

Article

Subjectively Measured Streetscape Perceptions to Inform Urban Design Strategies for Shanghai

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Abstract: Recently, many new studies applying computer vision (CV) to street view imagery (SVI) datasets to objectively extract the view indices of various streetscape features such as trees to proxy urban scene qualities have emerged. However, human perception (e.g., imageability) have a subtle relationship to visual elements that cannot be fully captured using view indices. Conversely, subjective measures using survey and interview data explain human behaviors more. However, the effectiveness of integrating subjective measures with SVI datasets has been less discussed. To address this, we integrated crowdsourcing, CV, and machine learning (ML) to subjectively measure four important perceptions suggested by classical urban design theory. We first collected ratings from experts on sample SVIs regarding these four qualities, which became the training labels. CV segmentation was applied to SVI samples extracting streetscape view indices as the explanatory variables. We then trained ML models and achieved high accuracy in predicting scores. We found a strong correlation between the predicted complexity score and the density of urban amenities and services points of interest (POI), which validates the effectiveness of subjective measures. In addition, to test the generalizability of the proposed framework as well as to inform urban renewal strategies, we compared the measured qualities in Pudong to other five urban cores that are renowned worldwide. Rather than predicting perceptual scores directly from generic image features using a convolution neural network, our approach follows what urban design theory has suggested and confirmed as various streetscape features affecting multi-dimensional human perceptions. Therefore, the results provide more interpretable and actionable implications for policymakers and city planners.

Keywords: subjective measure; human perception; street view image; computer vision; global comparison



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1. Introduction

Streets are important public spaces for residents to thrive [1]. Urban design qualities such as enclosure, human scale, transparency, complexity, and imageability directly affect a person's appreciation of a street space [2]. Conventional investigations on the quality of street design have largely relied on objective metrics, ranging from the height-to-width ratio [3] to pedestrians counts [2], which require extensive spatial data and human labor for observations [4,5]. Recently, with prevalence of street view imagery (SVI) data in environmental auditing [4], computer vision (CV) has been widely applied to extract streetscape features, making the understanding of large-scale urban scenes possible [6]. However, these emerging studies are still limited to objective measures. Only the view index of individual features such as trees and buildings are analyzed, while the overall perceptions of viewers are ignored. Human perceptions have subtle relationships that cannot be fully represented by individual view indices nor a simple combination of them [2,7].

Conversely, the “subjective measure”, which refers to evaluative scores collected from survey questions, can capture more subtle relationships [7]. It is more user centered [8] although the definitions of perceptual qualities are inconsistent across studies [2]. There is no standard procedure to handle the involved error margin to ensure the comparability and reliability from different raters [4]. Despite these drawbacks in costly labor and a lack of comparability for cross-studies, subjective measures can also be effectively integrated with objectively measured indicators. Several studies have correlated subjective scores from raters with the objective visual elements that appeared in video clips or SVIs to successfully operationalize seemingly subjective but indeed objective measures of urban perception [2,8,9]. However, these studies have limitations. Although the study from Ewing and Handy [2] was well designed and based on urban design theory, their approach had low-throughput. It took raters an hour to rate a single video clip [2]. While Naik et al. [8] provided an artificial intelligence (AI) based method, it was not rooted in urban design theory: the perceived safety was made based on generic image features such as color histograms or stacked HSV color channels that had been extracted from SVIs. In other words, their prediction of perception is a black box providing limited actionable urban design policy implications.

Therefore, the effectiveness of subjective measures in capturing more subtle human perceptions on various urban scenes using SVI data have not been adequately addressed. To bridge the gap between AI based urban analytics and classical urban design theory, we took Shanghai as an example and applied CV and Machine Learning (ML) to subjectively measure four perceptual qualities, namely the enclosure, human scale, complexity, and imageability. These perception qualities have been identified as important in affecting pedestrian behaviors, residence move choices, and home buyer willingness to pay [10]. Our work enriches subjectively measured urban perception studies. It is also the first cross-study for global cities. Urban renewal implications are derived for policymakers based on this global comparison. Furthermore, we contribute to future studies by proposing a framework that integrates AI applications with classical urban measurement frameworks.

