Assessing Street Space Quality Using Street View Imagery and Function-Driven Method: The Case of Xiamen, China

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Abstract: Street space quality assessment refers to the extraction and appropriate evaluation of the space quality information of urban streets, which is usually employed to improve the quality of urban planning and management. Compared to traditional approaches relying on expert knowledge, the advances of big data collection and analysis technologies provide an alternative for assessing street space more precisely. With street view imagery (SVI), points of interest (POI) and comment data from social media, this study evaluates street space quality from the perspective of exploring and discussing the relationship among street vitality, service facilities and built environment. Firstly, a transfer-learning-based framework is employed for SVI semantic segmentation to quantify the street built environment. Then, we use POI data to identify different urban functions that streets serve, and comment data are utilized to investigate urban vitality composition and integrate it with different urban functions associated with streets. Finally, a function-driven street space quality assessment approach is established. To examine its applicability and performance, the proposed method is experimented with data from part area in Xiamen, China. The output is compared to results based on expert opinion using the correlation analysis method. Results show that the proposed assessment approach designed in this study is in accordance with the validation data, with the overall $R^2$ value being greater than 0.6. In particular, the proposed method shows better performance in scenic land and mixed functional streets with $R^2$ value being greater than 0.8. This method is expected to be an efficient tool for discovering problems and optimizing urban planning and management.

Keywords: street view imagery; urban function; street vitality; street space quality assessment

1. Introduction

Street space is considered an essential component of urban public space, responsible for various public activities, and connects different functional areas in the city [1,2]. As the most frequently contacted public space in a citizen’s daily life, the space quality of streets directly affects the impression of users, including citizens and tourists, on urban space [3]. In this context, many design initiatives and urban renewal policies on streets have been proposed internationally, including the Urban Street Design Guide [4] and Xiamen Street Design Guidelines [5], etc.

So far, there are numerous methods invented and used for assessing street space quality, such as the stated-preference survey and behavior mapping [6]. To a greater degree, such methods here termed the traditional methods, deploy the questionnaire and field manual surveys to realize their objectives. In recent years, the rise of geographic information...
science and computer technology has brought new opportunities for processing and understanding street spatial structure more comprehensively than the previous times [2,7,8]. Compared with traditional data, big data shows the advantages of being freely obtainable and dynamically updated, and contains sufficient physical and objective information for describing the urban environment. In fact, utilizing multi-source big data, such as street view images (SVIs) and points of interest (POIs), current studies have investigated street space quality assessment in various perspectives, including urban environment, urban vitality, human perceptions, etc. [9,10]. For instance, Liu et al. [2] employed three quantitative indices (i.e., cleanliness, comfort and traffic) and proposed a new deep learning approach for the evaluation of street space qualities. Their research achieved the space quality quantitative analysis on Chengdu 2nd ring road. Shen et al. [11] used social media check-in data to characterize urban streets with land-use connectivity indices. Overall, these studies enrich the current description of street networks and enhance the assessment of street network performance.

Many scholars have been researching to understand street space quality based on the built environment using street-level imagery. Such data are often used because they contain a large amount of visual information regarding an urban physical built environment [12,13]. In addition, they provide a wide spectrum for learning street space quality by combining computer vision and semantic segmentation technology [14,15]. In this direction, Gong et al. [16], for instance, developed an estimating approach for extraction of street features (sky, trees, and buildings) and assessing urban street environments, using Google Street View (GSV) images and a deep-learning algorithm. Chen et al. [17] constructed an overall understanding of the urban environment, specifically the assessment of environmental quality, based on street view images and landscape vision application. Moreover, Li et al. [15] explored three measures on visual enclosure by applying machine learning algorithms on street view imagery, and the results were improved by including pedestrian volume and walk score.

For urban vitality quantitative assessment, various exploratory studies have been conducted from different perspectives that combine multi-source data (location-based service data, point of interest, social media review, online maps, etc.) [18]. Chen et al. [19] calculated spatially explicit indices to analyze the spatial pattern on the big data platform. This research focused on urban vitality assessment to address the increasing decentralized urban patterns and take precautions to urban decline. Dong et al. [20] adopted an ideal solution of TOPSIS for quantitative assessments of the urban vitality of metro-led underground space (MUS) based on multi-source big data. These attempts signify that using geo-data that reflects different types of human activities, we can accurately obtain the distribution of urban space vitality in various scales [21]. In other words, they confirm that using geo-data is possible to evaluate different kinds of functions and their corresponding vitality carried by street space effectively [22].

To date, many studies deploying geo-data for street space quality assessment take a wide range of urban streets as independent objects to explore their roles in greening, transportation and urban vitality [14,20,23]. Moreover, current studies have investigated urban functions in the field of street quality assessment. Hu et al. [24], for example, established an assessment model combined with street view image and urban function, which ignores the fact that urban vitality is also a constituent element of spatial quality. Despite their success and significant contributions, there are limitations requiring more attention. The understanding of street space quality in existing studies focuses more on evaluating material concepts of space, while street vitality and the function street serves have become a comprehensive concept, including material elements and citizen activities [25,26]. Another challenging problem which arises in this domain is how to comprehensively consider these factors.

