beilin District, Weiyang District, Xincheng District, Yanta District, Baqiao District, and Lianhu District in total six administrative divisions, with a total area of 843.56 square kilometers, accounting for 16.17% of the entire area of Xi'an City. The number of streets included in the scope of the study is 45,310. The overview of the study area is shown in Figure 2.

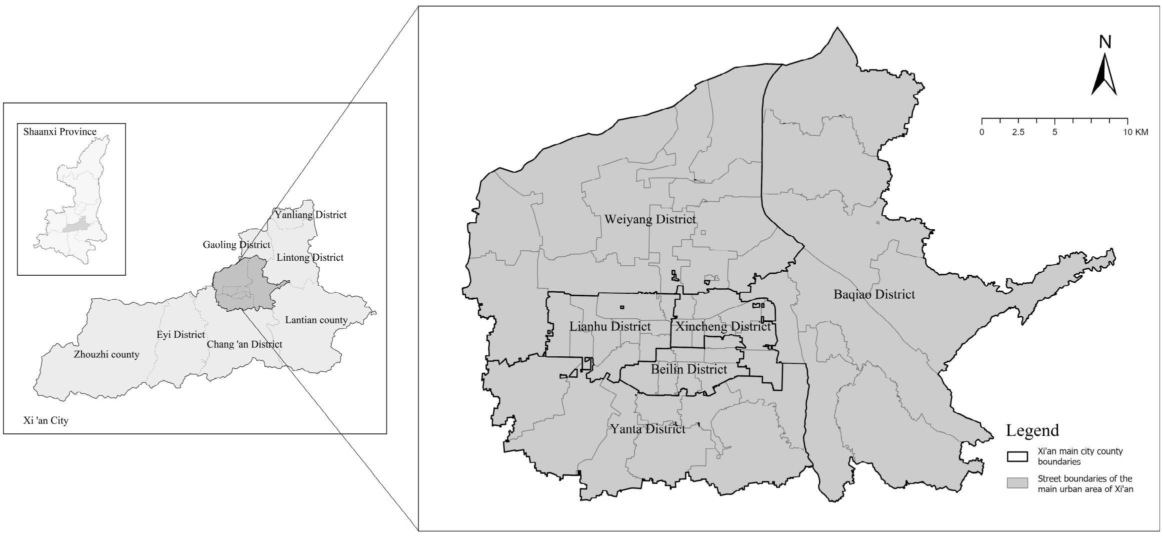

Figure 2. Research scope of Xi'an's main urban area.

2.3. Data

This paper mainly uses four types of data: POI data, road network data, Street View image data, and social media check-in data (Table 2). POI data were used to calculate the diversity of amenities for each street. Road network data were used to generate sampling points for requesting Street View images. We used street view image data to extract the proportion of street visual elements, and we used social media check-in data to assess street pedestrian flow.

Table 2. Data source and description.

Name	Data Description	Data Source
POI data	The specific geographical location of various business formats in space	AutoNavi Maps (https://lbs.amap.com/, accessed on 17 December 2023)
Administrative division data	Used to extract the boundary of the research area	National Basic Geographic Information Resource Catalog (https://www.webmap.cn/, accessed on 17 June 2023)
Street view image data	Quantitative Measurement of Street Space Quality	Baidu Map API (https://lbsyun.baidu.com/, accessed on 26 February 2024)
Road network data	Used for calculating street length and diversity indicators	OpenStreetMap open-source platform (www.openstreetmap.org, accessed on 17 June 2023)
Social media check-in data	Used to calculate the distribution of street pedestrian flow	Weibo open platform (https://open.weibo.com, accessed on 12 January 2024)

2.3.1. POI Data

POI is point-like data of real geographic entities containing spatial and attribute information. It has the advantages of high accuracy, large data volume, frequently updated, and detailed place categorization. It is widely used in urban research [31] and provides accurate geo-referenced data about the built environment and related urban facilities.

The POI data used in this study are from two different data sources: AutoNavi Maps as a source for general POI information and https://www.china.com/ (accessed on 17 December 2023) as a specialized source for residential POI information.

AutoNavi Maps is one of the largest map content and location service providers in China. In this study, we used Python to write a program to obtain the POI data of six districts of Xi'an, namely, Xincheng, Beilin, Lianhu, Yanta, Weiyang, and Baqiao, in 2022 from the AutoNavi Open Map platform. The downloaded data were then manually cleaned, and a total of 265,236 data records were kept. Each POI datum includes six attributes: name, type, address, longitude, latitude, and area name. According to the different functions of city streets combined with the AutoNavi Maps POI analysis system, the POI data are divided into the following nine categories: transportation, catering, shopping, life services, sports and leisure, health care, science, education and culture, finance, and environment (Table 3). On this basis, the commercial office buildings in the study area were screened according to the type of classification of POI data, and finally, 2115 data information were obtained.

Chain.com is one of the largest property listing platforms in China. We use Python to crawl the residential complex POI data of in Xi'an City in 2023 from Chain.com, including the name of the district, the address, the total number of buildings, the total number of households, and the latitude and longitude coordinates, and a total of 8108 pieces of data information are obtained.

Table 3. POI data classification table.

POI Classification	Number (pcs)	Proportion (%)
Transportation	17,740	6.69%
Dining	65,055	24.53%
Shopping	102,417	38.61%
Life Service	51,709	19.50%
Sports and Leisure	7726	2.91%
Healthcare	9130	3.44%
Science, Education, and Culture	3361	1.27%
Finance	6475	2.44%
Environment	1623	0.61%

2.3.2. Street Network Data

Open Street Map (https://www.openstreetmap.org, accessed on 17 June 2023), a crowd-sourced spatial database designed to provide users with free and easily accessible digital map services, is currently the most used data source for crowd-sourced geographic information. These data have the advantages of wide coverage and a frequent update speed compared with traditional geospatial data such as remote sensing images and land use type data. In this study, the Open Street Map open-source platform was used to download the road network data in the study area, including its location, road name, grade, and length. The data are further processed to simplify the network into topologically error-free road centerlines with ArcGIS. As a result, the road network data contain a total of 45,310 valid records.

2.3.3. Street View Image Data

We selected Baidu Street View as the data source for street view images in this study due to its extensive coverage. In order to obtain the street view, coordinates, angles, and other details of each sample location, a Python program was written to access the Baidu Street View map application programming interface (API). Specifically, after simplifying the road network, correcting the topology, and extracting the road's centerline, the requested points of the street view image were determined at 50 m intervals. A total of 16,773 sampling points were obtained. Among them, the southeast corner of the central city of Xi'an is the Qinling Mountains, so the Baidu Street View data failed to achieve coverage. A total of 10,472 valid sampling points were finally kept (Figure 3). The street view images were then downloaded via API by inputting the horizontal viewing angle, viewing width, and coordinates of the requested points. In order to reflect the whole environment of the street space, street view images from four viewing angles (0°, 90°, 180°, and 270°) were captured at each sampling point. Our algorithm automatically assembled the street view images from the same request point. As a result, a total of 10,472 street-view images were collected. The downloaded street-view images are shown in Figure 4.

2.3.4. Social Media Check-In Data

As the largest social media platform in China, with over 600 million active users and covering a broad spectrum of user groups, Weibo offers an ideal data source for quantifying the frequency of street usage. Microblog supports the user check-in function, and the geographical location data generated can be directly mapped to specific streets and places, which has strong timeliness and dynamics and can reflect the periodic characteristics and peak period of the flow of people. At the same time, the open API interface of Weibo also enables researchers to obtain and analyze relevant data. It is worth noting that the Weibo check-in data not only include the social activities of local residents but also covers the footprints of out-of-town tourists, which enables the analysis results to fully reflect the actual use of the street. Reasonable use of Weibo check-in data, combined with other data sources, helps to more accurately quantify the distribution and usage characteristics of street traffic, and provides valuable data support for urban planning, traffic management, etc. By writing Python programs to access the application program interface of the Weibo open platform, this study downloaded user sign-in data from November and December 2023 and finally obtained 12,216 pieces of data within the research range, including longitude and latitude coordinates, release time, content text and other key information.