2. Literature Review

2.1. Objective and Subjective Measures

Street environment significantly affects people’s appreciation of a place as well as the physical activities of the residents who live there, the choice to move, and the willingness to pay [11]. Street qualities have mostly been measured using objective quantities such as building height, street width, and number of trees [3]. However, physical features alone cannot represent people’s overall perceptions, which have more subtle relationships [2].

Conversely, subjective measures often derive from interviews and surveys. They explain people’s behavior more completely, as behavior is mediated by a “cognitive map” of the environment [12]. Conventional approaches have relied on interviews or telephone surveys to collect people’s overall perceptions, and these data collection methods have problems [2]. First, the consistency and reliability of the operation can be questioned due to individual differences. Secondly, measurements based on surveys is time-consuming and expensive. This low-throughput method limits the application of subjective measurement to larger geographic contexts [8]. Third, the results are difficult to interpret, providing less instructive implications for policymakers [7].

Nevertheless, the subjective and objective measures could be integrated. Ewing and Handy [2] reviewed 51 subjective perceptual qualities from a pile of urban design literature. They statistically correlated subjective scores rated by experts while watching street view video clips to the objectively quantified elements like people and trees from field survey. They successfully operationalized the objective measurement of five seemingly subjective perceptions.

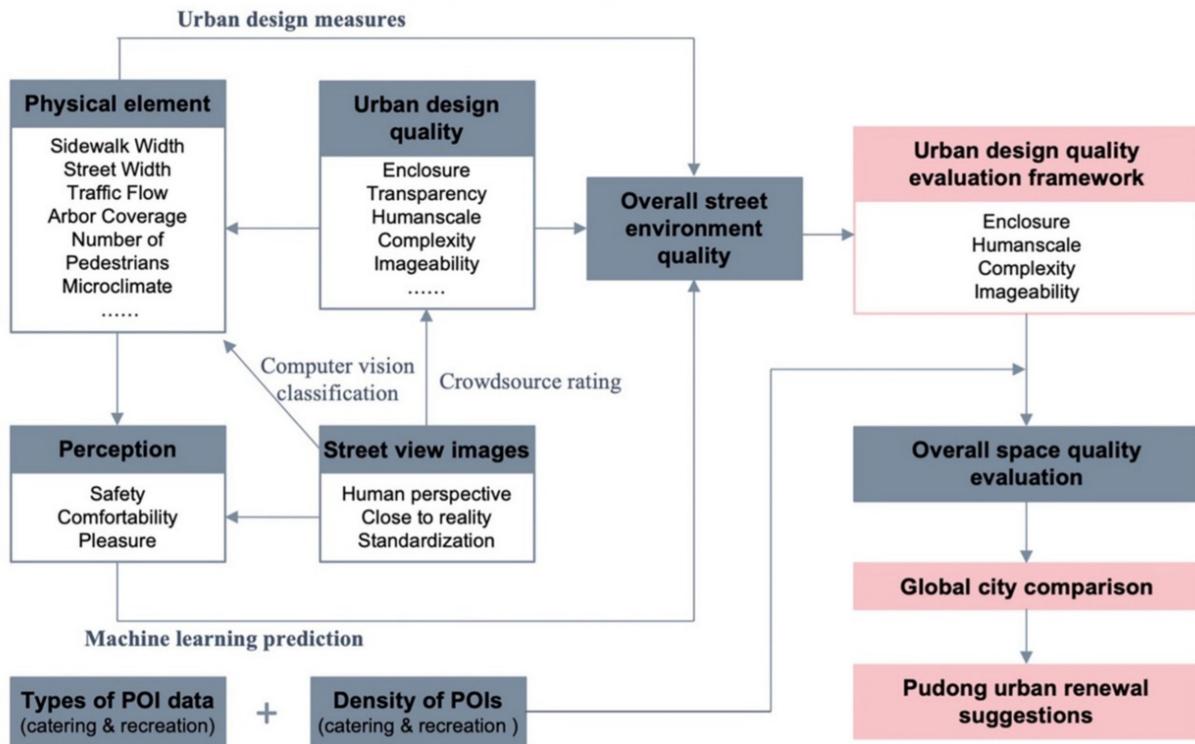
2.2. Computer Vision and Machine Learning in Street Measures