This paper is designed to address such gaps by integrating and discussing the relationship between street vitality, urban function and built environment in the same street space from a comprehensive perspective through objective analysis and subjective perception. A
new geographic information system (GIS) based prototype of deploying multi-source data with multi-perspective indicators is proposed for assessing street space quality, and this study introduces a new weight indicator system that integrates the urban function of the scenic land for assessing street space quality. This system provides more reasonable results, particularly in cities whose local characteristics are as tourism-oriented as the Xiamen City.

The remainder of this paper is organized as follows. Section 2 introduces the study area and multi-source data used in this study. Section 3 illustrates our proposed approach for street space quality assessment. Section 4 displays the results of the comparative assessment in the study area. Section 5 discusses the obtained results, and the last section concludes this work by providing a summary and future directions of this study.

2. Data Description

2.1. Study Area

The data that this study uses for presenting and analyzing street space quality were obtained from Xiamen, one of the most famous tourism-oriented cities in the southeast of Fujian Province, China. Specifically, three regions marked as Area I, II and III in Xiamen City are chosen to realize the objectives of this study, as seen in Figure 1. Area I is located in the southwest of Siming District. Area II, with a large area and lower road density than the other two areas, is located in Jimei District. Area III is situated in the middle of Siming District, and it includes the Xiamen Railway Station. Each street was treated as an individual unit to aggregate street view images and other multi-source data.

Figure 1. Specific areas studied in Xiamen, China.
2.2. Data Sources and Preprocessing

2.2.1. Street View Images

In this study, we use a total of 704 open street view images, which are provided by the organizers of the Xiamen Big Data Security, Open and Innovative Application Competition. The workflow of processing is presented in Figure 2.

The preprocessing of the street view images was done by using the histogram equalization method to eliminate the impact of image brightness under different light [27]. As shown in Figure 2, the original street view images are transformed from red-green-blue (RGB) space to hue-saturation-intensity (HSI) color space, then the brightness component is equalized in HSI color space. In this way, the local contrast will be enhanced without affecting the overall contrast. Finally, the image is cropped after conversion to RGB space (the size of cropped image is 300 × 600) to eliminate the influence of irrelevant factors on later data processing and analysis. Street view image samples are shown in Figure 3. Figure 3a,b are the original street view images, and their corresponding images after preprocessing are as seen in Figure 3c,d.

![Figure 2](image2.png)

Figure 2. The preprocessing of street view images.

![Figure 3](image3.png)

Figure 3. Street view image samples. (a,b) are original street view images; (c,d) are the same imagery after being preprocessed.

2.2.2. POI Data

The POI data were obtained from the Xiamen Big Data Security, Open and Innovative Application Competition organizers. Each data includes three attributes, i.e., name, XY coordinates and category. Before using, we merged and cleaned them by removing, e.g., redundant information. A total of 175,279 records of the POI data were retained after the
cleaning process, and their analysis was performed based on their geographic positions (i.e., XY coordinates) and other types of fields.

2.2.3. The Review/Comment Data

The comment data were retrieved from the Trip.com Group at https://www.ctrip.com (accessed on 3 October 2021). The Trip.com Group is one of China’s leading online travel service platforms. The data collected for this study includes the attractions, hotels, restaurants and shopping malls data. These data were retrieved together with their details, including name, coordinate and number of comments. A total of 5024 comment records were obtained in Xiamen. Then, a buffer radius of 800 m was utilised to obtain the available comment data in the study area. This approach produced a total of 1195 comment data points used for further research. Moreover, the road data of Xiamen is obtained from OpenStreetMap [28].

3. Methodology

In this research, we utilize multi-source geo-data, including street view images, comment data and POIs, to comprehensively evaluate street space quality based on the urban function. In the first step, street view images are segmented by the DeepLabv3 model to extract street space environment indicators. Then, we construct a weighted model of street vitality in combination with the accessibility model of a street road network to realize the simulation of street space vitality within a certain range. Finally, we utilize POIs to detect urban function. In the second step, we build street space quantification indicators for different urban functions. Then, we determine the weight type for different functions. Finally, the assessment of street quality is realized by the entropy technique for order preference by similarity to an ideal solution (Entropy TOPSIS). The second step utilizes the classification of urban functions in the first step and proposes strategies on street space quality description and weighting. The framework of street space quality assessment is displayed in Figure 4.

Figure 4. Workflow chart of the methodology proposed in this study.
3.1. Street View Image Segmentation Using CNN and Transfer Learning

As a mainstream deep learning architecture, convolutional neural networks (CNNs) specialize in extracting spatial context information, which makes it effective, especially in the fields of video recognition, image classification and segmentation [29]. In this work, we employ the DeepLabv3 model to learn the knowledge of a physical environment and utilize the deep representation of a scene image to extract the semantic information from street view images, such as for the sky and buildings [30]. DeepLabv3 employs atrous convolution with upsampled filters to extract dense feature maps and to capture a long range context. Due to the lack of training data sets in the study area, this study uses the transfer learning method and the Cityscapes Dataset [31] to realize semantic segmentation of street view images.

As shown in Figure 5, we apply transfer learning to this work by first training a DeepLabV3 model $M_s$ using the Cityscapes Dataset to carry out an image segmentation task, i.e., identify which category the pixel belongs to, and then training a DeepLabV3 model $M_t$ to predict the street view images in the study area by fine-tuning the pre-trained model $M_s$.