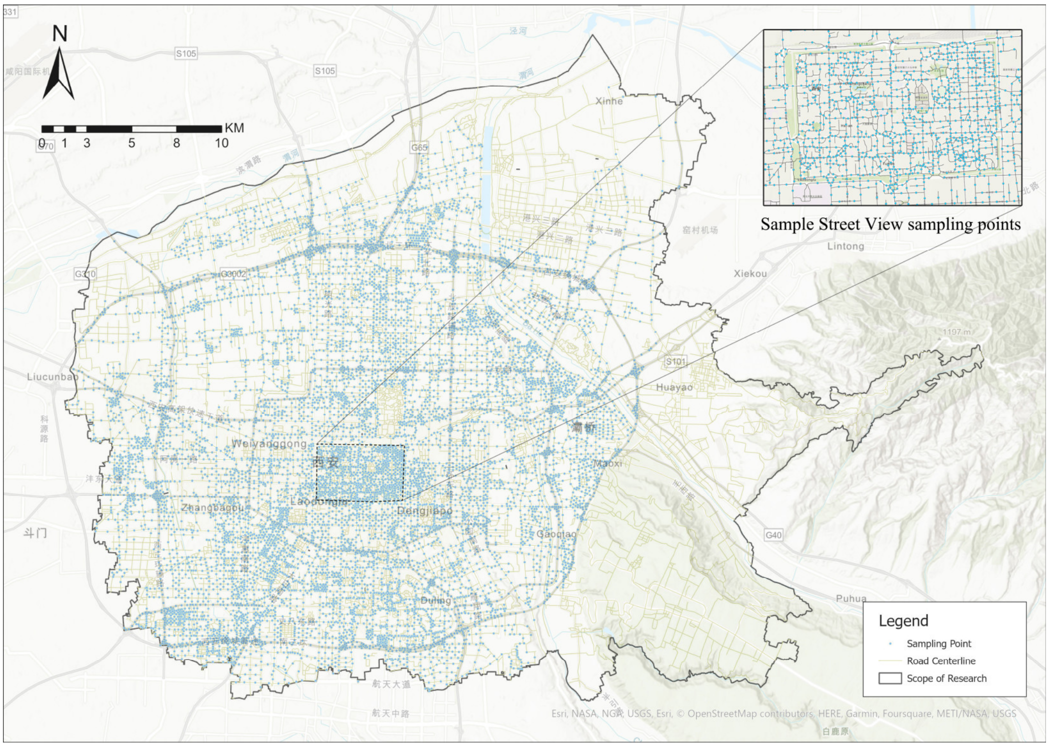

Figure 3. Distribution of sampling points for street view images.

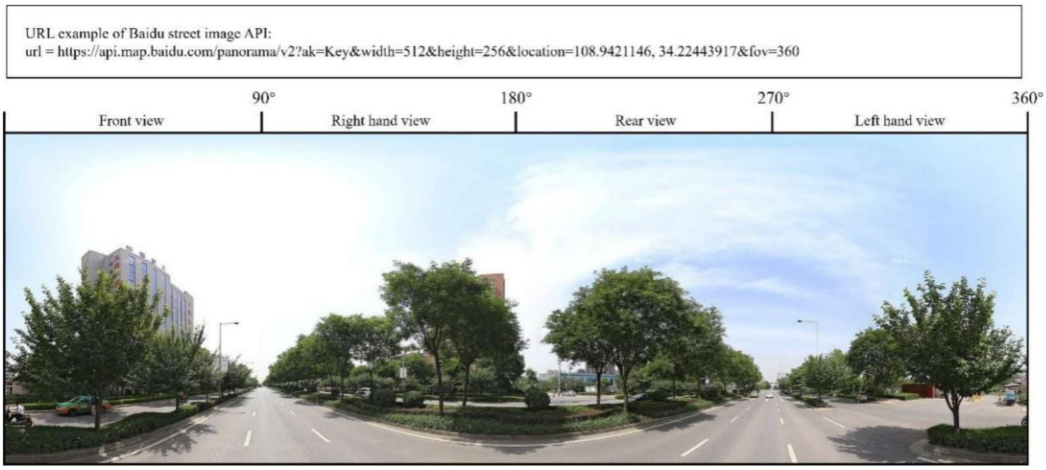

Figure 4. Panoramic view of streetscape sampling sites.

2.4. Methodology

2.4.1. Street Usage Frequency Analysis Workflow

The first stage of the study is constructing a street usage frequency matrix based on pedestrian visitation. The analysis is based on the Origin–Destination (OD) pair and route planning API. The OD pairs generation is based on the commute characteristics of Xi'an residents.

In OD pairs generation, we mainly considered the travel purpose and transportation mode choice. The travel purpose in Xi'an is dominant by commuting trips between home and office. According to the statistics of the Annual Report of Xi'an Urban Transportation Development in 2022, the proportion of commuting trips by Xi'an residents increased to 55.8%. Commuting trips occupy an absolute advantage over other purposes of the residents, such as shopping, leisure, and socializing [32]. This has is also verified by numerous research [33–35]. In terms of travel mode, rail and bus have become the first choice of travel for Xi'an citizens. The share of motorized travel by public transportation in Xi'an is 55.6% in 2022, and the trend of steady growth is maintained [32]. Despite the dominance of public transportation, trips to public transit stations are mainly based on walking. Previous studies by many scholars on the walking attraction range of public transportation generally suggest a radius of 400–800 m [36–39]. This study follows the general consensus of the walking attraction range for public transportation, using 800 m (about 10 min walking) as the radius threshold for proximity mobility.

Based on the above argumentation, the behavioral spatial characteristics of the main population in Xi'an are from the place of residence to the place of work. The means of transportation connecting the starting point and the end point are public transportation, including the subway and the bus, so the complete trajectory of the individual is "residence—walking—entrance to the subway station (starting point)—subway—exit from the subway station (end point)—walking—office " and "residence—walk—bus station entrance (start)—bus—bus station exit (end)—walk—office" (Figure 5). After removing the non-walking paths from the complete trajectory, walking paths are obtained, round-trip paths from the residence to the nearest subway or bus stop and round-trip paths from the office to the nearest subway or bus stop. After stacking the group paths, the path with the highest cumulative number of passes is recognized as the high-frequency walking path.

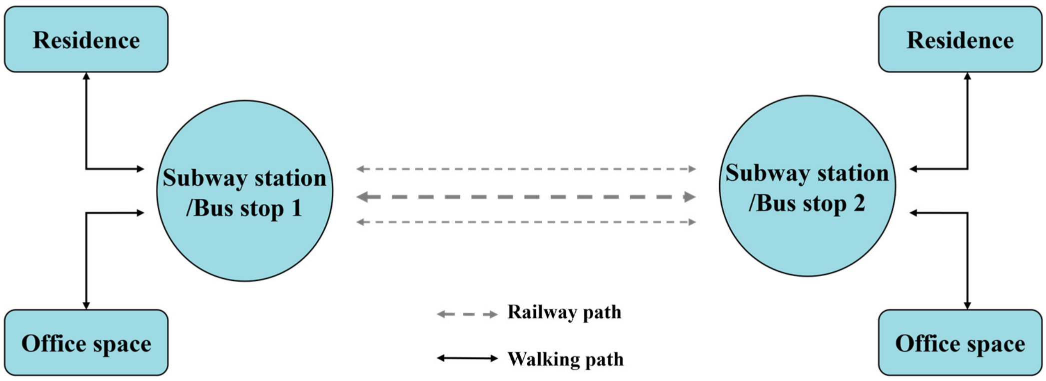

Figure 5. Schematic diagram of HF utilization path in Xi'an.

The specific operation of the "from the place of residence to the nearest subway station" walking path to obtain an example (Figure 6):

(1) the use of ArcGIS "Generate Near Table" tool to obtain the latitude and longitude of the OD coordinates. IN_FID inputs the POI data of the residence, Near_FID inputs the POI data of the subway station, NEAR_DIST is set to 800 m, the method of use is selected as planar, and check the box of "only find the nearest element", and the rest of the parameters are kept as defaults, so as to match the nearest subway station for each residence, and thus obtain the walking path in order to match each residential point with the nearest subway station to obtain the coordinates of the starting point of the walking path, and finally obtain a total of 5960 OD latitude and longitude data;

(2) Crawling walking path data using AutoNavi Maps. AutoNavi Maps offers a Web service API called Route Planning API (https://lbs.amap.com, accessed on 16 February 2024) that can provide precise route planning solutions. The API allows users to select the mode of transportation based on their needs, including walking, driving, taking public transportation, cycling, and more. At the same time, the API also supports a variety of query policies, such as the optimal path, the shortest path, etc., which can meet the different travel needs of users. We input the latitude and longitude coordinates of the starting point and the

ending point as parameters and set the travel mode as "walking" to extract all the walking paths, save the returned results in .shp format, and ultimately obtain a total of 5960 walking paths data. Finally, we obtained 7985 paths from residential neighborhoods to bus stations, 2109 paths from office buildings to bus stations, 5960 paths from neighborhoods to subway stations, 1731 paths from office buildings to subway stations, and 17,785 valid paths in total;

(3) Count the number of streets passed. The walking track data are imported into Arcgis, and all the walking paths are interrupted by the tool "Split Line at Folding Point", and then the walking paths are overlapped by the tool "Count Overlap Element". Then, the tool "Count Overlap Element" is used to count the frequency of overlap of the walking paths, and finally, the number of times each street is passed by walking is obtained;

(4) Based on the calculation results of the number of street walks, further integrate the social media check-in data to reflect the actual use of streets more comprehensively. The specific operations are as follows: First, the longitude and latitude coordinates of social media check-in data are used to drop user information to specific spatial points; secondly, set up a 50 m buffer with the coordinate points as the center; thirdly, the "spatial connection" tool is used to connect the sign-in data with the street network data, so that each street is assigned a value. Finally, the calculation results are added to the calculation results of the street walking times, and the final street usage frequency results are obtained. On this basis, the results are divided into 6 categories by geometric interval classification; the first 3 categories are the categories with low utilization degree, and the last 3 categories are the categories with low utilization degree.