Recently, new studies that are taking advantage of open-source big data and AI algorithms have emerged. First, SVI data covers a handful of cities and has rapidly spread to new cities since 2007, and this data can be used to measure street-level human eye views that are inaccessible from bird view [13]. A few recent studies have measured the built environment using SVIs. For example, Rundle et al. [14] used Google SVI to manually audit the neighborhood environment. Later, with the advance of AI such as CV and ML, automatically extracting features from images became possible. Yin and Wang [4] applied ML to measure visual enclosure from SVI. Their results showed that the ML algorithms performed well in their ability to recognize and calculate sky areas with 90% precision, allowing the measurement to be done reproducibly. They found that the visual enclosure variables are significantly negatively associated with the number of pedestrians and the walk score [4]. Other research has measured pedestrians, trees, sky, buildings, façade etc. with SVIs and using CV models effectively and accurately [10,13,15]. However, as discussed previously, these objective view indices cannot represent overall feelings that viewers have toward street scenes [16]. For perceptual qualities that were not familiar to the average person, such as imageability, a subjective framework exhibits better performance [16].

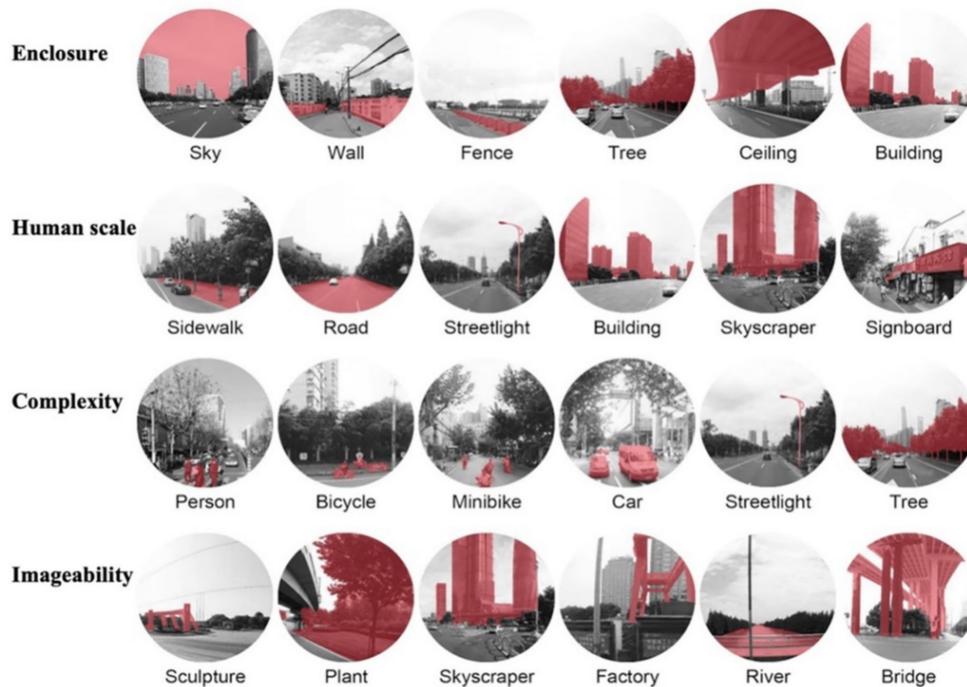
Besides open-source SVI data, integrating crowdsourcing with AI has become viable to uncover large-scale public perceptions [8]. Online data collection allows a greater number of participants to evaluate perceived qualities from images, largely increasing the accessibility of urban perception data [8,9]. Naik et al. [8] collected information on perceived safety of an urban area online by asking participants to rank pairwise street photos. These preferences were converted to ranked safety scores and became the training data to train ML models to predict the perceived safety score for 21 cities worldwide. The method was also applied to investigate the correlation between urban appearance and neighborhood income as well as housing prices [17].