![Figure 5. Framework of street view image segmentation.](image)

In this study, 70 street view images in the study area are labeled with 14 categories of pixels for fine-tuning the model. Table 1 shows the detailed description of the categories.

| Category    | Label | Category    | Label |
|-------------|-------|-------------|-------|
| road        | 0     | person      | 7     |
| sidewalk    | 1     | car         | 8     |
| building    | 2     | bike        | 9     |
| wall        | 3     | bridge      | 10    |
| greenery    | 4     | terrain     | 11    |
| sky         | 5     | bus         | 12    |
| traffic sign| 6     | others      | 13    |

3.2. Street Space Environment Indicator Extraction

Three individual element indicators and three multi-element indicators were selected and used in this study. We are not saying that these six chosen quantitative indices are the most appropriate or most important for this study. They are just at the beginning of this series of studies.
1. Individual element indicator

Among the 14 classes, we count the number of pixels for the identified three features, i.e., greenery, sky, and road, to analyze the feature of individual elements in each street view image, including visible green index, spatial openness, and street spaciousness.

2. Multi-element indicator

In addition to the indicators of individual elements, some of the street features are affected by several types of elements that affect users and the perception of the environment. We calculate three multi-element indicators to further analyze the street elements in the research area.

- Interface heterozygosiy

  This indicator refers to the enclosure degree of street space interface, which can reflect the restriction of buildings, walls, trees and other elements on both sides of the street, which is calculated as:

  \[ C_e = \frac{n_{\text{building}} + n_{\text{wall}} + n_{\text{vegetation}} - n_{\text{bridge}} - n_{\text{terrain}}}{N}, \]

  where \( N \) is the total number of pixels in the image, and \( n_{\text{building}}, n_{\text{wall}}, n_{\text{vegetation}}, n_{\text{bridge}} \) and \( n_{\text{terrain}} \) represent the number of pixels belonging to building, wall, greenery, bridge and terrain, respectively. Taking building as an example, when the proportion of building is relatively high, the street space is relatively compact, that is, the sense of enclosure of the space is strong.

- Motorization

  To present the interference of vehicle space on walking, we introduced the motorization indicator, which used five categories to calculate:

  \[ C_m = \frac{n_{\text{car}} + n_{\text{bus}} + n_{\text{road}} - n_{\text{sidewalk}} - n_{\text{terrain}}}{N}, \]

  where \( N \) is the total number of pixels in the image, and \( n_{\text{car}}, n_{\text{bus}}, n_{\text{road}}, n_{\text{sidewalk}} \) and \( n_{\text{terrain}} \) represent the number of pixels belonging to car, bus, road, sidewalk and terrain, respectively. The lower the degree of motorization, the less interference to pedestrians, and the more conducive to the development of walking activities.

- Walkability

  Having a pedestrian path with appropriate width is of great significance to improve the sense of security of citizens and tourists [32]. Walkability indicator is calculated as follows:

  \[ C_s = \frac{n_{\text{sidewalk}} + n_{\text{terrain}} + n_{\text{person}}}{N}, \]

  where \( N \) is the total number of pixels in the image. \( n_{\text{sidewalk}}, n_{\text{person}} \) and \( n_{\text{terrain}} \) represent the number of pixels belonging to sidewalk, person and terrain, respectively.

After completing the street view image content recognition, the street view collection points are matched with the corresponding street sections through spatial connection, the average value of various label pixels in each street section is counted, and the spatial distribution of some elements is visualized in ArcGIS for further analysis.

3.3. Construction of Street Space Vitality Model

Comment data are utilized to extract street vitality in this study. Different facilities have different effects on the vitality of street space, so we gave certain weights to different facilities according to the number of users (i.e., number of comments on the facilities, \( c_j \)), and then constructed the weight network model of street vitality in combination with the accessibility model of street road network, so as to realize the simulation of street space vitality within a certain range. We use the distance from facilities to street
intersection to represent accessibility of the street network. It is mainly divided into the following situations:

1. Distance of effective influence (800 m): the facilities outside this distance have no significant impact on spatial vitality, and the impact of these facilities will not change with the increase of distance. Limited by the appropriate walking distance, the maximum effective influence distance of facilities on street space is set as 800 m [33];

2. Influence range (25–800 m): according to the inverse-square law [34], in the street network, the influence of facilities on street vitality will weaken significantly, i.e., within the range of 25–800 m, the influence will decay to the power of 2 with the increase of distance;

3. Distance of direct influence (25 m): the facilities can most directly affect the vitality of the spatial streets within a certain distance. Within this range, the facilities have the greatest impact on the spatial vitality and will not change significantly with the increase of distance. In other words, the facilities within 25 m have the greatest and same impact on the spatial vitality [35].

Let \( x \) denote the distance from any point \( p \) on street \( S \) to the first intersection \( i \) of \( S \), \( dx_j \) denote the distance from point \( p \) to a facility point \( poi_j \), the function \( f(x) \) of \( dx_j \) to \( x \) after distance restriction is defined as:

\[
g(x) = \begin{cases} 
25 & f(x) \leq 25 \\
\frac{f(x)}{800} & 25 < f(x) \leq 800 \\
\frac{f(x)}{800} & f(x) > 800 
\end{cases}
\]

Then, the total impact of all facilities within the study scope on the vitality of a street intersection \( svi \) is calculated as:

\[
svi = \sum_j c_j \cdot g^2(x)
\]

where \( c_j \) represents the number of comments on \( j_{th} \) facility.