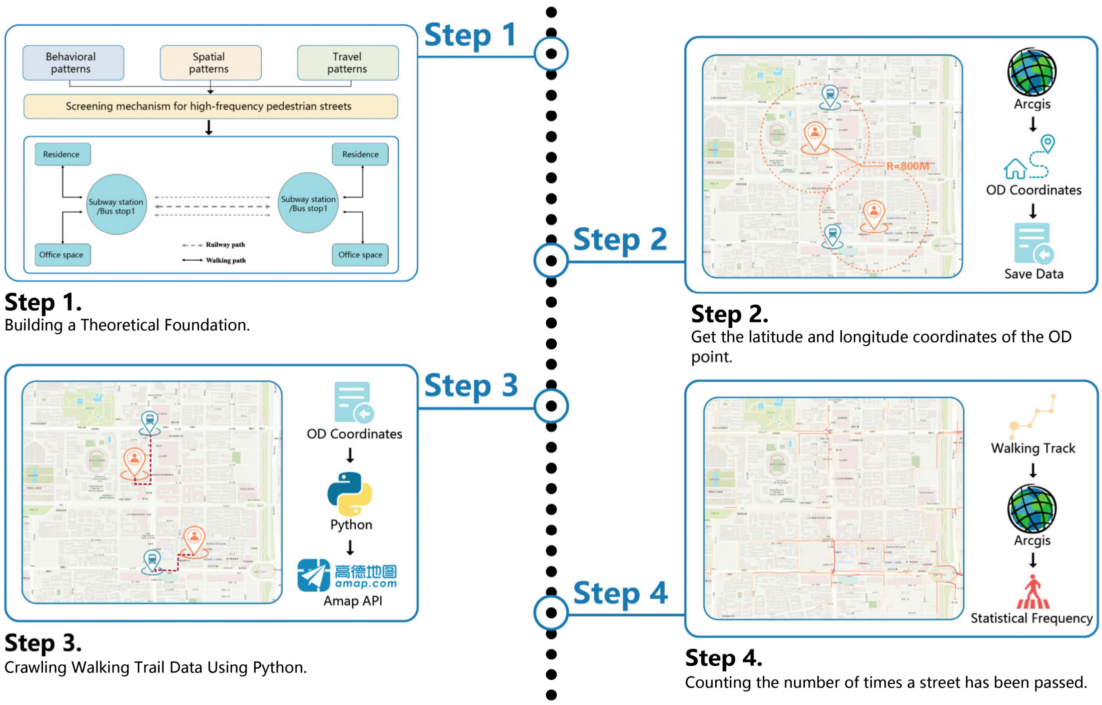

Figure 6. High-Frequency Walkway Analysis Process.

2.4.2. Street Environment Quality Evaluation

Previous literature on street quality evaluation often involves factors based on the aerial perspective, which is somewhat different from the actual street environment perceived by pedestrians. Under the influence of humanistic thinking, more and more scholars have begun to adopt the street quality evaluation index system from the humanistic perspective [1,3,40–43]. The evaluation index elements selected in this study are based on both classical literature and existing machine learning algorithms. The relevant evaluation indicators involved in the existing studies are summarized as shown in Table 4, from which the key evaluation indicators that are mentioned with high frequency are kept. In addition, some scholars have also added indicators such as a sense of safety [44,45] and vitality [46] to quantitatively measure the street environment based on the characteristics of the study area.

Table 4. Evaluation indicators on street quality from existing research.

Related Research	Evaluation Index	Visual Elements Involved
Zheng and Yang [42]	Green visual index, sky openness index, color atmosphere index, color richness index	Greenery, sky, buildings, walls, terrain, vehicles, motorized trails, walkways, street furniture, pedestrians
Ye et al. [3]	Street green visibility, sky visibility, building interface, pedestrian space, road motorization, diversity	Greenery, sky, buildings, motorized paths, non-motorized paths, street furniture
Zhou et al. [43]	Posting rate, sky occupancy, building occupancy, green occupancy	Greenery, Sky, Architecture
Tang and Long [1]	Wall continuity, intersection cross-section aspect ratio, green occupancy, sky openness, enclosure	Greenery, sky, buildings, motorized lanes, non-motorized lanes, street furniture, transit, pedestrians
Ma et al. [40]	Green visibility, sky openness, enclosure, walkability, intentionality	Greenery, sky, buildings, driveways, walkways, roadway paving, signage
Qiu et al. [41]	Enclosure, spatial scale, complexity, intentionality	Greenery, buildings, walls, road paving, signage, street furniture

This study selects six street space attributes, namely walkability, road greening, sky openness, enclosure, vitality, and sense of security, for computational analysis. Among them, walkability is characterized by the percentage of the area of pedestrian walkable space, which directly affects the choice of walking behavior of residents. The level of road greening and sky openness are accepted by most studies as the basic street visual quality evaluation indexes. The visibility of street greening eases the pressure of pedestrians in the space and affects the perceived safety [47]. The sky openness of the street affects the pedestrian's line of sight, and the level of which affects pedestrians' perception of pleasure and stress in the street [1]. The enclosure degree of the street affects the scale perceived by pedestrians and their willingness to stay. Narrow streets are more friendly to walking and daily life socialization than transitionally open streets [1]; enclosure in this study is derived from the street aspect ratio based on the image in streetscape evaluation. Buildings, walls, and greenery on both sides of the road are regarded as homogeneous interfaces to measure the impact of the spatial scale of the street on the human visual experience. Street vitality can be characterized by the ratio of pedestrians to bicyclists in a pedestrian's field of vision, the level of which directly or indirectly affects the pedestrian's motivation to walk [48]. A sense of safety directly affects residents' choice of walking behavior. Empirical studies have shown that convenient and safe crossing facilities, walking paths with a sense of safety, and abundant sidewalk facilities are all conducive to people's choice of travel by foot [44].

To calculate the street space attributes, this study performs semantic segmentation of street view images with a deep learning network. Visual feature elements are extracted in the street view image and used as the data basis for the evaluation of street environment quality. SegNet tool is used in this study for identifying elements in the image such as sky, sidewalk, driveway, building, greenery, etc. [24]. We use the pre-trained model developed by research scholars at the University of Cambridge. SegNet is an advanced deep convolutional neural network architecture that can imprint each image pixel into semantics for extracting the street scene image's visual elements. The deep convolutional neural network uses an "encoder-decoder" structure, where the encoder part consists of multiple convolutional and pooling layers to extract high-level features from the image, and the decoder part restores the feature map output from the encoder to the size of the original input image by transposing convolutional operations. Since empirical studies utilizing this algorithm in Chinese cities have worked well, we did not retrain it for this specific case [49].

In this study, the evaluation system of street environmental quality and the spatial characteristic elements corresponding to each type of indicator and their calculation formula are shown in Table 5.

Table 5. Street Quality Measurement Indicator System.

Indicator	Definition	Formula	Interpretation
Greening of street	Mean green plant pixel share for all sample points	$G_i = \frac{\sum_{k=1}^{n}(\frac{\sum_{j=1}^{4} g_{jk}}{4})}{n}$	G_i : Greening level of street i. g_{jk}; greening level of street i; greening level of street i in the jth street picture of the kth sample point in street i; the number of sample points in street i (hereafter). n: number of sample points in the articulated street i (below).
Walkability	Proportion of non-motorized roadway pixels to overall roadway pixels for all sample points	$W_i = \sum_{k=1}^{n}[\frac{\sum_{j=1}^{4} p_{jk}}{\sum_{j=1}^{4}(p_{jk}+r_{jk})}]$	W_i : Walkability level of street i. p_{jk}/r_{jk}: the percentage of non-motorized lane/motorized lane pixels in the jth street image at the kth sample point in street i.
Enclosure	Ratio of vertical (buildings and trees) feature pixels to horizontal (roads) feature pixels for all sample points	$E_i = \sum_{k=1}^{n}[\frac{\sum_{j=1}^{4}(b_{jk}+t_{jk})}{\sum_{j=1}^{4}(p_{jk}+r_{jk})}]$	E_i : Enclosure level of street i. $b_{jk}/t_{jk}/p_{jk}/r_{jk}$: Pixel share of buildings/trees/sidewalks/vehicle lanes in the jth street image at the kth person sample point in street i.
Sense of security	Sum of multiple street furniture pixel shares for all sample points	$S_i = \frac{\sum_{k=1}^{n}[\frac{\sum_{j=1}^{4}(f_{jk}+sl_{jk}+tl_{jk}+c_{jk}+w_{jk})}{4}]}{n}$	S_i : The level of security in street i; the $f_{jk}/sl_{jk}/tl_{jk}/c_{jk}/w_{jk}$: pixel share of fence/street light/traffic signal/camera/windows along the street in the jth street image at the kth sample point in street i.
Vitality	Sum of the percentage of pedestrian and bicycle pixels for all sample points	$V_i = \frac{\sum_{k=1}^{n}[\frac{\sum_{j=1}^{4}(pd_{jk})}{4}]}{n}$	V_i : vitality level of street I; pd_{jk}: the pixel share of pedestrians in the jth loadscape image at the kth sample point in road i.
Openness of the sky	Sum of the percentage of sky pixels in all sample points	$T_i = \frac{\sum_{k=1}^{n}(\frac{\sum_{j=1}^{4} sk_{jk}}{4})}{n}$	T_i : The degree of sky visibility in street i; the degree of sky visibility in street i. sk_{jk}: the percentage of sky pixels in the jth street image at the kth sample point in street i.