Despite the effectiveness of subjective measures in incorporating more subtle human perceptions, most studies using SVI data are limited to objectively extracted visual elements. Little has been done to construct global maps depicting the subjectively measured perceptions for the many perceptual qualities identified by classical urban design studies, such as imageability and complexity [2].

Therefore, our work aims to enrich the subjective measures of urban perceptions. It contributes to analytical frameworks by extending the classical urban design framework with AI and big data (Figure 1). While Ewing and Handy [2] relied on human labor to manually count physical features from video clips, we applied CV to extract the pixel ratios or counts of each important feature. While Naik et al. [8] only mapped the perceived safety score, we measured four important qualities identified by the literature in urban design and validated the scores with objective points of interest (POI) data, which refers to a specific physical location that someone may find interesting, such as restaurants, retail stores, and grocery stores. Furthermore, it is the first cross-study considering several global cities with the application of CV and ML, which sheds light on urban renewal implications for global studies.



(a) Analytical framework and key literature



(b) Four perceptual qualities and contributing streetscape features.

Figure 1. Analytical framework (a) based on literature in urban design qualities and (b) the selection of the four perceptual qualities and their contributing features.

3. Data and Methods

3.1. Study Area and Data Preparation

Pudong District in Shanghai is the financial center of China (Figure 2a). Since the housing reform in 1998, Pudong has become one of the most expensive and vibrant housing markets in China [15]. An empirical analysis for the street quality for the city-wide area of Pudong would provide essential implications for urban renewal. The data include (1) SVIs collected from Baidu Street View API (<https://api.map.baidu.com/lbsapi/> (accessed on 2 October 2019)), (2) POI data from DaZhongDianPing (<https://www.dianping.com/> (accessed on 8 October 2019)) and AutoNavi Map (<https://lbs.amap.com/> (accessed on 5 October 2019)), and (3) a shapefile of road networks from Open Street Map (<https://www.openstreetmap.org/> (accessed on 30 September 2019)).



(a) 300 SVI sample points

(b) A sample SVI

(c) Camera settings

Figure 2. Downloading Baidu SVIs (a) SVI sample sites. (b) A typical SVI downloaded for this study. (c) The camera settings were controlled using “heading”, “FOV”, “pitch”, and “resolution”.

3.2. Selection and Calculation of the Four Subjective Qualities

Motivated by classical measurement protocols for urban design quality [2,18], we chose “(visual) enclosure”, “human scale”, “complexity”, and “imageability” to present the perceived streetscape qualities. These four qualities have been operationalized by Ewing and Handy [2] and achieved widely agreed upon definitions created by urban designers and planners [2]. Specifically, enclosure refers to the extent that streets are visually defined by features such as trees, walls, and buildings [4]. Human scale measures the size of physical elements, their texture, and their articulation that match the scale and proportions of a person and correspond to the walking speed. Physical elements including pavement texture, facade details, street furniture, trees, and plants are considered important [2]. Complexity denotes the visual richness of a place, depending on the variety of and number of elements such as human activity, signage, street furniture, greenery, and buildings [2]. Imageability captures the quality of a place that makes it distinct, recognizable, and memorable [2].

3.2.1. Downloading Baidu SVIs

SVIs were downloaded from the Baidu Street View Static API with consistent camera settings. The “heading” was set using the street angle; the image size was 800×400 pixels. The FOV (the horizontal field of view) was 120 degrees. The “pitch”, which specifies the up or down angle of the camera was 0 degrees. To ensure our training images would cover most urban area types, 300 images were randomly sampled across the Shanghai region (Figure 2a).

3.2.2. Collecting Public Perceptions as Training Labels

To collect people’s preferences on street scenes as the training labels, we developed an online questionnaire platform (<http://140.143.239.153:3000/index.html#/> (accessed on 24 June 2020)) where people could select the image that they preferred in pairwise comparisons regarding the four perceptual qualities (Figure 3a). Human perception is comprehensive and subtle; therefore, viewers perceive the quality of a street scene through the overall

sensory information obtained by viewing the whole picture [2,8]. Taking “enclosure” as example, we first gave a qualitative definition on this quality. Participants were then asked, “Which place has better enclosure?”. To ensure the SVIs shown in the survey captured a variety of streetscapes ranging from city center, suburban, to countryside, the 300 SVIs used in the survey were randomly sampled from across the Shanghai area.