3.4. Sensing Spatial Distribution of Urban Function

To assess the quality of street space, the diversity of different types of streets needs to be considered. This research focuses on the quality assessment based on urban function categories. Based on Xiamen Street Design Guidelines [5], considering street activities and street space landscape characteristics, Xiamen streets are divided into five types: commercial-oriented street, life service-oriented street, landscape-oriented street, traffic-oriented street and mixed-function street. On this basis, we used POI data to detect the functions of urban blocks, including commercial, living, traffic, scenic land and mixed-function. Table 2 shows typical examples of the five types of streets in Xiamen.

Firstly, mesh-based analysis was utilized to calculate urban function scores by using POI data [36]. Indicators, such as the number of POIs, in each mesh grid were calculated. Then, the score of four urban function categories, i.e., commercial, living, traffic, and scenic land, was obtained. Among them, the commercial functional area mainly includes office land, and the living functional areas include residential land, supermarkets and other life service facilities. The transportation functional area has transportation hubs, such as subway stations and bus stations. In the end, a decision method was applied to classify urban function into five categories: commercial function, living function, traffic function, scenic land and mixed-function.

Determination of the specific function type is the most important step for detecting urban function. The determination steps are as follows:

**Step 1.** If the score of scenic land is equal to 0 (regardless of the scores of other types), it will be judged as the category of scenic land, otherwise it will be judged in Step 2.

**Step 2.** If it does not belong to scenic land, and the maximum score (\( C_A \)) is more than twice the second largest score (\( C_B \)), it will be judged as type A, otherwise it will be the mixed-function.
In particular, we divided each road into 100 m × 100 m regular grids to measure urban function. Due to the particularity of Area II, the grid size was set to 400 m × 400 m. Then, the property fields of mesh grids were spatially joined to the street view data points, which enables data aggregation of street view images and POI data.

### Table 2. Street types and the corresponding urban functions.

| Street Type               | Street View Image | Description                                                                 | Urban Function   |
|---------------------------|------------------|-----------------------------------------------------------------------------|------------------|
| Commercial-oriented street| ![Commercial](image) | Streets with retail, catering and other commercial facilities and certain service capacity or characteristics. | Commercial function |
| Life service-oriented street | ![Life](image) | Streets dominated by life service businesses (convenience store, barbershop, etc.), small and medium-sized retail, catering and other businesses, as well as public service facilities (community clinic, activity centers, etc.). | Living function |
| Landscape-oriented street | ![Landscape](image) | Streets with landscape and historical features concentrated with leisure facilities along the line. | Scenic land |
| Traffic-oriented street | ![Traffic](image) | Streets with non-open interfaces and strong traffic functions. | Traffic function |
| Mixed-function | ![Mixed](image) | Streets with high degree of mixed functions and interface types, or streets with more than two types of characteristics. | Mixed-function |

### 3.5. Assessment of Street Space Quality

Since various factors are involved in street space quality, it is a typical multi attribute decision making problem for its quantitative assessment. In this study, the TOPSIS method was applied to measure the level of street space quality. TOPSIS has been proved reasonably practical for performance assessment based on the similarity of the investigated alternative to an ideal solution [37]. TOPSIS is based on the idea that the best performance should have
the shortest distance from the positive ideal solution, and on the other side, the farthest distance from the negative ideal solution [38].

There were 704 samples in the three areas analyzed in this case study. Considering the urban function of streets, we calculate weights on each function category (mentioned in Section 3.3) by the entropy weight method (EWM) [39]. When performing TOPSIS analysis, it is also critical to determine whether an indicator is a gain type (the bigger, the better) or a cost type (the smaller, the better). According to Xiamen Street Design Guidelines [5], the basic hypothesis is outlined as follows: historical blocks (i.e., scenic land in this study) require streets to have strong walkability, rich street activities and street landscape with local characteristics; commercial blocks require convenient transportation, appropriate service facilities and beautiful environment; living-oriented blocks require streets to have a comfortable walkability, appropriate parking space and good living atmosphere; traffic-oriented blocks require convenient transportation, wide streets and sufficient parking space. For different urban functions, we adopt the ultimate weight type of each indicator in the form of Expert Choice. For example, as for the traffic functional area, it is expected that the motorization indicator is a gain type, while in the living functional area, the intermediate value of this indicator will be the best. As such, the weight type of selected indicators are shown in Table 3. “g” denotes the gain type, “c” denotes the cost type, and “—” denotes the middle type. Moreover, the final assessment results were normalized to (0, 100). The steps of TOPSIS analysis are as follows.

**Step 1.** Determine assessment indicators by multi-source data collection and data processing (see Table 2).

**Step 2.** Establish the initial assessment matrix based on the acquired indicators.

\[
X_{ij} = \{x_{ij}\}_{m \times n}, \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n,
\]  

where \(x_{ij}\) denotes the value of the \(j\)th assessment indicator for the \(i\)th sample.

**Step 3.** Established the normalized assessment matrix.

\[
W_{ij} = \{w_{ij}\}_{m \times n}, \quad i = 1, 2, \ldots, m, \quad j = 1, 2, \ldots, n,
\]

\[
w_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad j = 1, 2, \ldots, n
\]

where \(w_{ij}\) represents the value of the \(j\)th normalized assessment indicator for the \(i\)th sample.

