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Measuring the perceptual features of coastal streets: a case study in Qingdao, China

Mei Lyu1,2,* , Yumeng Meng1, Weijun Gao3,4,* , Yiqing Yu4, Xiang Ji5, Qingyu Li6, Gonghu Huang5,6 and Dong Sun5
1 School of Art and Design, Shenyang Jianzhu University, Shenyang, People’s Republic of China
2 Faculty of Environmental Engineering, The University of Kitakyushu, Kitakyushu, Japan
3 ISMART, Qingdao University of Technology, Qingdao, People’s Republic of China
4 School of Architecture and Urban Planning, Shenyang Jianzhu University, Shenyang, People’s Republic of China
* Author to whom any correspondence should be addressed.

E-mail: gaoweijun@me.com

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Abstract

The coastal streets are the most attractive urban space, improving spatial quality and public perception of coastal streets is an important work of urban regeneration. The study used machine learning semantic segmentation, GIS and Semantic difference (SD) etc methods to obtain the spatial data and perceptual evaluation of coastal streets in Qingdao. Each of the six perceptual features, imageability, enclosure, human scale, transparency, complexity and nature, was taken as dependent variables and the corresponding physical features was taken as independent variables. The six regression models were established and the influence rules of spatial parameters on public perception were obtained. Meanwhile, based on the results of perceptual features evaluation, the overall coastal streets are divided into three types, open streets, mixed streets and biophilic streets. In all the three types coastal streets, the nature was the most significant perceptual feature due to the high greenness; the complexity was the lowest perceptual feature because of the low landscape diversity. The research results provided theoretical and technical support for the urban regeneration and spatial quality improvement of coastal streets in Qingdao.

1. Introduction

Nowadays, the urban construction has changed from ‘speed first’ to ‘quality-oriented’ in China (Tang et al 2016, Huai et al 2018, Cheng and Wang 2021). The urban environment is increasingly linked to public well-being (Dubey et al 2016, Xu et al 2022). Meanwhile, scholars pay more attention to the human perceptual experience in urban space (Long and Ye 2016, Hao and Long 2017, Dai et al 2021). The core task of urban regeneration is to build an attractive urban space by improving the quality of urban space and displaying urban imagery (Cao et al 2019, Hu et al 2020, Qiu et al 2021a, 2021b).

Waterfront street is the most attractive composition part in the urban space (Li 1999, Wang and Lyn 2001, Yang et al 2013, Liu 2016, Wang et al 2020). It plays a positive role in maintaining the urban vitality (Ewing et al 2006, Shach-Pinsly et al 2021, Lang 2012).

Urban waterfront space is made up of natural and artificial landscape elements(Chen et al 2021). Urban waterfront space quality affects style and features of urban landscape (Liu and Dong 2009, Gao 2015), public behavior (Sun et al 2021, Wang et al 2021, Xi et al 2021), physical and mental health (Foley and Kistemann 2015, Kati and Jari 2016, Othman et al 2021). Several studies have discussed the impact of urban waterfront space on public aesthetics and emotions (Yang and Li 2013, Ragheb and EL-Ashmawy 2020). In fact, the effective problem-solving step is to accurately quantify the public perception of the built environment for improving the quality of waterfront street space (Huai et al 2018, Zhang 2019).

Therefore, applying an efficient method and constructing an accurate model are particularly important, which can measure and predict human perception of urban space.
The most attractive and charming distinct of Qingdao is the coastal street space (Jiang 2015, Li et al 2020), which obvious identifiable (Li 1999). Urban style and features can express the external image of Qingdao (Lang 2012). However, some problems such as enclosed street, poor permeability interface, blocked seascape view and monotonous streetscape elements have seriously affected the Qingdao coastal streets quality during the rapid expansion of urbanization in the past decades (Liu and Dong 2009, Lang 2012, Lu 2017).

Coastal landscape in Qingdao can enhance urban imagery (Yang and Li 2013) and improve environmental quality (Gao 2015). The high quality environment in the coastal streets can promote the development of tourism and economy. The blue-green spaces played an important role in the mental health (Vries et al 2003, Gascon et al 2018, Dai et al 2021, Pouso et al 2021), such as urban parks, groves, rivers and coasts (Irvine et al 2013). Therefore, how highlight the features of waterfront streetscape, coordinate the relationship between landscape elements, satisfy the needs of the public aesthetic become the important contents of human settlements environment research in Qingdao (Lang 2012).

In summary, the most critical questions in the study of Qingdao coastal streets are as follow: (1) Identifying the landscape elements quickly and accurately. (2) Measuring the main landscape perceptual features (3) Revealing relationship among streets quality, landscape elements and landscape perceptual features.

The traditional methods for the street features are used field survey and available data to obtain the streets information (Whyte 2012, Tang and Ding 2015). Scholars have proposed some methods to calculate sky openness, such as geometric analysis method, projection computation method, GPS method, spherical calculation method, shading calculation method (Zhou et al 2019a, 2019b). Tang found the influence of street interface signs on pedestrian behaviour by mapping methodology (Tang 2013). Greenness is studied by photography method. The greenery information in the photos need to be simplified and calculate the proportion (Deng and Wang 2002, Zhou et al 2019a, 2019b).

Previous studies have shown that vision was essential to the public perceptual and space activities (Cafuta 2015, Cheng et al 2017, Zheng 2021). The public perceptual of streets quality has a relationship with landscape elements. It depends on the physical components of the streetscape (Proshansky 1978, Ye et al 2019, Lee et al 2022), such as buildings, fences, greening, road width, pedestrian space, motorization and sky. (Lang and Long 2019, Yun et al 2019, Wu et al 2021, Jiang et al 2022). Physical feature is an interesting and important part or characteristic of the streets elements that can be seen by human. The physical features can quantify street environment based on the visual information, such as floor area ratio, greenness, enclosure, height-to-width ratio, streets scale and tidiness (Alexander et al 1977, Henry 1993, Moniruzzaman and Paëz 2012, Harvey et al 2015). Reid Ewing and Handy explored five physical features of street: imageability, enclosure, human scale, transparency, complexity, which were possible to measure urban design quality (Ewing and Handy 2009, Ewing and Clemente 2013, Hamidi and Moazzeni 2019, Nagata et al 2020, Li et al 2021, Qiu et al 2021a, 2021b).

Ewing and Clemente have pointed out that systematic exploration of the measurement and performance of street space form is a necessary condition for constructing space and public life (Ewing and Clemente 2013, Long and Tang 2019, Zhang et al 2019a, 2019b). Classic academic studies demonstrated the physical space and street form were the basis for street activity (Lynch 1984, Gehl and Rogers 2013, Gehl and Svarre 2013).