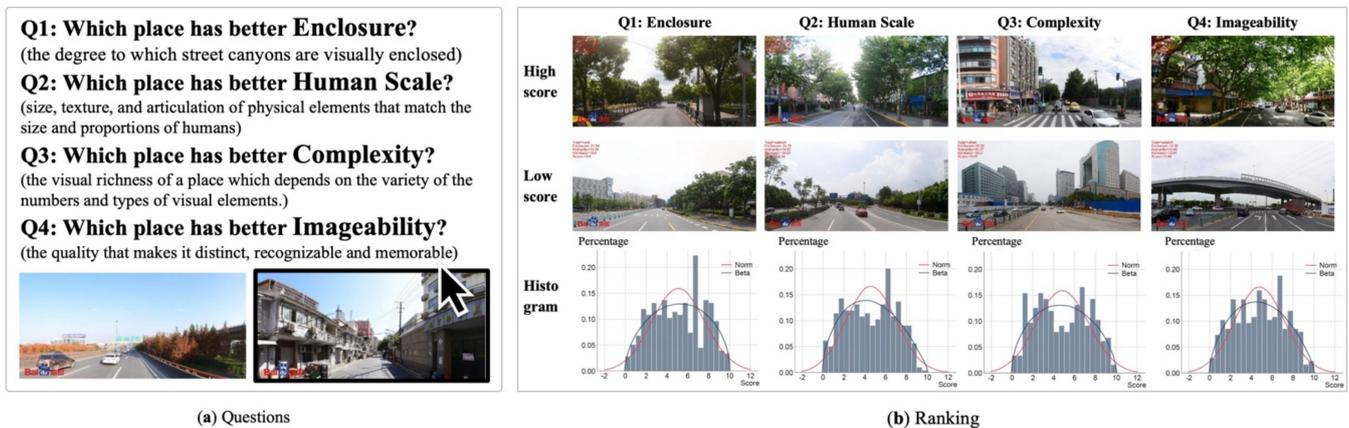


Figure 3. Collecting collaborative images of streetscapes with an online survey platform. (a) Our online survey system asked participants to click on one image in a pair of SVIs in response to evaluative questions. (b) High score and low score example images as well as the histogram of score distribution for each of the four perceived street qualities.

These preferences were then translated to ranked scores with the TrueSkill Algorithm [19], which has also been applied to rank perceived safety scores that were collected through a crowdsourcing survey in which participants were asked to rank pairwise images by Naik et al. [8]. During a one-week period, we collected 3120 valid entries from 23 volunteers who were mostly architecture students in Shanghai. On average, an image was compared to 10 other images, which is sufficient for the TrueSkill algorithm (<https://github.com/sublee/trueskill> (accessed on 30 June 2020)) converge the results [8]. The ranked scores were normalized onto a 0–10 scale. People seemed to favor streetscapes with less sky exposure, more trees, and more pedestrians (Figure 3b). These 300 labelled images become our training data.

3.2.3. Physical Feature Classification

A few physical features from street scenes have been statistically identified to relate to how humans perceive street design quality [2,5,10]. Among these studies, the pixel ratios of individual elements such as trees, buildings, cars, and people were often extracted from SVIs as view indices to proxy street quality [10]. Formally, a view index is the percentage of pixels of a feature to the total pixels of an image [20], which can capture the importance of a visual element from eye-level view. For example, the green view index measures the share of tree pixels. Therefore, we use the general formula, Formula (1), to measure various view indices for all of physical features shown in the SVIs.

$$VI_{obj} = \frac{\sum_{i=1}^n PIXEL_{obj}}{\sum_{i=1}^m PIXEL_{total}}, \quad obj \in \{tree, building, sky, etc\} \quad (1)$$

where, VI_{obj} is the view index, $\sum_{i=1}^m PIXEL_{total}$ is the total pixels of the image, and $\sum_{i=1}^n PIXEL_{obj}$ is the pixels of the physical feature obj .