**Step 4.** Determine the weight of each kind of assessment indicator by the EWM method.

**Step 5.** Calculate the Euclidean distance of each sample from the positive ideal solution and the negative ideal solution.

\[
d_i^+ = \sqrt{\sum_{j=1}^{n} w_j \times (m_{ij} - m_j^+)^2}, \quad i = 1, 2, \ldots, m,
\]

\[
d_i^- = \sqrt{\sum_{j=1}^{n} w_j \times (m_{ij} - m_j^-)^2}, \quad i = 1, 2, \ldots, m,
\]

where \(d_i^+\) and \(d_i^-\) denote the Euclidean distance of the \(i\)th sample from positive ideal solution (PIS) and negative ideal solution (NIS), and \(m_j^+\) and \(m_j^-\) denote the value of PIS and NIS of \(j\)th assessment indicator.

**Step 6.** Calculate the value of street space quality of each alternative at the current indicator level.

\[
Q_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, 2, \ldots, m,
\]

**Step 7.** Conduct the previous algorithm repeatedly from the lower level to the higher level to acquire the final consequence of street space quality.
Table 3. Data source and the weight type of selected indicators.

| Factor                   | Indicator                                      | Commercial Function | Living Function | Traffic Function | Scenic Land | Mixed-Function |
|--------------------------|-----------------------------------------------|---------------------|-----------------|-----------------|-------------|----------------|
| Street built environment| visible green index                          | —                   | g               | —               | g           | —              |
|                          | motorization                                 | g                   | —               | —               | —           | —              |
|                          | spatial openness                             | —                   | —               | —               | g           | g              |
|                          | space enclosure                              | —                   | —               | —               | c           | —              |
|                          | street spaciousness                          | g                   | —               | g               | c           | c              |
|                          | walkability                                  | g                   | g               | c               | g           | —              |
| Urban vitality           | urban vitality                                | g                   | —               | g               | —           | —              |
| Urban function           | density of transportation facilities         | —                   | c               | g               | —           | —              |
|                          | density of residential area                  | c                   | g               | c               | c           | —              |
|                          | density of scenic land                       | c                   | c               | c               | g           | —              |
|                          | density of green and plaza land              | g                   | —               | g               | —           | —              |
|                          | density of commercial facilities             | g                   | c               | c               | c           | —              |
|                          | density of life service facilities           | c                   | g               | g               | c           | —              |
|                          | density of public service facilities         | —                   | —               | —               | —           | —              |

“g” denotes the gain type, “c” denotes the cost type, and “—” denotes the middle type.

4. Results
4.1. Results Analysis of Street Built Environment

Figure 6 shows the visualisation results of the visible green index in study areas. When viewing the distribution as a whole, streets with a higher visible green index are generally distributed in parks and main roads with better natural conditions. The roads with excellent greening quality in Area I and Area III are more concentrated; however, the green space is scattered and the green quantity is obviously insufficient in some old towns, as shown in Figure 6a,c. Living areas and the universities, such as the Huaqiao University, are mainly distributed in Area II, which leads to a relatively high value of the visible green index. Moreover, the interior of Area I is mostly old urban areas with low greening degrees, while the west is close to the sea and has important tourist areas of Xiamen city, e.g., Gulangyu Islet in the southwest of Area I. Therefore, the visible green index of the streets in Area I can vary up to 70%. However, the difference of visible green index between the streets in Area III is the lowest. Area III is located near Xiamen Railway Station, dominated by commercial and office land, which affects the overall level of visible green index to a certain extent.

Figure 6. Visualisation results of the visible green indicator in (a) Area I, (b) Area II, and (c) Area III.
As shown in Figures 7 and 8, the distribution of space enclosure and spatial openness is approximately opposite, i.e., streets with dense buildings have narrow sky views, while streets with few buildings have wider sky views, which are also consistent with our sensing in daily life. Specifically, in terms of space enclosure, the overall distribution in Area I is high in the west and low in the east (Figure 7a). In Area III, the overall distribution of space enclosure is high in the periphery and low in the middle, while in the south, adjacent to the scenic spot, the value of space enclosure is higher than its adjacent area. In Area II, higher spatial openness and lower space enclosure generally appear along the main road.

![Figure 7](image1.png)

Figure 7. Visualisation results of space enclosure in (a) Area I, (b) Area II, and (c) Area III.

![Figure 8](image2.png)

Figure 8. Visualisation results of spatial openness in (a) Area I, (b) Area II, and (c) Area III.

Except for some areas without street view data, places with high space enclosure basically have high road network density. Areas with dense road networks are generally developed earlier, with relatively narrow street scale and low aspect ratio, resulting in a high proportion of buildings in the visual field (Figure 8a). The distribution of streets with a higher value of spatial openness in the visual field has two obvious characteristics. Firstly, it is more distributed along the coast because there is a less visible occlusion near the sea.
Secondly, streets with higher spatial openness have lower street network density and wider roads, as shown in Figure 9.

![Figure 9](image_url)  
**Figure 9.** Visualisation results of street spaciousness in (a) Area I, (b) Area II, and (c) Area III.