With the advance of built environment quantitative studies, the measuring method of street physical space were developed, but there were few integrated applications of multiple methods. In recent years, street view image has became an important data source in urban studies, which provided the advantage of high accessibility, high resolution and wide coverage. (Dubey et al 2016, Ye et al 2019, Zhang et al 2020). Corresponding, street view image is extensively implemented in urban studies (Long and Tang 2019, Wang et al 2019, Ma et al 2021). Almost 34% of studies used urban street view (He and Li 2021, Tao et al 2022). Street view image has been used to measure features including street (Gong et al 2018, Li and Ratti 2019, Bromm et al 2020), buildings (Gong et al 2018, Qiu et al 2021a, 2021b), water (Helbich et al 2019) and greening (Li et al 2015a, 2015b, Ye et al 2018, Lu et al 2019, Ki and Lee 2021). Some scholars have confirmed the reliability of street view image for studying the quality of the street environment by comparing the street view image with the results of field scoring (Griew et al 2013, Kelly et al 2013, Yin and Wang 2016, Liu et al 2017, Ye and Fei 2019).

The series of emerging techniques such as ArcGIS, Python and Machine Learning have provided possibilities to deal with large-scale data (Tang et al 2016, Zhang et al 2018, Zhang et al 2019a, 2019b, Qiu et al 2021a, 2021b). Be supported and inspired by developments of data set such as Cityscapes (Cordts et al 2016), Synthia (Ros et al 2016), KITTI (Geiger et al 2012), especially machine learning techniques, many studies have been conducted to analyse human perceptions of urban appearance (Naik et al 2014, Ordonez and Berg 2014, Dubey et al 2016, Glaeser et al 2016, Zhou et al 2019a, 2019b).

Semantic segmentation is a classification method of computer vision technology. It can automatically divide the landscape elements along their boundaries in the image (Kido et al 2021). Semantic segmentation provides an objective measure of physical features in the street environment (Yin and Wang 2016, Bromm et al 2020). It is not only possible to assess vegetables (Seiferling et al 2017, Ye et al 2018), but also various landscape indices such as openness by extracting sky areas (Liang et al 2017, Long and Liu 2017, Zeng et al 2018), and fences can be evaluated by extracting built-up areas (Tang and Long 2019). DeeplabV3+ is an important Semantic segmentation model and proposed by Liang-Chieh (Chen et al 2018, Chen et al 2018).
Perception is the process of attaining awareness or understanding of sensory information (Ewing and Handy 2009). The Semantic Differential (SD) Method was used for the visual perception of landscape and other fields (Yang et al 2004, Liu and Xu 2011, Yu 2011). The SD Method was proposed by the US psychologist Charles E Osgood in 1957 (Osgood et al 1957, Echelberger 1979). It is a type of (Wright 2015). The SD is universally applicable in semantic rating scale that captures the affective and cognitive components of respondents’ attributions to selected concepts environment, landscape and architecture researches (Kang and Zhang 2010, Cao et al 2020, Li et al 2021, Sun et al 2021).

In the study, The Qingdao coastal landscape streets were determined as the site. First, the street view images in 344 sample points were obtained by Baidu data source. We divided the landscape elements and quantified the physical features in the coastal street. Second, the 69 typical samples points were selected to evaluate the six perceptual features. Finally, the relationships between the physical features and perceptual features were comprehensive analyzed.

The research results can be applied to the construction and management in the urban coastal streets. It provided theoretical and technical support for the urban regeneration and space quality improvement.

2. Methods

2.1. Study area and data
Qingdao is a typical coastal city in the Shandong Peninsula of China. The study site is located in the waterfront district of south Qingdao (figure 1). Its 17.2 km-long winding coastline between Xilingxia Rd and Donghai Middle Rd features seascape, mountainous views, and historical and cultural artifacts that make it a unique urban landscape and tourist destination.

The emerging online street view images derived from providers, such as Google, Baidu and Tencent, offered an ideal training dataset for deep learning techniques (Ma et al 2021). Baidu map (https://map.baidu.com/), one of the largest online map, was selected as the main data source for obtaining street view images.

Users can obtain static street view images from different angle by modifying the Baidu Maps API (Dai et al 2021).

In the study, we used the ‘Create Random Points’ in ArcGIS, to generate sample points along the streets. Based on the visual distance of pedestrians and the previous researches (Lu 2018, Helbich et al 2019), we chose the 50 meters interval criterion (Ki and Lee 2021). A total of 344 sample points were generated (figure 1).

To ensure that the simulated visual field and horizontal sight were close to the real experience of pedestrians (Ma et al 2021), the pitch angle was set at 0 (Li et al 2015a, 2015b) and the heading angles respectively were set at 0, 45, 90, 135, 180, 225, 270 and 315 (figure 2). Then, Baidu Street View (BSV) images in the eight horizontal directions at each sample point can be automatically obtained by Python. Moreover, with the help of the “Time Machine” in Baidu Maps, more than 90% of the BSV images which taken in May and June from 2017 to 2021 were obtained. It could avoid the impact of seasonal changes.
2.2. Calculating the physical features

The study used Deeplabv3+ to divide the landscape elements in street view images. Deeplabv3+ is an advanced deep Convolutional Neural Network architecture that extracts pixel semantic information such as sky, buildings and roads in the BSV images. Deeplabv3+ is more efficient than other deep learning architectures, especially in memory footprint and execution time (Ma et al. 2021). It has more accurate for labels such as buildings, sky, cars and roads (Badrinaryanan et al. 2017). Meanwhile, Deeplabv3+ has superior segmentation performance for the low resolution images. The street elements are divided into 20 labels, and the overall accuracy rate can achieve 90.40% (Zhao et al. 2017). The BSV images were input into Deeplabv3+, as shown in figure 3, which can clearly extract the streetscape elements.

In addition, we used the Open Street Map and remote sensing images tools in ArcGIS, to obtain sidewalk widths, road widths and building height. Meanwhile, we borrowed from Harvey’s creative way which combining...
GIS with SVP data, automatically obtaining information such as Spatial Walk Index, Car Travel Index and Building Height. Based on previous studies (Ewing and Handy 2012, Long 2014, Dai et al 2021, Zheng 2021), we selected and identified 25 important street physical features (table 1). Furthermore, all physical feature indices can be calculated by semantic segmentation and ArcGIS.