In order to evaluate the environmental quality of streets more objectively, this study invited 20 experts in urban planning, architecture, and other disciplines to participate in this study by using the Analytic Hierarchy Process (AHP). According to the grading results of the importance of each participant, the judgment matrix of each participant is formulated, and the consistency of each judgment matrix is calculated. Among them, CR is generally used as the criterion to judge the consistency of the matrix, and CR is the ratio of the consistency index CI and the average random consistency index RI. If CR < 0.1, it indicates that the matrix meets the requirements without modification. Then, the samples that fail the consistency test are removed from the valid sample pool, and the mean of the score results is taken as the final weight of each indicator. The final weights of the six street environmental quality indicators are shown in Table 6:

$$a_{ij} = \frac{1}{a_{ji}} \tag{1}$$

$$A = (a_{ij})_{n\times n} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \tag{2}$$

Table 6. Calculation of street environment quality weights.

Dimension Category	Weighting of Levels
Greening of streets	0.4024
Sense of security	0.1142
Openness of the sky	0.0394
Street walkability	0.2751
Street Vitality	0.1383
Enclosure	0.0306

2.4.3. Function Richness of Street Facilities Evaluation

Function dimension refers to the attributes related to land use in streets, and early studies often used this as a key indicator of urban spatial diversity [36]. However, these types of data are often outdated, difficult to obtain, and cannot truly reflect people's perception of urban functions, while POI data can make up for the above shortcomings. In recent years, the evaluation of functional density and diversity based on POI has gradually emerged [31,50,51]. To evaluate the function richness of streets accurately, this study attempts to integrate the density and diversity of amenities in streets to develop a more refined measurement approach. In this way, the diversity measurement is divided into two parts: (1) calculating the ratio of the number of POIs contained in each street to the length of the street and (2) measuring the POI diversity indicator through the Shannon-Wiener index. Because of its good performance in built environment research [52,53], we chose the Shannon-Wiener index [54], which was first applied in ecology, to evaluate the functional diversity of streets. A higher value means that it receives a wide variety of facilities, and the number of facilities is evenly distributed. It indicates that the street can provide a variety of functional services to meet the needs of different users. The specific calculation formula is as follows:

$$D_i = N_i \times SW_i \tag{3}$$

$$N_i = \frac{\sum_{i=1}^{n} a_i}{L} \tag{4}$$

$$SW_i = -\sum_{i=1}^{R} p_i \times lnp_i \tag{5}$$

where Di represents the final diversity value of type i facilities in the street segment, Ni represents functional density, and SWi represents functional diversity. ai represents the number of type i facilities, L is the length of the street, pi represents the proportion of type i facilities in the overall street, and R is the total number of major functional classifications, which are nine in this analysis.

2.4.4. Street Classification Based on Multi-Dimensional Street Evaluation

This study integrates the environmental quality and facility function of street space. It combines the element of human frequency of use, establishes a multi-dimensional evaluation system of human (frequency of use)-environment (quality)-facility (richness) applicable to human scale, identifies the current status of the street space and the potential for renewal, and proposes a targeted planning and design strategy based on this, so as to link research and practice.

Specifically, based on the analysis of the three indicators, the calculation results of the three indicators for evaluating streets are all divided into six levels by means of set geometric intervals, with the first three levels being the categories of relatively low numerical level of the indicators and the last three levels being the categories of relatively high numerical level of the indicators, which can be integrated to classify the streets into eight types of streets, such as high-frequency walking/high environment quality/high facility richness, high-frequency walking/high environment quality/low facility richness, and so on.

3. Experiment and Results

According to the calculation results of the three indicators of the street quality evaluation system, 11,311 streets in central Xi'an can be classified into high-frequency streets. They account for 24.96% of the total number of streets included in our study scope. Streets with high environmental quality total 7085 and account for 15.64% of the city's total. Streets with higher functional richness total 9900 streets and account for 21.85% of the city's total. By comparing the values of each index, it can be seen that the number of streets with a high frequency of use is the largest in the downtown area of Xi'an, followed by the number of streets with rich facilities and functions, and the number of streets with good environmental quality is the least.

3.1. Street Walking Frequency Analysis

Further research shows that the street usage frequency in the downtown area of Xi'an presents a spatial distribution law of "high inside and low outside" (Figure 7). The calculation results show that the average frequency of street use in the downtown area of Xi'an is 4.75 times, and the frequency of street use in the inner ring area (Beilin District, Lianhu District, Xincheng District) is significantly higher than that in the outer ring area (Yanta District, Weiyang District, Ba Qiao District), which indicates that the traffic pressure and human flow in the inner ring area are relatively large. In the inner ring city, the streets in Beilin district are used the most frequently, with an average of 8.1 times per street. This was followed by Xincheng District and Yanta District, with 7.2 and 5.9 times respectively. In the outer ring city, Yanta District has the highest street use frequency, 3.8 times on average. This was followed by Baqiao District and Weiyang District, with 2 and 1.5 times, respectively. This result reveals the imbalance in the distribution of human flow and traffic between the inner and outer ring districts.

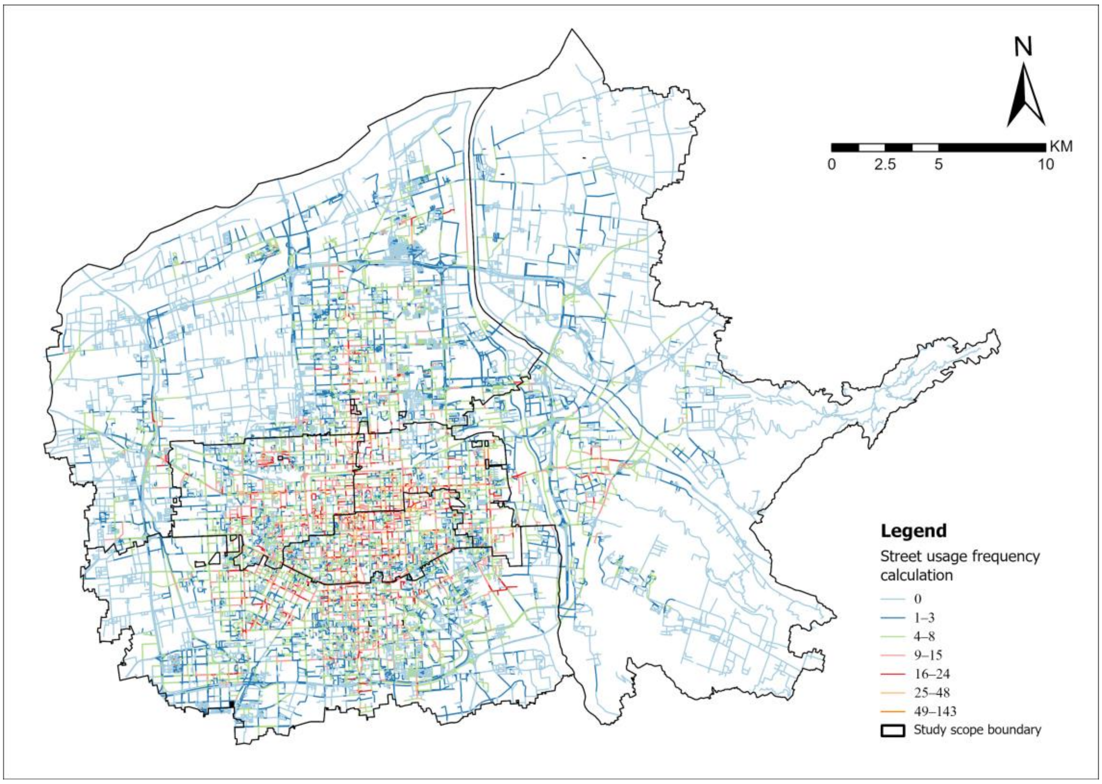

Figure 7. Frequency of walking path selection.

In order to more intuitively observe the spatial distribution characteristics of street use frequency, Getis-Ord Gi* analysis was used to identify significant hot and cold areas with different confidence levels. Figure 8 shows that the street usage frequency in the downtown area of Xi'an has a significant central-agglomeration feature in spatial distribution. In addition, streets are used more frequently in the southern part of the city than in the northern part, and in the western part of the city than in the eastern part. Hot spots basically cover the inner ring city, while there are only some hot spots in the outer ring city, such as Xiaozhai Road, the high-tech Industrial Development Zone, Beiguan Street, and Textile City street. Among them, as the core of modern trade and advanced manufacturing industry in Yanta District, Xiaozhai Road, and high-tech Zone have high population flow and perfect traffic facilities; Beiguan Street is adjacent to Xi'an Railway Station. As an important transportation hub of the city, Beiguan Street connects urban areas with peripheral areas. It also has a high population flow and perfect transportation facilities. As a comprehensive reconstruction area of the old industrial base in Baqiao District, the Textile City area has a large number of industrial enterprises and their supporting residential areas and facilities. It can be seen that the high-frequency use of these hot spots is directly related to the planning of the business service industry, population distribution, and distribution of transportation facilities.