Walkability and motorization reflect the activity pattern and prosperity of urban streets. In terms of the spatial distribution of walkability (Figure 10), sidewalks are more distributed in the central of Area I and the northwest of Area II, and pedestrian trails in Area II are mainly distributed in the main roads, e.g., Sunban South Road and Xinglinwan Road. In general, the distribution of sidewalks varies greatly among streets in the study area. As for the non-pedestrian street, it is of great significance to have sidewalks of suitable width to improve the sense of security of citizens and tourists [32].

![Figure 10](image_url)  
**Figure 10.** Visualisation results of walkability in (a) Area I, (b) Area II, and (c) Area III.

Moreover, the distribution of walkability and motorization is inversely related, as shown in Figures 10 and 11. Streets with higher motorization have greater interference to sidewalks, and it may not be conducive to walking activities, so the street has lower walkability and fewer sidewalks.
Moreover, the distribution of walkability and motorization is inversely related, as shown in Figure 13. Therefore, street vitality is closely related to the functions in which the research area is located.

4.2. Results Analysis of Urban Street Vitality

The spatial visualisation analysis of the comments data was conducted using the Kernel Density tool in ArcGIS [36]. The results are shown in Figure 12. Siming district is at the center of Xiamen and has rapid economic development and densely distributed infrastructure. Amoy Yat-Sen Rd is one of Xiamen’s most prosperous commercial streets, with daily passenger counts above 300,000 on weekends [40]. Figure 12a shows that the spatial distribution of the location of comment data in Area I and Area III of Siming District is widely distributed. In contrast, the spatial distribution of the location of comment data in Area II (Jimei District) is more scattered. As shown in Figure 12b, the density of the comment quantity is more concentrated compared to that of comment data, and the maximum value is distributed in Amoy YatSen Rd and its surrounding areas in Siming District, and the next highest value is located in Xiamen Station. The number of comments in Jimei District is less dense and scattered, which is also related to the spatial distribution of comment data.

Figure 12. Visualisation results of (a) density distribution of comment data and (b) density distribution of the number of comments.
Figure 13 shows the visualisation results of street vitality measuring levels in the study area. In general, the street vitality of Siming District shows a higher trend than that of Jimei District. Area I and Area III are located in Siming District, the main urban area of Xiamen, which has more shopping, education and medical institutions in the surrounding area, with various types of and densely distributed infrastructure, driving up the street vitality of the surrounding area. Xiamen Railway Station is located in Area III, with high population density and higher street vitality. Area II is located in Jimei District, where many higher education institutions, such as Jimei University, are located, so the overall street vitality value is low. Generally speaking, Area I is oriented toward commercial and tourism-oriented functional areas, Area II tends to be educational-oriented functional areas, and Area III is oriented toward living-oriented functional areas. Therefore, street vitality is closely related to the functions in which the research area is located.

4.3. Street Quality Assessment

The results of the street quality assessment are displayed in Figure 14. As shown in Figure 14, the urban function represents the five urban function detection results. For street quality, the rank is from 1 to 5, which indicates the street quality assessment results range from bad to good, where the worst is level 1, and the best is level 5. On this basis, partial results of the street quality assessment are displayed in Table 4. As shown in Table 4, the urban function represents the functional type of the urban block where the street is located. For example, ‘traffic’ means that this road is more oriented toward traffic than toward commercial and living urban functions.

Street quality assessment results are obtained by comprehensive evaluation combined with different urban function elements in particular. Due to the lack of street view images and POI data, the visualisation results of Area II are generally worse than those of the other two study areas.

From Figure 14a, the areas dominated by the commercial function are located in the middle of Area I. The scenic land in this area accounts for a relatively large proportion compared to others. From Figure 14c, the living and commercial functional regions in Area III occupy large areas compared to others. Most of the traffic functional areas in Area III are located near the Xiamen Railway Station. The high-density areas for traffic and living functions in Area II are more scattered, and the mixed functional areas are more abundant.
4.3. Street Quality Assessment

The results of the street quality assessment are displayed in Figure 14. As shown in Figure 14, the urban function represents the five urban function detection results. For street quality, the rank is from 1 to 5, which indicates the street quality assessment results range from bad to good, where the worst is level 1, and the best is level 5. On this basis, partial results of the street quality assessment are displayed in Table 4. As shown in Table 4, the urban function represents the functional type of the urban block where the street is located. For example, 'traffic' means that this road is more oriented toward traffic than toward commercial and living urban functions.

Table 4. Street quality assessment results of some roads.