2.3. Perceived features evaluation
The choice of feature adjective pairs is important before the evaluation of perceptual features using SD method (Tan and Peng, 2020). By using the Delphi expert method, six SD features and corresponding adjective pairs were selected (table 2). The imageability, enclosure, human scale, transparency and complexity were summarized by Reid Ewing from the 51 perceptual features of urban spaces quality. They were the most important and easy-to-operate to measure the street environment. Many studies have proved that they were effective (Tang and Long 2017, Ma et al 2021).

We added nature features as the sixth perceptual feature. A lot of studies have confirmed that nature and the street environment quality were closely related (Xu et al 2017, Tong et al 2020, Dai et al 2021). Moreover, the proportion of plants and water was high, which also made nature to be a necessary feature in Qingdao coastal streets. The coastal streets were divided into street segments at 500 meter intervals, and two sample points were selected as typical sample points which could fully represent the landscape features of each street segment. A total of 69 (appendix appendix) typical sample points were selected out for SD experiments to further investigate the relationship between perceptual features and physical features (figure 4). SD evaluation usually requires 20–50 observes with relevant expertise (Yu 1995, Qi et al 2017). Therefore, the observes of the experiment included 30 Master students and 10 professional teachers who had academic backgrounds in architecture, urban planning, and landscape design. During the evaluation process, the perceptual features and corresponding pairs of adjectives were first explained to the 40 observers. Moreover, they were asked to focus on the streetscape rather than the quality of photos. Each photo was shown two minutes apart, the questionnaire used the Likert scale, the evaluation criteria were divided into five grades (1 low-5 high), the positive and negative adjectival expressions were compared with current events (Jakobovits and Steinberg 1971). By examining the evaluation results, 40 questionnaires were returned. After checking, all of them were valid.

2.4. Statistical analysis
We took perceptual features as dependent variables, screened out relevant physical features (table 1) as independent variables through stepwise method. the correlation and regression analysis also were carried out. The relationship between the perceptual features and the corresponding physical features at typical sample points was established by SPSS 25.0.

Then, we used the six regression equations of typical samples to calculate the predictive perceptual features of all sample points. K-Means Cluster Analysis was performed on the predicted values of 344 sample points. It is a classic and effective clustering analysis method (Mao and Li 2019, Shao et al 2021, Zhao et al 2021). According to the elbow rule, the number of clusters were set 2–4 to obtain the best clustering results. Finally, k = 3 was considered to be the best.

K-Means Cluster Analysis provides a research ideas to analyze the spatial variability in the coastal streets (Shokoohyar et al 2020), which is conducive to revealing the rules for styles and features in Qingdao coastal streets.
| Physical features | Formula or source | Expression | Definition |
|-------------------|------------------|------------|------------|
| **Imageability**  |                  |            |            |
| Building with identifiers | $B_l = \frac{1}{n} \sum_{i=1}^{n} P_l$ | $P_l$ denotes the proportion of pedestrian pixels, the sum indicates the total number of pedestrian pixels in each image. | It refers to the buildings with unique style, complex shapes, large sizes and are impressive |
| Pedestrians       | $P_i = \frac{1}{n} \sum_{i=1}^{n} P_i$ | $P_i$ denotes the proportion of pedestrian pixels in the overall street space pixels. | It refers to the ratio of pedestrian pixels in the overall street space pixels include rider, standing and sitting person. |
| **Lawn**          | $L_i = \frac{1}{n} \sum_{i=1}^{n} L_i$ | $L_i$ denotes the proportion of lawn pixels, the sum indicates the total number of lawn pixels in each image. | It refers to the ratio of lawn pixels with large area in the overall street space pixels. |
| Spatial indicative | $S_l = \frac{1}{n} \sum_{i=1}^{n} S_l + \frac{1}{n} \sum_{i=1}^{n} T_l + \frac{1}{n} \sum_{i=1}^{n} P_l$ | $T_l$ denotes the proportion of traffic light pixels, $S_l$ denotes the proportion of traffic signs, $P_l$ denotes the proportion of pole pixels. | It refers to the ratio of light and traffic signs pixels in the overall street space pixels. |
| **Enclosure**     |                  |            |            |
| The number of landscape with identifiers | $L_i = \frac{1}{n} \sum_{i=1}^{n} S_l$ | $B_i$ denotes the proportion of building pixels, $T_i$ denotes the proportion of tree pixels, $W_i$ denotes the proportion of wall pixels. | It refers to the conspicuous landscape. |
| The vertical interface | $V_l = \frac{1}{n} \sum_{i=1}^{n} B_i + \frac{1}{n} \sum_{i=1}^{n} T_l + \frac{1}{n} \sum_{i=1}^{n} W_i$ | $B_i$ denotes the proportion of north side buildings, $T_i$ denotes the proportion of south side buildings, $S_i$ denotes the proportion of sky pixels, the sum indicates the total number of sky pixels in each image. | It refers to the ratio of landscape elements pixels to the vertical interface pixels. |
| Interface buildings difference | $IBD = |B_l - B_r|$ | $B_l$ denotes the proportion of north side buildings, $B_r$ denotes the proportion of south side buildings. | It refers to the differences between the buildings vertical interface on the sides in the street space. |
| **Openness**      | $O_i = \frac{1}{n} \sum_{i=1}^{n} O_i$ | $O_i$ denotes the proportion of visible sky pixels in the overall pixels in the vertical interface. | It refers to the ratio of visible sky pixels to the overall pixels. |
| Interface enclosure degree | $IED = \frac{1}{n} \sum_{i=1}^{n} B_i + \frac{1}{n} \sum_{i=1}^{n} T_i + \frac{1}{n} \sum_{i=1}^{n} W_i$ | $B_i$ denotes the proportion of building pixels, $T_i$ denotes the proportion of tree pixels, $W_i$ denotes the proportion of wall pixels, $P_i$ denotes the proportion of pavement pixels, $F_i$ denotes the proportion of fence pixels, $R_i$ denotes the proportion of road pixels. | It refers to the degree which spatial interface is enclosed by landscape elements in the streets. |
| Transparency      |                  |            |            |
| Interfacial porosity | $IP_i = \frac{1}{n} \sum_{i=1}^{n} IP_i$ | $IP_i$ denotes the interface pore space pixels in the vertical interfacial. | It refers to the ratio of interface pore space pixels to the overall pixels in the vertical interface. |
| **The openness of coastal interface** | $OCI = S_o$ | $S_o$ denotes the proportion of sky pixels oriented to the coastal side in image | It refers to the open degree in the coastal interface. |
| **The openness of inland interface** | $OHI = S_i$ | $S_i$ denotes the proportion of sky pixels oriented to the inland side in image | It refers to the open degree in the inland interface. |
### Table 1. (Continued.)