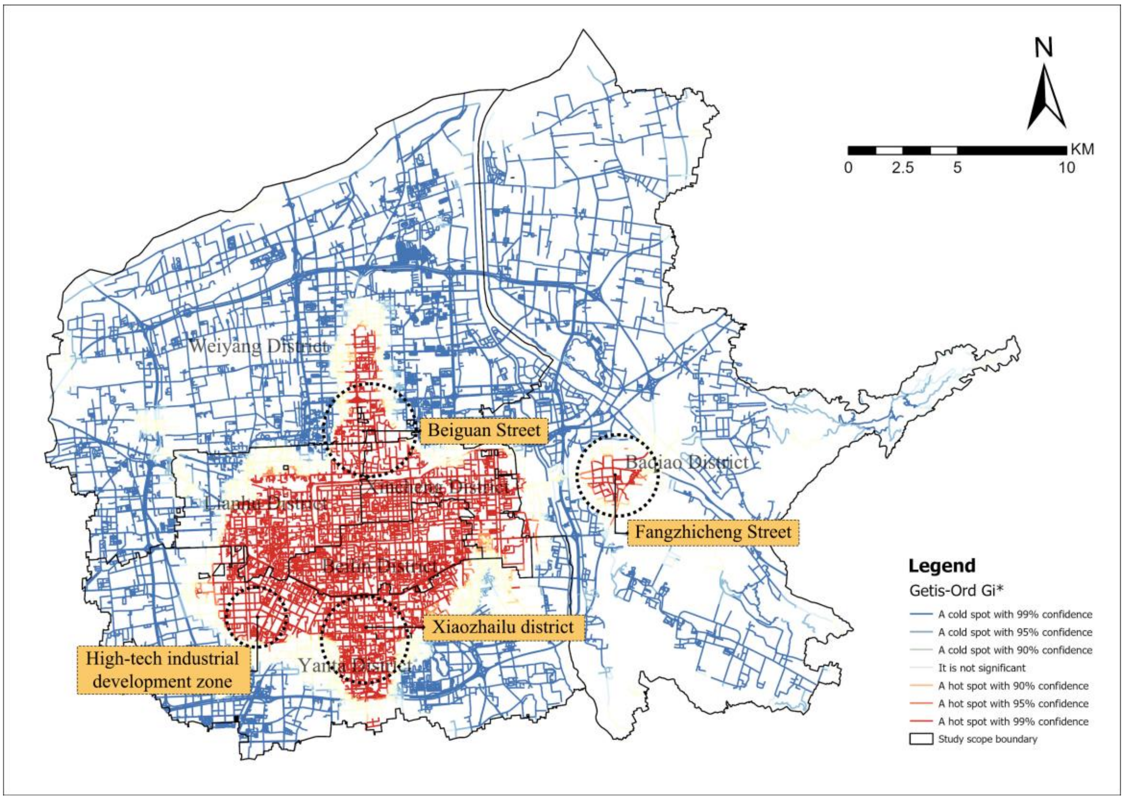

Figure 8. Street usage frequency hotspot analysis.

3.2. Street Environment Quality Evaluation

As can be seen from Figure 9, the street environment quality in the downtown area of Xi'an presents a distributed small-range agglomeration feature in space. From the perspective of quantitative calculation, the average street environmental quality score of the downtown area of Xi'an is 8.16, among which the environmental quality score of the inner ring area is slightly higher than that of the outer ring area, indicating that the environmental management and maintenance of the inner ring area is relatively better. According to the street environmental quality score from high to low, it was ranked as follows: Beilin District (9.04), Xincheng District (8.69), Lianhu District (8.64), Yanta District (8.45), Weiyang District (7.98) and Baqiao District (6.18). This result reveals that there are some regional differences in street environment quality in the downtown area of

Xi'an, which reflects the different effects and investments in environmental governance in different areas.

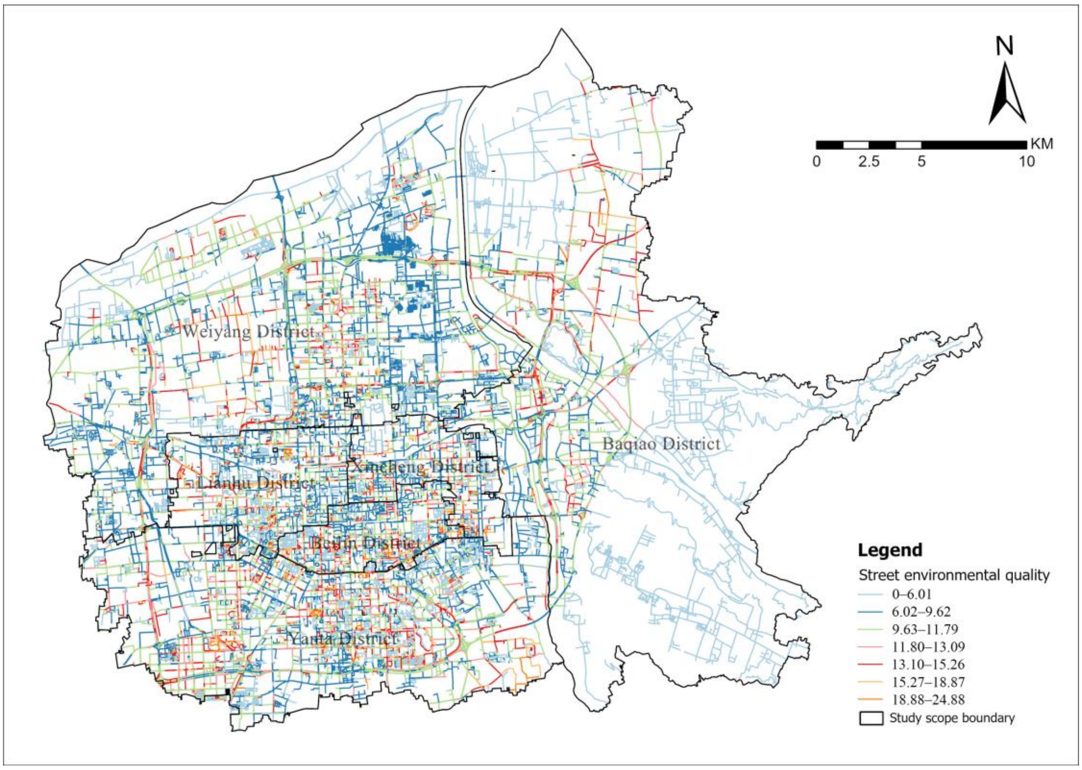

Figure 9. Comprehensive street environment quality assessment.

According to the Getis-Ord Gi* analysis results of environmental quality (Figure 10), the street environmental quality in downtown Xi'an presents spatial differentiation between high-value areas and low-value areas. Hot spots are mainly distributed in the central and southern parts of the city, such as Beilin District, Xincheng District, and Lianhu District, and the street environmental governance effect in these areas is more prominent. Conversely, the cold spots are concentrated in the eastern and northern parts of Weiyang District and Baqiao District, where the governance of the street environment might be relatively weak. In terms of spatial distribution, areas with high environmental quality are mainly situated in and around the city center, while areas with low environmental quality are more distributed at the urban fringe. This distribution pattern reflects the disparity in the governance and quality construction of the street environment between the inner and outer urban areas, which poses new challenges and opportunities for future urban development planning and environmental governance. Improving the governance level of low environmental quality areas and promoting the balanced distribution of resources will be an important direction to achieve the overall improvement of the city's environmental quality in the future.

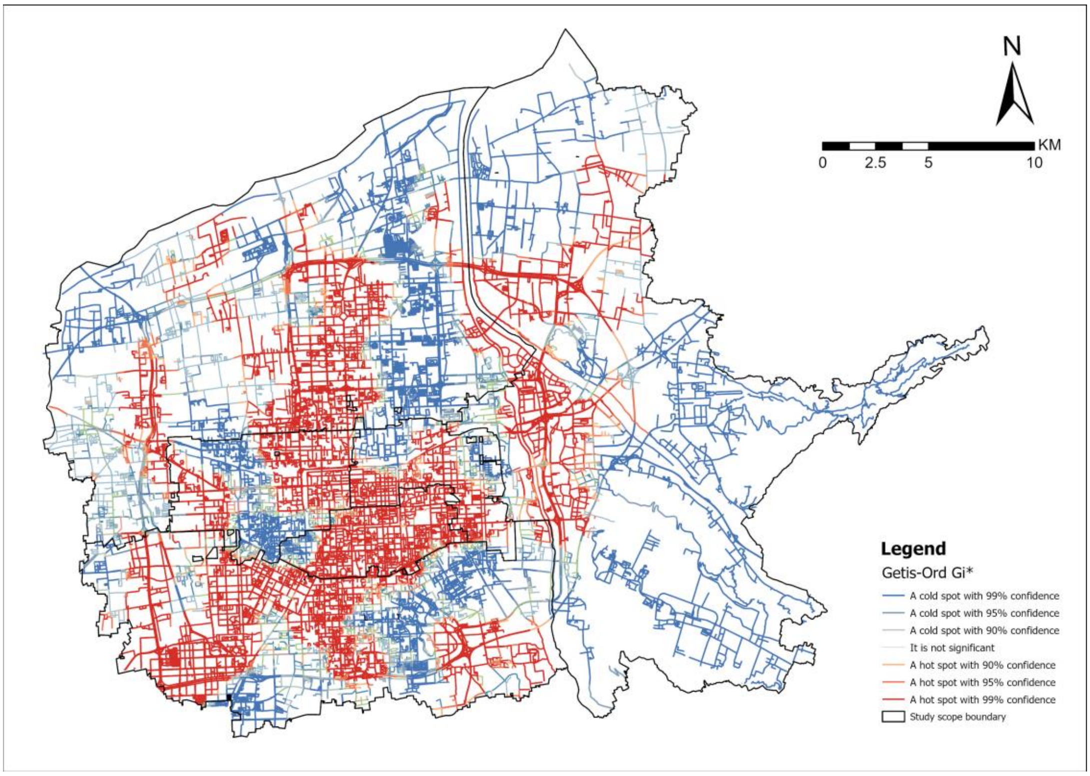

Figure 10. Street environmental quality hotspot analysis.