| ID | Road                                                                 | Urban Function   | Area | Rank |
|----|----------------------------------------------------------------------|-----------------|------|------|
| 1  | Shanziding Lane                                                      | Scenic Land     | I    | 1    |
| 2  | Siming South Road (at the junction of Zhongshan Road)               | Living          | I    | 1    |
| 3  | South of Lujiang Road (Shuixian road to Zhenhai Road)              | Traffic         | I    | 2    |
| 4  | Kaiyuan Road                                                        | Scenic Land     | I    | 2    |
| 5  | East of Zhongshan Road                                             | Traffic         | I    | 3    |
| 6  | North of Siming North Road                                         | Living          | I    | 3    |
| 7  | Siming West Road                                                   | Commercial      | I    | 4    |
| 8  | West of Zhenhai Road                                               | Scenic Land     | I    | 4    |
| 9  | Jukou West Street                                                  | Commercial      | I    | 5    |
| 10 | Middle of Jimei Avenue                                            | Mixed           | II   | 2    |
| 11 | Xingjin Road                                                        | Traffic         | II   | 3    |
| 12 | Middle of Sunban South Road                                        | Living          | II   | 3    |
| 13 | Middle of Haixiang Avenue                                         | Mixed           | II   | 4    |
| 14 | North of Haixiang Avenue                                          | Traffic         | II   | 5    |
| 15 | Chengzhi North Road                                                | Mixed           | II   | 5    |
| 16 | South of Binshui Road                                              | Traffic         | II   | 5    |
| 17 | North of Binshui Road                                              | Mixed           | II   | 5    |
| 18 | East of Hubin South Road (Hubin East Road to Fengyu Road)           | Mixed           | III  | 1    |
| 19 | Zhanxi 1st Road                                                    | Commercial      | III  | 2    |
| 20 | East of Xiahe Road                                                 | Mixed           | III  | 2    |
| 21 | West of Xiahe Road                                                 | Living          | III  | 2    |
| 22 | Huiwen Road                                                        | Living          | III  | 3    |
| 23 | Jinhua South Third Road                                            | Scenic Land     | III  | 3    |
| 24 | Zhannan Road                                                       | Traffic         | III  | 4    |
| 25 | West of Hubin South Road (Houdaixi Road to Jinhua West Road)       | Traffic         | III  | 5    |
| 26 | South of Hubin East Road                                           | Commercial      | III  | 5    |

For street quality assessment results, the quality of streets of Area I is higher than that in Area III, and hence, we associate this observation with its large percent of the scenic land. The quality of other streets is relatively low, and we think this is related to the current situation of the protection and development of ancient buildings in Xiamen. It can be seen from Section 4.2 that although the overall facility density in Siming District is higher than...
that of Jimei District, street quality will not necessarily be improved due to increased facility density. From Figure 14b, we can see that the quality of several streets in Area III are higher than that of the other two areas, indicating the importance of complete urban supporting services for the residential experience of citizens. With mixed functions and convenient transportation, the streets show to have a high comprehensive space quality.

Moreover, in the northwest of Area I and the central area of Area III, the functions of some streets are relatively single. They lack diversified street space functions, resulting in a low level of street quality.

4.4. Validating the Assessment Results

The difficult part is to produce a totally definitive verification due to the absence of a standard reference. Therefore, we compared the evaluated results with the subjective assessment of experts. For accuracy assessment, we chose the street view of the sampling point to describe and verify the results for the street quality assessment. Verification images are randomly generated using a random sampling approach for a total of 84 sampling street view images, covering all function types. On this basis, subjective assessment was applied to validate and confirm the assessed results. Considering citizens’ subjective perceptions of street quality, the subjective assessment of street quality is carried out from the following five indicators: comfort, cleanliness, safety, vitality and beauty. Among them, the comfort indicator mainly considers the subjective comfort brought by the streets, while the safety indicator mainly considers whether the streets contain street lights, zebra crossings and other safety facilities. The Vitality indicator mainly considers whether the streets contain service facilities such as supermarkets and whether the flow of people is dense, and the beauty indicator considers whether the street scenery is beautiful from the perspective of human sensing.

We selected five volunteers with relevant majors to rate the dataset. In order to ensure the objectivity of the manual grading scoring, we took the following measures. Firstly, we held a seminar for the volunteers to understand the scoring rules (Table 5) of street space quality. Then, we asked all the volunteers to score the 84 images until their scores were consistent in most cases. The scoring range is 1, 3 and 5. Finally, we calculated the average score of all volunteers on one indicator of an image as the scoring value of that indicator of the image.

The final subjective assessment results are obtained based on the scores and weights of the different urban functions. The weight of each indicator for different urban functions were calculated by using the method of constructing judgment matrix of analytic hierarchy process (AHP) [41]. In particular, the relative weights of these five indicators under different urban functions, and the consistency ratios (C.R.) of the judgement matrices are calculated. If there is any matrix with an unacceptable C.R. value, i.e., > 0.10, we will make judgement on that matrix again. Thus, we obtained the weights through the method of judgment matrix construction, and subjective measurement results are obtained by weighted superposition calculation.

A scatter plot (Figure 15) shows the relationship between the values of the street quality calculated using the proposed method and the subjective values. The proposed method has provided excellent and reasonable results, with the overall $R^2$ value being greater than 0.6. $R^2$ values on different urban functions are shown in Table 6. For scenic land and mixed functional streets, the $R^2$ value can reach more than 0.8, while $R^2$ values are greater than 0.6 for commercial and living functional streets. As for the traffic functional street, the situation of traffic arteries is complex, which will lead to the discrepancy between the experts scoring results and assessment results obtained by the proposed method. This reflects that urban planning should give more consideration to people’s subjective feelings in order to improve quality of urban development. In short, there is a good match between the evaluated results and the general understanding of the experts.
Moreover, in the northwest of Area Ⅰ and the central area of Area Ⅲ. Among them, the functions and the constructions of some streets are relatively single. They lack diversified street space functions, resulting in the low comfort and safety scores. The central area of Area Ⅰ and the central area of Area Ⅲ are relatively commercial and mixed functional streets. Scenery evaluation mainly considers whether the streets contain street lights, zebra crosswalks, and other safety facilities. The comfort indicator mainly considers whether the streets contain street lights, zebra crosswalks, and other safety facilities. The beauty indicator mainly considers whether the street scenery is beautiful from the perspective of human sensing.