| Perceptual features | Physical features | Formula or source | Expression | Definition |
|---------------------|-------------------|-------------------|------------|------------|
| Proportion of active uses | $A_i = \frac{1}{n} \sum_{i=1}^{n} A_i \{i \in (1, 2, ..., n)\}$ | $A_i$ denotes the proportion of active uses pixels, the sum indicates the total number of active uses pixels in each image. | It refers to the ratio of the places with specific uses to the overall pixels. | |
| Human scale | Walkable area | Source: GIS | $W_1 = \frac{1}{n} \sum_{i=1}^{n} P3_i + \frac{1}{n} \sum_{i=1}^{n} F1_i + \frac{1}{n} \sum_{i=1}^{n} R_i \{i \in (1, 2, ..., n)\}$ | $P3_i$ denotes the proportion of pavement pixels, $F1_i$ denotes the proportion of fence pixels, $R_i$ denotes the proportion of road pixels. | It refers to the width of the sidewalk. |
| | Traffic Space | Source: GIS | $W_2 = \frac{1}{n} \sum_{i=1}^{n} W_2_i \{i \in (1, 2, ..., n)\}$ | $W_2$ denotes the proportion of water pixels. | It refers to the width of the roadway. |
| | Walkable Streets | | $W_{3i} = \frac{1}{n} \sum_{i=1}^{n} P3_i + \frac{1}{n} \sum_{i=1}^{n} F1_i + \frac{1}{n} \sum_{i=1}^{n} R_i \{i \in (1, 2, ..., n)\}$ | $P3_i$ denotes the proportion of pavement pixels, $F1_i$ denotes the proportion of fence pixels, $R_i$ denotes the proportion of road pixels. | It refers to the ratio of walkable street pixels to the overall pixels. |
| | Building height | Source: GIS | $H_i = \frac{H_{nS} + H_{nN}}{D_i} \{i \in (1, 2, ..., n)\}$ | $H_{nS}$ denotes the average value of south buildings height, $H_{nN}$ denotes the average value of north buildings height, $D_i$ denotes the street width. | It refers to the height of the tallest building in the street. |
| | Street height to width ratio | | $V_i = \frac{1}{n} \sum_{i=1}^{n} C_i + \frac{1}{n} \sum_{i=1}^{n} T2_i + \frac{1}{n} \sum_{i=1}^{n} B2_i + \frac{1}{n} \sum_{i=1}^{n} T3_i \{i \in (1, 2, ..., n)\}$ | $C_i$ denotes the proportion of car pixels, $T2_i$ denotes the proportion of truck pixels, $B2_i$ denotes the proportion of bus pixels, $T3_i$ denotes the proportion of train pixels, $R_i$ denotes the proportion of road pixels. | It refers to the proportion of vehicle attendance in the road space. |
| Complexity | Landscape diversity index | | $SHDI = \frac{1}{n} \sum_{i=1}^{n} (B^n P_i)$ | $B^n$ denotes the landscape log, $P_i$ denotes the proportion of the entire community made up of landscape elements $i$. | It refers to the richness degree of the landscape elements that be observed in the street. |
| | Vehicle occurrence rate | | $V_i = \frac{1}{n} \sum_{i=1}^{n} C_i + \frac{1}{n} \sum_{i=1}^{n} T2_i + \frac{1}{n} \sum_{i=1}^{n} B2_i + \frac{1}{n} \sum_{i=1}^{n} T3_i \{i \in (1, 2, ..., n)\}$ | $C_i$ denotes the proportion of car pixels, $T2_i$ denotes the proportion of truck pixels, $B2_i$ denotes the proportion of bus pixels, $T3_i$ denotes the proportion of train pixels, $R_i$ denotes the proportion of road pixels. | It refers to the proportion of vehicle attendance in the image. |
| | Architecture color diversity | | $CEI_i = 1 - \frac{1}{n} \sum_{i=1}^{n} \left( \frac{P_i}{\sum_{i=1}^{n} P_i} \right)^2 \{i \in (1, 2, ..., n)\}$ | $P_i$ denotes the number of $j$ buildings color pixels in $i$ image, $i$ indicates the total number of the building colors in $i$ image. | It refers to the richness degree of the building colors that be observed in the streets. |
| Nature | Natural landscape | | $N_i = \frac{1}{n} \sum_{i=1}^{n} W2_i + \frac{1}{n} \sum_{i=1}^{n} F2_i \{i \in (1, 2, ..., n)\}$ | $W2_i$ denotes the proportion of water pixels, $F2_i$ denotes the proportion of forest pixels. | It refers to the ratio of the natural landscape pixels to the overall pixels. |
| | Greenness | | $G_i = \frac{1}{n} \sum_{i=1}^{n} T1_i + \frac{1}{n} \sum_{i=1}^{n} G_i \{i \in (1, 2, ..., n)\}$ | $T1_i$ denotes the proportion of trees pixels, $G_i$ denotes the proportion of grass pixels. | It refers to the ratio of trees and grasses pixels to the overall pixels. |
| | Natural to artificial ratio of the vertical interface | | $V_i = \frac{1}{n} \sum_{i=1}^{n} T1_i + \frac{1}{n} \sum_{i=1}^{n} B1_i \{i \in (1, 2, ..., n)\}$ | $T1_i$ denotes the proportion of tree pixels, $B1_i$ denotes the proportion of building pixels. | It refers to the ratio of the natural pixels to the artificial pixels in the vertical interface. |
Table 1. (Continued.)

| Perceptual features | Physical features | Formula or source | Expression | Definition |
|---------------------|-------------------|-------------------|------------|------------|
| Natural to artificial ratio of the horizontal interface | | \( H_i = \frac{\sum_{n=1}^{i} G_n}{\sum_{n=1}^{i} W_{2n}} + \frac{\sum_{n=1}^{i} W_{2n}}{\sum_{n=1}^{i} R_n + \sum_{n=1}^{i} P_{3n}} \) | \( G_n \) denotes the proportion of grass pixels, \( W_{2n} \) denotes the proportion of water pixels, \( R_n \) denotes the proportion of road pixels, \( P_{3n} \) denotes pavement pixels. | It refers to the ratio of the natural pixels to the artificial pixels in the horizontal interface. |
3. Result

3.1. Perceptual features and physical features

All data acquired by semantic segmentation and GIS were brought into the equations (table 1) to calculate the physical features of the 344 sample points. And the perceptual features of 69 typical sample points are evaluated. The six perceptual features: imageability, enclosure, human scale, transparency, complexity and nature were respectively the dependent variables. The corresponding physical features were the independent variables. The correlation and regression analysis were performed to create six multiple linear regression models.