We further aggregate the results at the administrative district level to provide further renewal and renovation policy suggestions for street quality in a quantitative way. Combined with the spatial distribution pattern of street environmental quality in each district of Xi'an (Figure 11), it can be seen that street greening shows the overall distribution characteristics of hollowing out, i.e., the phenomenon that the street greening rate of the streets in the central area is low while that of the streets in the peripheral areas is high. The greening level of the streets in QJ street, DYT street, XZL street, and TYL street is higher, while the central area in BYM street, NYM street, JFM streets, and CLXL streets have significant areas of low values. The walkability measure values show an overall distribution of high in the center and low in the outer areas, except for FZC street in the peripheral area; the rest of the streets with high measure values are concentrated in the center area, such as BYM street, QNL street, JFM street, and BSL street. Enclosure measurement values in the central region form the center of high values and display a spatial pattern of "high in the west and low in the east, high in the south and low in the north". The high-value areas include QNL streets, BSL streets, and BYM streets. The spatial distribution of the safety measure values shows an overall low internal and high peripheral pattern, with obvious hollowing-out characteristics, and its high-value areas are mainly distributed in CLZL streets, HZS streets, HQ streets, and CT streets. The street vitality measure shows the distribution characteristic of "high in the center and low in the periphery" except for the high value of WYH street; the rest of the high-value areas are mainly distributed in the center of the city, including QNL street, BYM street, BSL street, and CLF street. The street openness measure shows the distribution pattern of increasing circles from the inside to the outside. The values of street sky openness measurements show a circled increasing distribution pattern from inside to outside as well as the hollowing out characteristics of low inside and high outside, forming continuous high values in the edge areas of the city.

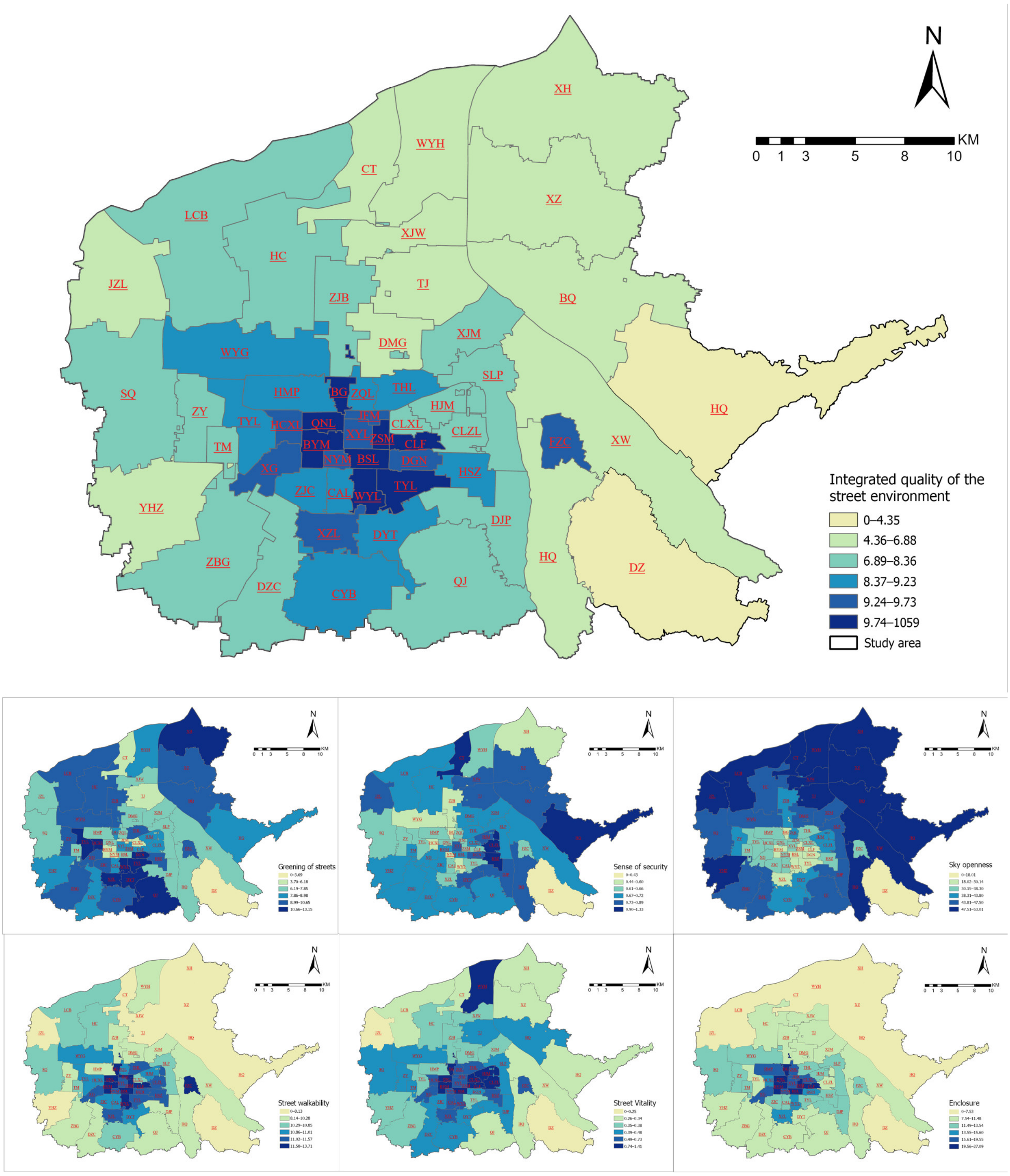

Figure 11. Evaluation of the environmental quality of each street office.

In summary, the distribution of different dimensions of street environment quality in the overall space is characterized by different features. Combined with the comprehensive evaluation results of street environmental quality, the overall spatial distribution presents the characteristic of decreasing from the center to the periphery in a circle-like manner. The streets with better comprehensive quality are mainly concentrated in the old city area, including QNL street, BYM street, BSL street, ZSM street, CLF street, TYL street, BG street, and WYL street.

3.3. Assessment of Street Facilities Richness

According to Figure 12, the richness of street facilities in the downtown area of Xi'an presents a spatial distribution feature of "high in the center and low in the periphery". According to the calculation results, the average richness of street facilities in the central urban area of Xi'an is 5.46, and the richness of street facilities in the inner urban area is significantly higher than that in the outer urban area, indicating that the number and types of infrastructure in the inner urban area are relatively more perfect. According to the richness score, Beilin District (8.99), Lianhu District (7.47), Xincheng District (6.67), Yanta District (5), Weiyang District (2.94), and Baqiao District (1.71) were ranked in order from high to low. This result reveals that there is an obvious problem of unbalanced distribution of street facilities in the downtown area of Xi'an, and there is a big gap between the relatively rich street facilities resources in the inner ring area and the outer area.

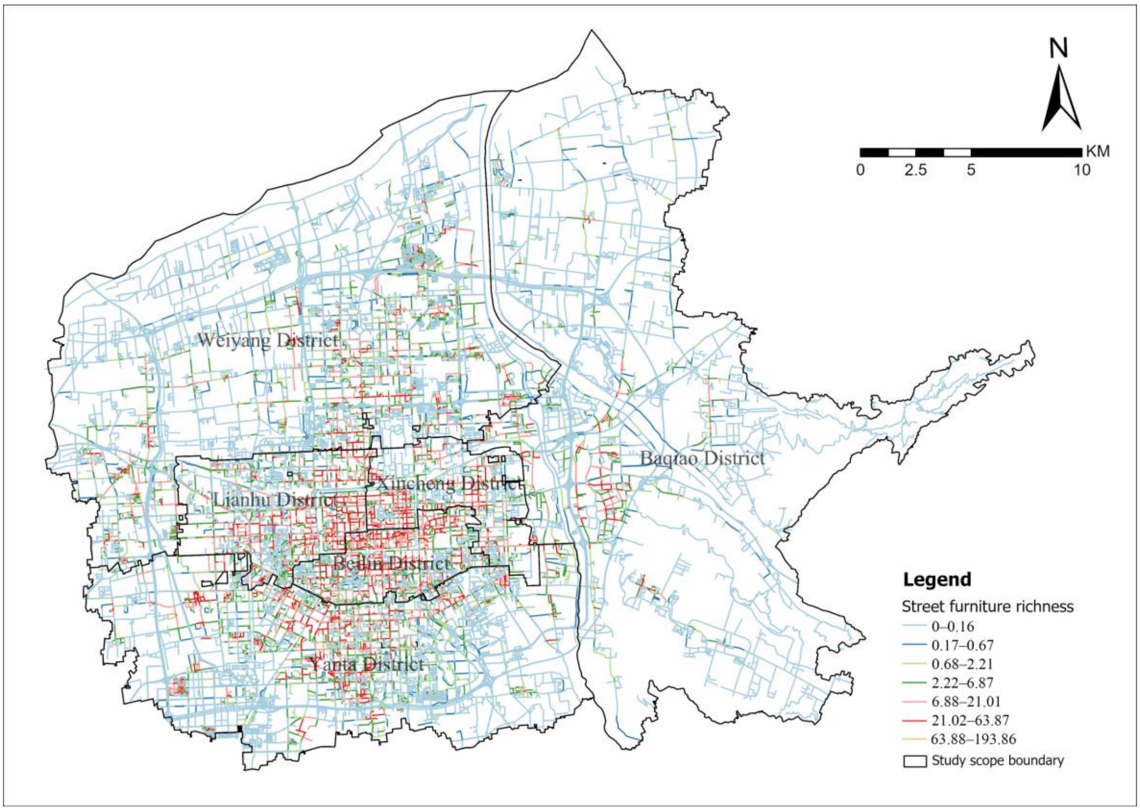

Figure 12. Evaluation of the richness of street functions and facilities.