Firstly, we held a seminar for the volunteers to understand the scoring rules (Table 5) of the five indicators. Secondly, the manual grading scores were calculated. If there is any matrix with an unacceptable C.R. value, i.e., > 0.10, we will make adjustments and rescore the expert scoring results and assessment results obtained by the proposed method. This reflects that urban planning should give more consideration to people's subjective feelings and the general understanding of the experts.

The final subjective assessment results are obtained based on the scores and weights of the five indicators. The evaluation criteria are shown in Table 5. The correlation between the street quality assessment score and subjective assessment score is shown in Figure 15. A weighted superposition calculation was conducted. The relative weights of these five indicators under different urban functions are shown in Table 6. For scenic land and mixed functional streets, the weights of comfort and beauty are 0.6 for commercial and living functional streets. As for the traffic functional street, the weights of comfort, cleanliness, and safety are 0.6. For the vitality indicator, the weight in the commercial functional street is 0.5, the mixed functional street is 0.4, and the traffic functional street is 0.2. The weight of the aesthetics indicator is 0.2.

Table 5. Evaluation criteria.

| Street View Image | Comfort | Cleanliness | Safety | Vitality | Beauty |
|-------------------|---------|-------------|--------|----------|--------|
| ![Street View Image](image1.png) | 1       | 1           | 1      | 3        | 1      |
| ![Street View Image](image2.png) | 1       | 3           | 3      | 3        | 1      |
| ![Street View Image](image3.png) | 5       | 5           | 5      | 3        | 5      |
| ![Street View Image](image4.png) | 3       | 5           | 5      | 1        | 5      |
| ![Street View Image](image5.png) | 1       | 3           | 1      | 1        | 1      |
| ![Street View Image](image6.png) | 3       | 5           | 5      | 5        | 3      |

$$y = 17.953x−8.2613$$

$$R^2 = 0.649$$

Figure 15. Relationship between street quality assessment score and subjective assessment score.
Table 6. $R^2$ values on different urban functions.

| Urban Function    | $R^2$ |
|-------------------|-------|
| Commercial Function | 0.6070 |
| Living Function    | 0.6504 |
| Traffic Function   | 0.5832 |
| Scenic Land        | 0.8548 |
| Mixed Function     | 0.8475 |

5. Discussion, Conclusions and Future Directions

5.1. Discussion and Conclusion

Through analysis of multi-indicator assessment results, it is evident that five classes of urban function distribution and street quality score in research areas reflect the difference between Siming District and Jimei District in general. As a famous tourist city in China, Siming District of Xiamen is densely populated compared to Jimei District. Siming District provides high priority to the high-profit industry such as commercial and office businesses, with relatively higher density in traffic, and is more complete in supporting facilities including science and cultural facilities, medical facilities and public facilities. On the other hand, the industries with natural scenery, institutions of higher learning and residence are given high priorities of development in Jimei District. As universities and high-tech parks cover a large area, the neighborhood has a broader vision and more scattered business. Compared with others, the Jimei District has a higher living comfort level and lower inconvenience level. This conclusion suggests evidence for those working on understanding the reciprocal interactions among the urban built environment, city planning and human behavior. This framework is also promising to assess if the development of a city is oversupplied or insufficient by observing the relationship between urban physical environment and human activities.

At present, there are few studies on street space assessment in Xiamen city. Compared with current studies, the innovations of this study can be concluded as follows. First, this work has presented a new GIS-based method to assess street space quality using multi-source data instead of surveying street quality from a single perspective, considering local characters for tourism-oriented cities. Second, since streets are regarded as a basic component for identifying urban structure, it is vital for policy makers to investigate whether an independent street can adapt to various urban functions. Lower assessment ranking shows that the current streets can be improved in specific functions to support public services.

Although the accuracy of street space quality assessment is difficult, especially when involving multiple parameters and quantitative calculations, we have proved that with our new method, it is possible, as demonstrated in this study.

5.2. Limitations and Future Prospects

Although the proposed adaptive street quality assessment approach has obtained satisfactory results, there are still some limitations requiring more attention in the future. Some regions, especially Area II, for example, lacked street view images, and this deficit led to the other challenge of obtaining their multi-source data. Other research should consider using complete datasets covering entire areas of study for more promising results. For the street vitality model, our work utilized the comment data from the Trip.com Group that lacks the description of street vitality by other life service facilities. Future studies should consider addressing this problem by expanding data sources to include, e.g., street view data from other platforms, and on-site investigation and shooting to simulate street view images.

Another issue is concerned with the descriptions of street-level urban functions. Generally, a variety of urban functions are defined within parcels. This study used four main types of urban functions and partly ignored the impact of others on the street space quality.
To make the method more robust, it is advised for researchers to extend this study by increasing the volume of data and other functional parameters in their research. Besides, the number of volunteers we chose is limited in the validation. The follow-up research will continue to enrich the quantity of questionnaires and define assessment indicators from the perspective of residents to form a more accurate indicator system by combining subjective and objective methods.

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