3.1.1. The correlation analysis

As the correlation analysis shown in table 3.

(1) Imageability
The physical features strongly positively correlated with imageability were landscape with identifiers, building with identifiers, pedestrians.

(2) Enclosure
The physical features strongly positively correlated with enclosure included the vertical interface and interface enclosure degree. The openness had a strong negative correlation with the enclosure.

(3) Transparency
The three physical features (the openness of coastal interface, interfacial porosity and the openness of inland interface) had a strong positive correlation with the transparency.

(4) Human scale
The physical features strongly negatively correlated with human scale were building height and traffic space.

(5) Complexity
The two physical features (the landscape diversity index and architecture color diversity) had a strong positive correlation with the complexity.

(6) Nature
The physical features strongly positively correlated with the nature were greenness, natural to artificial ratio of the vertical interface.

3.1.2. The regression analysis

The six perceptual features were used as dependent variables and the physical features screened by the correlation analysis were used as independent variables. The independent variables were allowed to enter the regression model using stepwise regression analysis. The unsuitable physical features were removed one by one. Finally, the six models of the perceptual features were established (table 4).

It can be seen from table 4. The R-squared of the six models were from 0.464 to 0.752. It indicated a good fit for the regression line to the observations. The p-value for the F-test is 0.000 in all six models; The t-values and corresponding p-values for the six models were in the ‘t’ and ‘sig’ columns, with sig values less than 0.05. The VIF values of the independent variables in the six equations were less than 10. In summary, the perceptual features (imageability, enclosure, transparency, human scale, complexity and nature) were able to establish six valid regression analysis models with the corresponding physical features (table 4).

After obtaining the linear regression models for the typical samples, the physical features of the 344 sample points were brought into the linear regression models to obtain the all predicted data for the perceptual features.
3.2. Cluster analysis of perceptual features and spatial heterogeneity
To further analyze the styles and features in Qingdao coastal streets, K-Means Cluster Analysis was used to classify 344 sample points based on the six perceptual features.
Finally, the clustering result with $k = 3$ was selected. Combining the characteristics of various types of streets, the first type street nodes are defined as open street; the second type street nodes are defined as mixed street and the third type street nodes are defined as biophilic street.

Figure 4. The images of 69 typical sample points.
| Imageability         | Building with identifiers | Pedestrians | Lawn | Spatial indicative | Landscape with identifiers |
|----------------------|---------------------------|-------------|------|-------------------|-----------------------------|
| Pearson correlation  | .574**                    | .337**      | .176 | .331**            | .742**                      |
| Enclosure            | The vertical interface    | Interface buildings difference | Openness | Interface enclosure degree |                           |
| Pearson correlation  | .825**                    | −0.177      | −.856** | .620**            |                             |
| Transparency         | Interfacial porosity      | The openness of coastal interface | The openness of inland interface | Proportion of active uses |                             |
| Pearson correlation  | .720**                    | .831**      | .581** | .241**            |                             |
| Human scale          | Walkable area             | Traffic space | Walkable streets | Building height | Street height to width ratio |
| Pearson correlation  | −0.214                    | −.555**     | .387** | −.613”            |                             |
| Complexity           | Landscape diversity index | Vehicle occurrence rate | Architecture color diversity |                             |                             |
| Pearson correlation  | .602**                    | .337**      | .568** |                             |                             |
| Nature               | Natural Landscape         | Greenness   | Natural to artificial ratio of the vertical interface | Natural to artificial ratio of the horizontal interface |                             |
| Pearson correlation  | 0.105                     | .632""     | .593"" | .301"             |                             |

** Correlation is significant at the 0.01 level.
* Correlation is significant at the 0.05 level.
Table 4. Regression analysis results.

| Dependent variables | Model | Unstandardized Coefficients | Standardized Coefficients | t | Sig. | VIF | R2 | FSig | Regression model |
|---------------------|-------|-----------------------------|---------------------------|---|-----|-----|----|------|------------------|
|                     |       | B                           | Std. Error                | Beta |     |     |    |      |                  |
| Imageability        | (Constant) | 2.87                        | 0.053                     | 53.711 | 0.000** | 0.694 | 0.000** |           | Y1(Imageability) = 0.439*X(Landscape with identifiers) + 0.254*X(Pedestrians) + 0.144*X(Building with identifiers) + 2.87 |
|                     | Landscape with identifiers | 0.439                     | 0.063                     | 0.559 | 6.942 | 0.000** | 1.378 | | |
|                     | Pedestrians | 0.254                     | 0.057                     | 0.324 | 4.421 | 0.000** | 1.138 | | |
|                     | Building with identifiers | 0.144                     | 0.064                     | 0.183 | 2.238 | 0.029 | 1.424 | | |
| Enclosure           | (Constant) | 3.297                     | 0.07                      | 47.299 | 0.000** | 0.752 | 0.000** |           | Y2(Enclosure) = −0.863*X(Openness) + 0.198*X(Interface enclosure degree) + 3.297 |
|                     | Openness | −0.863                     | 0.087                     | −0.753 | −9.887 | 0.000** | 1.544 | | |
|                     | Interface enclosure degree | 0.198                     | 0.087                     | 0.173 | 2.269 | 0.027 | 1.544 | | |
| Transparency        | (Constant) | 2.667                     | 0.077                     | 34.805 | 0.000** | 0.74 | 0.000** |           | Y3(Transparency) = 0.88*X(The openness of coastal interface) + 0.307*X(The openness of inland interface) + 2.667 |
|                     | The openness of coastal interface | 0.88                     | 0.087                     | 0.716 | 10.113 | 0.000** | 1.272 | | |
|                     | The openness of inland interface | 0.307                     | 0.087                     | 0.249 | 3.524 | 0.001** | 1.272 | | |
| Human scale         | (Constant) | 2.928                     | 0.094                     | 31.028 | 0.000** | 0.572 | 0.000** |           | Y4(Human scale) = −0.617*X(Building height) − 0.533*X(Traffic Space) + 2.928 |
|                     | Building height | −0.617                     | 0.097                     | −0.523 | −6.366 | 0.000** | 1.041 | | |
|                     | Traffic space | −0.533                     | 0.097                     | −0.451 | −5.491 | 0.000** | 1.041 | | |
| Complexity          | (Constant) | 2.529                     | 0.062                     | 40.735 | 0.000** | 0.505 | 0.000** |           | Y5(Complexity) = 0.275*X(Landscape diversity index) + 0.222*X(Vehicle occurrence rate) + 0.215*X(Architectural color diversity) + 2.529 |
|                     | Landscape diversity index | 0.275                     | 0.085                     | 0.384 | 3.232 | 0.002** | 1.85 | | |
|                     | Vehicle occurrence rate | 0.222                     | 0.063                     | 0.309 | 3.54 | 0.001** | 1.003 | | |
|                     |             | 0.215                     | 0.085                     | 0.299 | 2.526 | 0.014 | 1.847 | | |