According to the Getis-Ord Gi* analysis of the richness of street amenities, it can be seen (Figure 13) that there is an obvious spatial imbalance in the functional richness of street amenities in the downtown area of Xi'an. The central city, especially Beilin District, Xincheng District, and Lianhu District, formed the "hot spot" area with high facility richness, while the outer ring city only a few areas showed "hot spot" areas, such as Sanqiao Street, Yuhuazhai Street, Zhangbaigou Street, Textile City Street, and Beiguan Street. The distribution characteristics of "central point agglomeration and peripheral point dispersion" indicate that the street facilities construction in the central urban area is relatively perfect, while the infrastructure construction in the peripheral urban area needs to be strengthened.

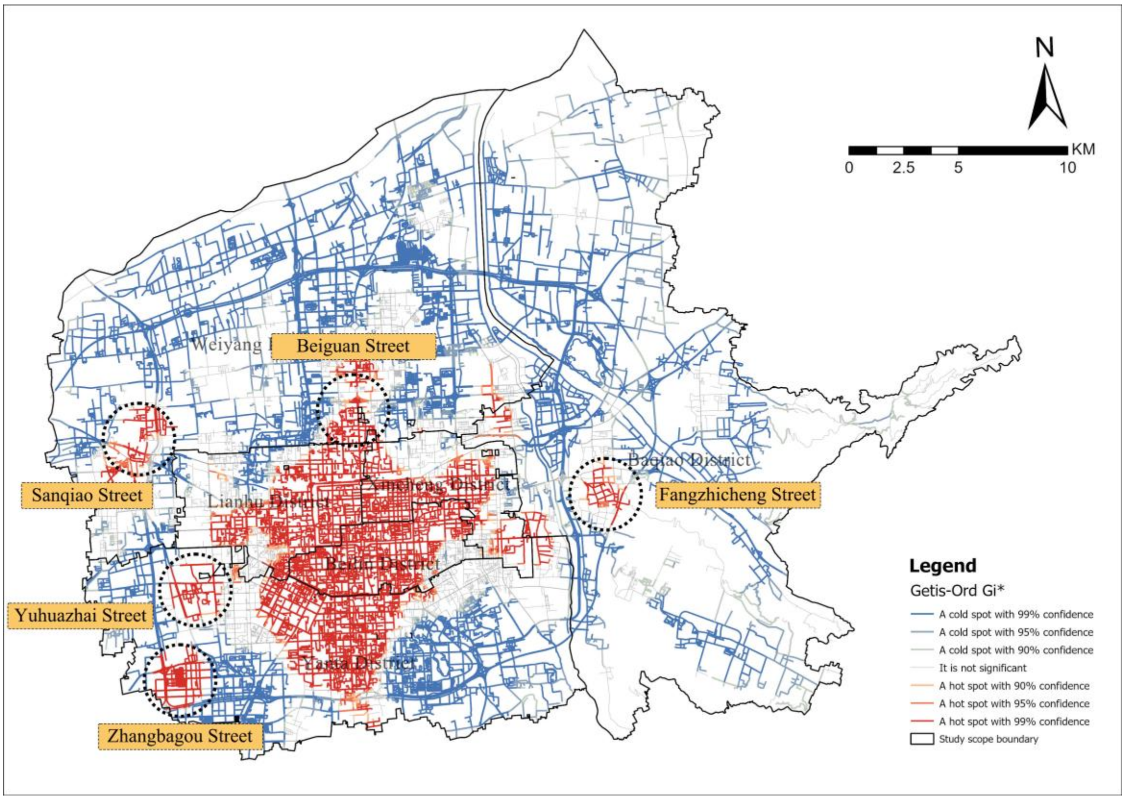

Figure 13. Street facility richness hotspot analysis.

3.4. Overlay Analysis of Three-Dimensional Evaluation Indicators

By overlaying and analyzing the results of the calculation of three indicators, namely street usage frequency, environmental quality, and the richness of facilities, we can precisely identify the existing problems of street space and determine the priority areas in the improvement of the quality of urban streets.

As shown in Figure 14, streets in the central urban area of Xi'an have significant imbalances in three aspects: environmental quality, facility richness, and use frequency. Among the 45,310 streets in the study area, there are 11,311 high-frequency streets in daily use, accounting for 24.96% of the total. Among these high-frequency streets, only 786 streets have good environmental quality and rich facilities, accounting for 6.95%; 1387 streets had good environmental quality but insufficient facilities, accounting for 12.26%; 3230 streets had poor environmental quality but rich facilities, accounting for 28.56%; There were 5908 streets with poor environmental quality and inadequate facilities, accounting for 52.23%. These characteristics reflect the main characteristics of high-frequency daily use of pedestrian streets in the downtown area of Xi'an. On the one hand, this distribution is affected by the overall facility level and environmental quality, and on the other hand, it is also closely related to the dislocation of the spatial distribution of these three types of indicators.

In addition, this study identifies priority areas in the quality improvement efforts of urban streets through an overlay analysis of three dimensions: frequency of use of the streets, environmental quality, and facility richness. Specifically, these streets with high walking frequency but poor environmental quality or insufficient facility functions should be prioritized for renovation because they are frequently used by people but lack good environmental quality and rich facility functions. Studies have shown that increasing greenery, improving lighting, and improving infrastructure can not only improve the environmental quality of streets but also enhance street vitality and resident satisfaction [3,31,50]. On the contrary, high-frequency pedestrian streets with high environmental quality and rich facility functions will be frequently used by people and are directly related to their daily sense of urban experience and well-being. Therefore, priority should be given to high-frequency streets with low space quality and inadequate facilities. Based on this understanding, Figure 15 identifies the streets that need to be prioritized for renovation, marking the areas where the streets are located with red to blue markers.

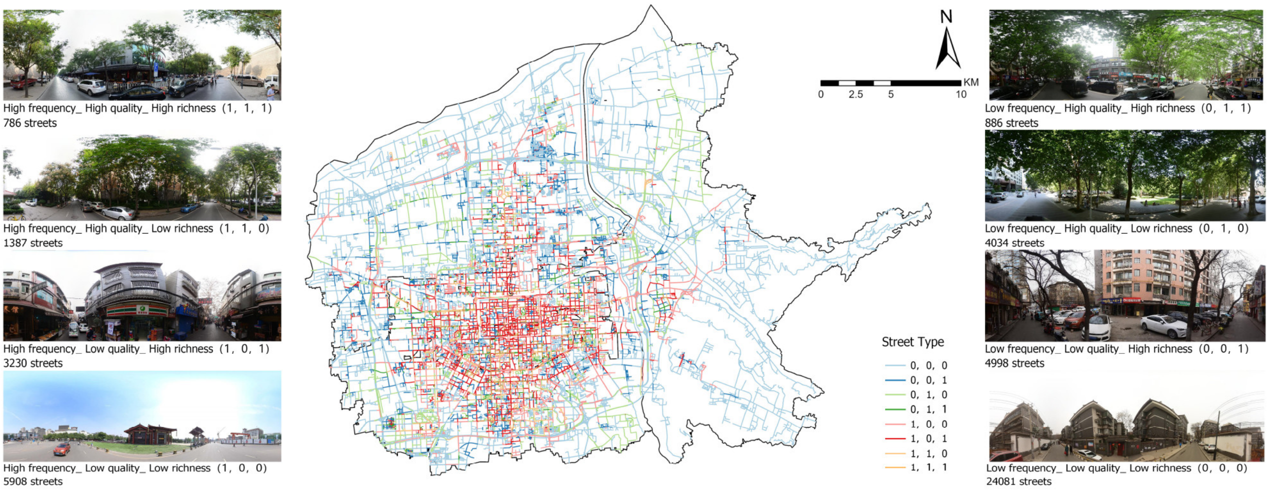

Figure 14. Distribution of the eight street types and examples.