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| Dependent variables | Model | Unstandardized Coefficients | Standardized Coefficients | t | Sig. | VIF | R2 | F Sig | Regression model |
|---------------------|-------|----------------------------|---------------------------|---|------|-----|----|-------|------------------|
|                     |       | B                          | Std. Error                |   |      |     |    |       |                  |
| Architecture color  |       | 3.906                      | 0.067                     | 57.894 | 0.000** | 0.464 | 0.000** | Ŷ(Nature) = 0.323*X (Greenness) + 0.245*X (Natural to artificial ratio of the vertical interface) + 3.906 |
| diversity           |       | Nature                     |                           |     |      |     |    |       |                  |
| (Constant)          |       | 0.323                      | 0.087                     | 3.708 | 0.000** | 1.643 |     |       |                  |
| Greenness           |       | 0.245                      | 0.087                     | 2.814 | 0.006** | 1.643 |     |       |                  |
| Natural to artificial ratio of the vertical interface | | 0.323 | 0.325 | 0.245 | 0.087 | 3.708 | 0.000** | 1.643 | Ŷ(Nature) = 0.323*X (Greenness) + 0.245*X (Natural to artificial ratio of the vertical interface) + 3.906 |

** It is significant at the 0.01 level.
* It is significant at the 0.05 level.
The figure 5 represented the spatial distribution of three types streets. The open streets were mostly located in Xilingxia Road, the east and west parts of Taiping Road, Nanhai Road, Donghai West Road, the west part of Aomen Road, the west part of Donghai Middle road. The mixed streets were mostly located in the middle part of Taiping Road and Laiyang Road, the Taipingjiao 4th Road, the east part of the Aomen Road, Zhuhai Branch Road and the east and west parts of the Donghai Middle Road. The biophilic streets were mostly located in the Huiquan Road, the east and west parts of Laiyang Road, Shanhaiguan Road, Huanhai Road, Taipingjiao 1st road and the east part of Aomen road.

3.2.1. Perceptual features of overall Qingdao coastal streets
By analyzing the results of six perceptual features (table 5) in 344 sample points, the mean value of nature and enclosure were higher. The mean value of nature was highest and the standard deviation was lowest, which showed that the nature was outstanding and balance in overall coastal streets; The mean value of transparency was lower and the standard deviation was higher; The mean value of complexity was lowest and the standard deviation was medium. It showed that the interface transparency and the landscape complexity needed to be improved in the overall coastal streets.

3.2.2. Perceptual features comparative analysis of the three types street space
A comparative analysis for six perceptual features of three types streets was conducted to study the spatial distribution of perceptual features more clearly. In the open streets, the transparency, imageability and complexity were outstanding; In the mixed streets, all perceptual features were medium; In the biophilic streets, the nature, enclosure and human scale were outstanding.

As shown in table 5 and figure 6, the nature was high perceptual feature in all three types streets. It showed that there were high plant coverage and the richness layers of the plants in Qingdao coastal streets. Meanwhile the nature was the highest in the biophilic streets.

The transparency was high perceptual feature and the standard deviation was medium in the open streets. The transparency was low in the mixed streets and the biophilic streets.

The enclosure was high perceptual feature in the mixed streets and the biophilic streets. It was low in the open streets.

The human scale was high perceptual feature, and the standard deviation was low in the biophilic streets. It showed that the biophilic streets conform the human scale; The human scale was low in the mixed streets and the open streets, but the standard deviation was high.

| Perceptual features | Overall coastal streets | The open streets | The mixed streets | The biophilic streets |
|---------------------|-------------------------|------------------|------------------|-----------------------|
|                     | Mean value | Standard deviation | Mean value | Standard deviation | Mean value | Standard deviation | Mean value | Standard deviation |
| Imageability        | 2.870      | 0.625             | 3.304      | 0.667             | 2.715      | 0.410             | 2.424      | 0.368             |
| Enclosure           | 3.297      | 0.934             | 2.365      | 0.405             | 3.493      | 0.440             | 4.484      | 0.524             |
| Transparency        | 2.667      | 1.043             | 3.789      | 0.439             | 2.270      | 0.552             | 1.509      | 0.439             |
| Human scale         | 2.928      | 0.840             | 2.663      | 0.803             | 2.743      | 0.841             | 3.688      | 0.300             |
| Complexity          | 2.529      | 0.488             | 2.722      | 0.366             | 2.657      | 0.411             | 2.002      | 0.401             |
| Nature              | 3.906      | 0.479             | 3.537      | 0.212             | 3.920      | 0.273             | 4.483      | 0.484             |

Figure 5. Distribution of three types streets.

Table 5. The result of perceptual features for various types streets.
The imageability was high perceptual feature and the standard deviation was high in the open streets. It showed that the imageability distribution was not balanced. The imageability was low perceptual feature in the biophilic streets and mixed streets. Due to lacking of iconic landscape and landscape diversity, it could not deepen the impression of the observers.

The complexity was the low perceptual feature and stably distributed in three types streets.

3.2.3. Comparative analysis of the six perception features for each type street space interior

It could be concluded from figure 6, in the open streets, Transparency > Nature > Imageability > Complexity > Human scale > Enclosure. The transparency and nature were high, the enclosure was low. Compared with other features, the transparency and nature were better perceived by the pedestrians in the open streets.

In the mixed streets, Nature > Enclosure > Human Scale > Imageability > Complexity > Transparency. Therefore, the nature and enclosure were high, the transparency was low. The large-size buildings and the dense street trees formed the enclosed interface in the mixed streets.

In the biophilic streets, Enclosure > Nature > Human Scale > Imageability > Complexity > Transparency. The enclosure and nature were extremely high, human scale was high, the complexity and transparency were low. The dense street trees were full of vision. The layered and lush natural landscape not only promoted the nature of the street, but also reduced the transparency of the street interface. The biophilic streets conformed the human scale. However, the significant plants landscape caused monotonous landscape space, and the complexity was reduced.

3.2.4. Comprehensive analysis of perceptual features and physical features

We counted the mean values of perceptual features (table 5) and physical features (table 6) in the coastal streets, and respectively compared the overall streets with the three types of streets.

In the open streets, the mean value of the four perceptual features: transparency (3.789 > 2.667), imageability (3.304 > 2.870), enclosure (2.365 < 3.297), nature (3.537 < 3.906) were significant different with
the overall streets. By comparing and analyzing physical features in the open streets with the overall street, it could be seen that the vertical interface and interface enclosure degree were low in the open streets, while the openness, interfacial porosity, openness of coastal interface, openness of inland interface and walkable area were high. The greenness and natural to artificial ratio of the vertical interface were low, which caused that the nature was reduced and the transparency of the street interface was improved. The building with identifiers and landscape with identifiers were higher. It showed that there were many unique buildings and landscapes in the open streets, the streetscape was more attractive to the observers.

In the mixed streets, the transparency (2.270 < 2.667) were lower than overall street. The other five perceptual features were similar to the overall street. In addition, the low interfacial porosity, the high interface enclosure degree and vertical interface indicated that the street interface transparency was poor in the mixed streets.

In the biophilic streets, all perceptual features: the nature (4.483 > 3.906), human scale (3.668 > 2.928), enclosure (4.484 > 3.297), complexity (2.002 < 2.529) and transparency (1.509 < 2.667), imageability (2.424 < 2.870) were very different with the overall street. The greenness and natural to artificial ratio of the vertical interface were high, particularly, the natural to artificial ratio of the vertical interface was the highest. The result indicated that the plants coverage was extremely high, and the building density were low. Moreover, there were many high trees caused stronger nature.

The vertical interface and interface enclosure degree were high. The openness, interfacial porosity, openness of coastal interface and openness of inland interface were low. The high-density vegetation and buildings formed the continuous and enclosed street interface, which enhanced the nature in the biophilic streets. However, they blocked view and caused the lower transparency. The street height to width ratio and walkable streets were higher, the traffic space and building height were lower. The result indicated that the streets had strong walkability. The small-size buildings created a street space which conformed to the human scale.

In addition, the landscape diversity index, vehicle occurrence rate and architecture color diversity were lower in the biophilic streets. The landscape elements and architectural colors were monotonous that reduced the complexity. Meanwhile, the building with identifiers and landscape with identifiers were lower. It indicated that the biophilic streets lacked the attractive landscapes and buildings that caused the low imageability.

| Table 6. The mean value of physical features. |
|-----------------------------------------------|
| **Perceptual features** | **Physical features** | Overall coastal streets | The open streets | The mixed streets | The biophilic streets |
|-------------------------|-----------------------|-------------------------|-----------------|-----------------|---------------------|
| **Imageability**        | Building with identifiers | 1.753                  | 2.377           | 1.597           | 1                   |
|                         | Pedestrians            | 0.008                  | 0.011           | 0.006           | 0.008              |
|                         | Lawn                   | 0.062                  | 0.069           | 0.055           | 0.064              |
|                         | Spatial indicative     | 0.007                  | 0.008           | 0.008           | 0.006              |
|                         | Landscape with identifiers | 2.276                | 2.908           | 2.09            | 1.563              |
| **Enclosure**           | The vertical interface | 0.43                   | 0.277           | 0.462           | 0.625              |
|                         | Interface buildings difference | 0.128              | 0.143           | 0.137           | 0.09               |
|                         | Openness               | 0.258                  | 0.392           | 0.229           | 0.09               |
|                         | Interface enclosure degree | 1.529                | 0.928           | 1.576           | 2.426              |
| **Transparency**        | Interfacial porosity   | 0.399                  | 0.519           | 0.359           | 0.269              |
|                         | The openness of coastal interface | 0.296            | 0.522           | 0.211           | 0.073              |
|                         | The openness of inland interface | 0.144            | 0.227           | 0.124           | 0.043              |
|                         | Proportion of active uses | 0.128               | 0.145           | 0.108           | 0.134              |
| **Human scale**         | Walkable area          | 4.519                  | 5.412           | 4.269           | 3.488              |
|                         | Traffic Space          | 9.696                  | 9.319           | 11.388          | 7.475              |
|                         | Walkable Streets       | 0.443                  | 0.422           | 0.366           | 0.607              |
|                         | Building height        | 2.654                  | 2.294           | 2.69            | 1.475              |
|                         | Street height to width ratio | 1.529              | 0.928           | 1.576           | 2.426              |
| **Complexity**          | Landscape diversity index | 1.881                 | 1.961           | 1.973           | 1.599              |
|                         | Vehicle occurrence rate | 0.104                 | 0.117           | 0.107           | 0.075              |
|                         | Architecture color diversity | 2.157            | 2.615           | 2.269           | 1.225              |
| **Nature**              | Natural landscape      | 0.009                  | 0.017           | 0.006           | 0.002              |
|                         | Greenness              | 0.344                  | 0.187           | 0.366           | 0.559              |
|                         | Natural to artificial ratio of the vertical interface | 9.701 | 2.99 | 7.306 | 24.619 |
|                         | Natural to artificial ratio of the horizontal interface | 0.243 | 0.245 | 0.222 | 0.276 |
4. Discussion

4.1. Perceptual features and physical features

The study discussed the impact of physical features on perceptual features in the streets.

The results of imageability were consistent with Quercia, the high imageability means the streetscapes are unique and attractive (Quercia et al 2014). Some studies also showed that the iconic buildings and landscape elements can attract public attention and make the street space more unique (Appleyard 1969, Evans et al 1982, Ewing et al 2006).

The results of the enclosure showed that the denser buildings and plants led to the less sky and higher enclosure (Harvey et al 2015, Ma et al 2021). It indicated that the plants, buildings and walls have a positive impact on the enclosure, and promote the public to form the sense of direction.

The openness of coastal interface was the most positive physical feature impacting transparency. The transparency is related to visual landscapes elements and human activity in the streets (Hooi and Pojani 2019). The transparency can be enhanced by reducing the density of buildings and tall shrubs. It can improve the visibility of the seascapes.

Human scale was negatively correlated with the traffic space and building height. It indicated that high-rise buildings and wide streets led to streets oppressiveness and affected the perception of human scale (Alexander et al 1977, Henry 1993).

Complexity was strongly correlated with landscape diversity index and architectural colour diversity. Ewing thought that complexity is mainly influenced by architectural diversity and landscape elements. Rapoport found the complexity is related to the frequency of apparent differences seen by the observers (Rapoport 1990).

The greenness was the main physical features that impacting nature. The result was the same as Xu, the greenness positively influenced the human perception on the nature in the streets (Xu et al 2017). The plants have positive impact on the urban streets design quality (Camacho-Cervantes et al 2014). As the mainly element, it could improve the sense of nature by increasing the plants coverage (Wolf 2005).