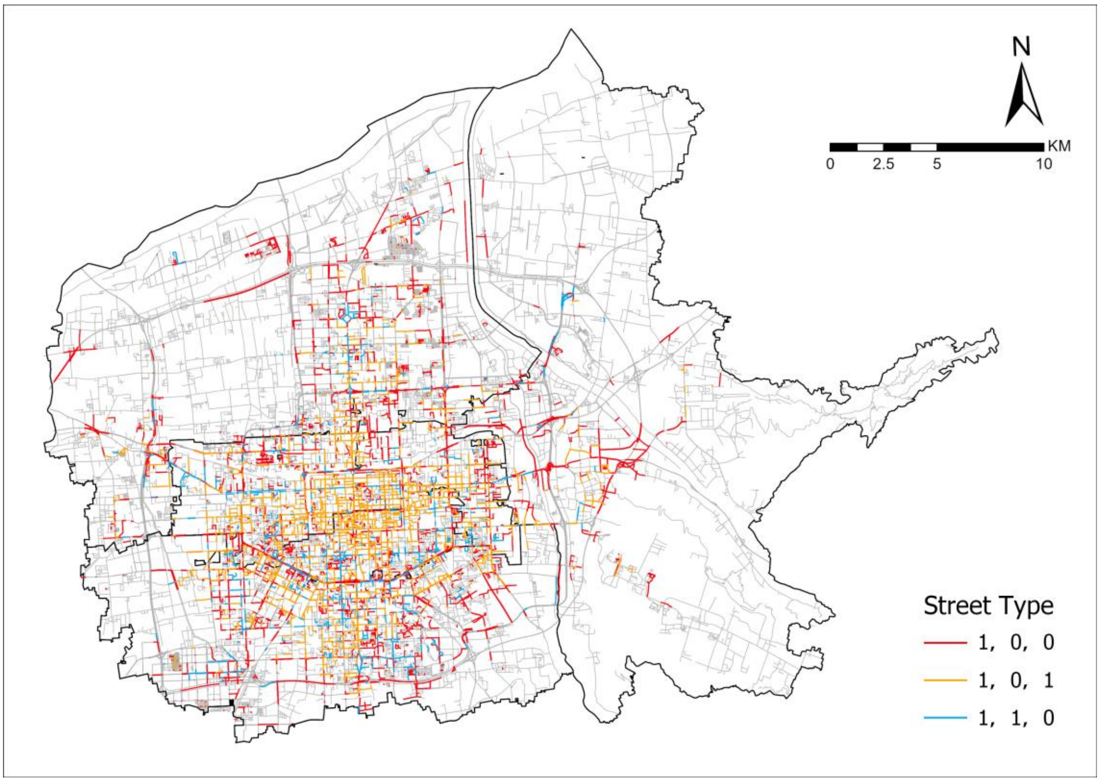

Figure 15. Xi'an Central City priority street renovation.

Among them, the blue-marked streets are characterized by high-frequency use, good environmental quality, and insufficient facility functions, corresponding to the planning and design path of exploring potential. The functional attributes and facility density of this type of street are insufficient, and the facilities are more homogeneous, resulting in a boring and monotonous walking experience.

Streets marked in orange are characterized by high frequency of use, poor environmental quality, and rich functionality of facilities, and the corresponding planning and design path is quality improvement. These streets are mainly distributed in the old city, which has less greening, poor walking experience, high building density, and severe aging.

Streets marked in red are characterized by high-frequency use, poor environmental quality, and insufficient facility functions, and the planning and design path is a total renovation. This type of street is mainly distributed on the main urban roads that are dominated by vehicular traffic, which makes the infrastructure and style perception of this type of pedestrian street poor. Therefore, it is not only necessary to improve the environmental quality of the street but also to enrich the richness of the facilities on both sides of the street.

4. Discussion

4.1. Multi-Dimensional High-Frequency Pedestrian Street Quality Evaluation

Streets, as important parts of urban public space, have received increasing attention in recent years. However, the number of streets in cities is so large that large-scale holistic street reconstruction programs are not the best way to allocate resources. High-quality environmental facilities without the frequency of crowd use are inefficient, and high-frequency street use without high-quality environmental facilities is dysfunctional. The balance between environmental supply and crowd-use demand can realize efficient and high-performance resource allocation. Therefore, this study considers three dimensions, namely, usage frequency, environmental quality, and facility function, to comprehensively evaluate the matching relationship between environmental supply and usage demand of urban streets. This evaluation system has the advantages of comprehensiveness and universality compared with traditional qualitative and single-dimension quantitative research. First, the three-dimensional evaluation system proposed in this study comprehensively considers the street ontology, street facilities, and user objects, which is more conducive to deriving planning and design strategies than single-dimensional measurements. Secondly, the combination of new technology and new data can significantly save time and efficiently conduct large-scale analysis compared with traditional field research and questionnaire collection methods. These methods can be applied in multiple cities to assess street spatial quality at the urban and even regional scales while maintaining human-scale fineness. In addition, by analyzing the results of the evaluation matrix, we were able to prioritize the renewal of high-frequency pedestrian streets and further explore the characteristics and reasons for the matching of environmental supply and use demand, thus providing guidance for different planning and design paths.

4.2. Practical Application of Urban Design and Refined Urban Regeneration

The framework of urban street spatial quality assessment proposed in this study has high operability in current urban renewal, pedestrian-friendly city construction, and other planning practices based on large-scale analysis at the human scale. A large number of past studies have shown that by improving different street environment elements and design details, street space quality can be significantly improved, making the street more suitable for pedestrians [55,56]. In contrast, by combining street view data with machine learning algorithms, this study can comprehensively assess street quality at the city scale, analyze specific elements in detail, and accurately identify the problems of a single street, providing a basis for the refined management and update of street views. In addition, by integrating social media check-in data, this study provides an effective method to reflect actual pedestrian activity, filling the gap in attention paid to high-frequency streets in previous studies. Overall, the framework provides new research perspectives and strong support for future urban renewal and street renovation projects.

4.3. Research Limitations and Future Explorations

The innovation of this study lies in the combination of multi-source big data and advanced deep learning techniques to conduct a comprehensive overlay analysis, which serves as a means to integrate environmental quality, facility functionality, and usage frequency for determining the quality of streets and their potential for renewal. Nevertheless, this study encounters certain limitations, primarily in the aspect of data.

This study relies heavily on spatially suggested data provided by Amap and ArcGIS in assessing the frequency of visits to streets. Although this approach lacks actual pedestrian walking trajectory data, such as activity trajectories captured through GPS devices, we compensate for this deficiency by integrating social media check-in data. Social media check-in data, as user-initiated recorded behaviors, can reflect people's real activities and frequency of visits on specific streets, thus significantly improving the accuracy and reliability of the assessment. In addition, this study also realizes that the failure to include specific demographic data for individual residential areas and office buildings may have some impact on the frequency of walking route use. Admittedly, including different types of workplaces, such as institutes and factories, and their associated demographic data could further enrich the depth and breadth of the study results. Future studies will consider these variables for a more comprehensive assessment.

Another issue is the perspective bias of the Baidu Street View data, which mainly captures auto-rickshaws, while this study focuses on walking spaces commonly used in daily life. This discrepancy may lead to a distorted view of the street environment. In addition, the current limitations of deep learning algorithms and Street View image resolution mean that our environmental quality assessment system is not yet fully mature. Important metrics such as "cleanliness and maintenance" and "interface permeability" are missing from the current study, which may affect the accuracy of our street quality assessment. Future work will improve the accuracy of recognizing street environment elements by training more complex image semantic segmentation models. This will help to gradually overcome the current limitations. In addition, the scope of this study was limited to analyzing the travel patterns of residents on weekdays, so further research is needed to investigate weekend behavior and other mid-frequency walking activity patterns.

In summary, although this study is an innovative attempt at a multi-dimensional evaluation of the spatial quality of urban streets and provides new perspectives and methods for future research, there is still room for improvement in terms of data and methods. We expect to further improve this evaluation framework in the future with more comprehensive and fine-grained data to provide stronger support for urban renewal and planning.

5. Conclusions

This paper takes the central city of Xi'an as the research object, based on the spatial pattern and movement pattern of the urban population's daily travel behavior, and constructs the screening mechanism of urban high-frequency pedestrian streets from the bottom up. Combining path planning, points of interest (POI), Street View imagery, social media check-in data, and deep learning network models, we can assess street quality from the perspective of People's Daily behavior. Although there are some limitations, this study is helpful in understanding the supply-demand matching relationship between the supply and use demand of the street environment in the downtown area of Xi'an. In terms of method, the combination of street view image and semantic segmentation model is an effective and high-precision street environment quality assessment method. The combination of crowd travel behavior patterns and path planning data provides a new idea and method for evaluating the frequency of street use. Social media check-in data further complements refined data on street traffic; POI data provide new data support for human-scale research on pedestrian perceptions of street furniture functions. Taking advantage of these advantages, the coupled evaluation system that covers the trinity of environment, facilities, and people proposed in this study can intuitively identify the problems and potentials of streets so as to guide different planning and design paths. With the help of the evaluation system, it identifies three types of high-frequency streets in urgent need of renovation: "high environmental quality, insufficient facility function", "low environmental quality, rich facility function", "low environmental quality, insufficient facility function", and puts forward corresponding planning and design paths of "activation potential", "quality improvement" and "overall transformation" respectively. The results show that the comprehensive evaluation results of environmental supply and utilization demand are consistent with people's impressions of the study area. It shows that the spatial quality evaluation system and data are accurate and effective and can provide a basis for subsequent planning and design. At the same time, this method can locate the evaluation results for each street and provide a refined demonstration for the public space renewal scheme of small and medium-sized streets so as to link design research with design practice.

Author Contributions: Conceptualization, L.L. and Y.T.; Data curation, Y.T. and P.W.; Formal analysis, Y.T. and M.S.; Investigation, H.L.; Methodology, Y.T.; Project administration, Y.T.; Software, Y.T. and H.L.; Supervision, L.L.; Validation, L.L., M.S., P.W. and J.H.; Writing—original draft, L.L., Y.T. and H.L.; Writing—review and editing, Y.T. and M.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the MOE (Ministry of Education in China) Project of Humanities and Social Sciences (Project No.21YJC760047).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

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