4.2. The streets clusters

By combining with previous studies on Qingdao coastal streets (Liu 2003, Han 2006, Guan et al 2021), the result of streets clusters was almost consistent with the geographical distribution of three types style and features districts which proposed by Han.

In addition, Jiang pointed out that the architectural style was slightly cluttered in some historic nodes (Jiang 2019). Lang proposed that the spatial perception and walking experience were low on the old town sidewalk (Lang 2012). It also confirmed the results of K–Means Cluster Analysis.

In fact, the K–Means Cluster Analysis can accurately classify the spatial features of coastal streets. It obtains the features of each spatial type and the difference of various spatial types.

4.3. Spatial heterogeneity

According to the comprehensive analysis of perceptual and physical features, it was found that the overall coastal streets were full of nature and vitality. The natural environment had significant impact on human perception (Wohlwill 1976, Kaplan and Kaplan 1989). Vegetation is the important component of the urban ecosystem (Dai et al 2021). The vegetation coverage was generally high in Qingdao coastal streets. It had positive impact on emotions and psychology (Wang et al 2019), and enhanced aesthetic perception (Wolf 2005).

There were obvious difference in the Spatial features among the three types coastal streets.

In the open street, buildings were multiple styles and Medium-sized. The nature, imageability and transparency were high value feature, the enclosure was low. The imageability make streets unique, the iconic landscapes and buildings facilitate the public to perceive street space (Hamidi and Moazzeni 2019). Medium-sized buildings can avoid the view blocked (Yin and Wang 2016). The natural atmosphere and unobstructed view created the street space with sense of nature and transparent interface. In the blue space of waterfront streets, the depressing atmosphere can be reduced by the lower enclosure (Dai et al 2021). But the lower interface enclosure degree limits the street walkability and leads to less walking behaviors (Qiu et al 2021a, 2021b). In the construction of open street, the sense of enclosure should be Improved by enhancing the vegetation density.

In the mixed street, there were many modern buildings, high-rise buildings and wide streets. The complex streetscape enriched the visual perception. The nature and enclosure were significant, the human scale was lower. The enclosed streets can create the sense of safety, and provide the communication opportunities for the public (Naik et al 2014, Dai et al 2021). But the high-rise buildings and wide roadways caused the worse perception of the human scale, Ewing considered that the human scale directly influence the public experience in urban street design (Ewing and Handy 2009). Therefore, the sidewalk should be appropriately widen to enhance the human scale.
In the biophilic street, there were many historic buildings and lush landscape. The biophilic street had the high nature, enclosure and human scale. But the imageability, transparency and complexity were low. The rich plant improved the vitality and nature, it created pleasant mood (Dubey et al 2016). The degree of street enclosure is closely related to the density of buildings and trees (Dai et al 2021). The building density was low, and the lush vegetation formed a enclosed street interface. It enhanced the sense of enclosure and safety, but the enclosed interface blocked the views of seascape. Reid Ewing mentioned that trees play more important role than buildings for defining space in the streets with low density building (Ewing et al 2006).

Due to the plants were the dominant landscape element and buildings were less colorful in overall coastal streets, the complexity and imageability were both lower. The attraction of streets was depended on the complexity of streetscape (Kaplan et al 1972, Bartholomew and Ewing 2013). In addition, the imaginability and transparency have important impact on walkability (Hamidi and Moazzeni 2019). The comfortable walking experience is good for physical and mental health of people (Bahrainy and Khosravi 2012) and social and economic development (CABE 2007). The transparency of coastal streets and the attractiveness of seascape can be enhanced, by reducing the plants on the seaview side, increasing the openness of the coastal viewing areas, enhancing the visibility of blue space, and controlling the rhythm between the openness and enclosure in the coastal street (Ma et al 2021). In addition, the complexity and imaginability of the coastal streets can be enhanced by adding iconic buildings and landscape nodes.

4.4. Limitations and future studies
The limitations of the study are also worth discussing.

First of all, the street view images were mainly taken in May and June during the last five years. Therefore, some images could not fully represent the existing street environment. In the future study, the latest updated street view data samples will be collected for further analysis. Street view images is effective to accurate prediction of static streetscape elements, but cannot fully represent the instantaneously moving elements such as motor vehicles and pedestrians. It is necessary to further combine with traffic heatmap and crowd heatmap to improve precision of research. The human perception can be contacted with visual landscape elements by street view images. However, it is difficult to describe sounds, smells, noises, culture, history by visual images.

Secondly, urban perception is related to many factors such as building styles and features, public mental condition, climate. The street view image could only represent the visual part of urban perception. For example, the imageability only covered some physical features such as iconic buildings and landscapes, signs and symbols, which had some deviations. The identification of building styles and features, the location of iconic landscape will be carried out to improve the imageability in the future studies.

Thirdly, this study analyzed coastal streets by expert evaluation. The difference between expert and public preference is also worthy of further discussion. Meanwhile, for different street types, some differences between street view image evaluation and field survey might be existed. It should be further discussed in the future.

Finally, in this study, the image data originated from the Qingdao coastal streets. The street features, vegetation types and urban environment were varied, the regression model may not be applicable to all coastal streets. Moreover, other coastal spaces such as bathing beaches, beach boardwalks, and waterfront platforms are also the important parts of coastal district, they should be studied.

5. Conclusions
The study showed that the perceptual features was influenced by the physical features. The nature was the most prominent perceptual features, the greenness was the most important physical features in overall coastal streets and three types streets.

Except the nature. In the open streets, the imageability and transparency were significant, meanwhile the iconic buildings, iconic landscapes and interface openness were the main physical features; In the mixed streets, the enclosure was stronger and the transparency was weaker, and the enclosure was positively influenced by interface enclosure; In the biophilic streets, the enclosure and human scale were obvious, but the complexity and transparency were weaker, meanwhile the landscape diversity and vehicular space were the main physical features.

The study revealed the relationship of the spacial physical features to the human perceptual features in the coastal streets of Qingdao. The results can be applied to the construction and management in urban coastal streets. It is not only important for improving the design quality, but also providing theoretical and technical support for the urban regeneration and space quality improvement.
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Appendix A
Data availability statement

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

ORCID iDs

Mei Lyu https://orcid.org/0000-0002-6273-8487
Yumeng Meng https://orcid.org/0000-0001-5050-0271
Weijun Gao https://orcid.org/0000-0003-0299-3686
Yiqing Yu https://orcid.org/0000-0003-2014-0767
Xiang Ji https://orcid.org/0000-0001-8202-6914
Qingyu Li https://orcid.org/0000-0001-9382-7389
Gonghu Huang https://orcid.org/0000-0003-0151-6896

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