The pyramid scene parsing network (PSPNet) is a pixel-level object recognition and classification algorithm that produces reliable results in semantic segmentation, achieving more than 93.4% pixel-level accuracy [21]. It has been applied by several prior studies [20,22] to extract streetscape features such as trees, sky, and building views from SVIs to inform the urban environment [22] and housing prices [20]. We used PSPNet to extract

the pixel ratios of individual features as view indices from SVIs. More than 30 streetscape elements were detected (Figure 4a). Furthermore, for the quantity of cars, people, signs, and street furniture, the pixel ratio makes less sense. Therefore, we applied MASK R-CNN [23] to count the absolute amounts (Figure 4b).

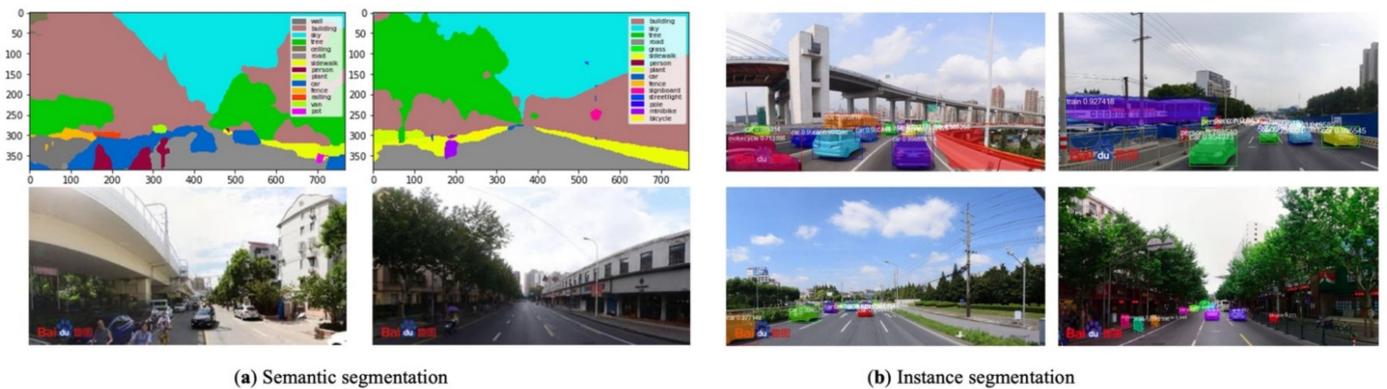


Figure 4. CV Segmentation results. (a) Pairwise PSPNet semantic segmentation results with its raw input. (b) Mask R-CNN instance segmentation results counting objects.

3.2.4. Streetscape Feature Selection

Notably, from the perspective of both the feature engineering of statistics [24] and urban perception theory [2,5], not all streetscape features classified from SVIs will have a significant effect on human perceptions. For example, based on the literature, the sky, tree, plants, sidewalk, road, building, person, and bike view indices were significant in affecting perceptions [2,5]. Therefore, the selection of streetscape features as explanatory variables to predict perception scores were based on literature and feature engineering. We used the widely applied Gini importance (GI) [25], also known as the mean decrease in impurity, to rank the feature importance. Specifically, each feature's GI was calculated based on the impurity reduction of splits, as the sum over the number of splits across all of the trees that include the feature, proportionally to the number of samples it splits during the random forest process using the Python Scikit-learn package [26]. Only features identified either as significant and important in affecting human perception or receiving high GI scores would be kept.

3.2.5. Predicting Subjective Scores

The target output variables of this study are the four perceived scores, the data type for which is continuous. The input of the ML model was 30 streetscape features obtained from Section 3.2.3. Thus, regression algorithms are required. Meanwhile, the algorithm must be able to identify the feature importance for the street view features to inform urban design. Therefore, neural network algorithms were not considered because they are a complete black-box that cannot provide guidance on the importance of each streetscape feature identified by urban design theory [5,18].

Based on the above two conditions, we chose eight ML algorithms (Table 2), which included linear regression, K-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), decision tree (DT), voting selection (VS), gradient boosting (GB), and adaptive boost (ADAB), to predict the four perceptions. Those algorithms are classical and mature in supervised learning. In urban related studies, they have been extensively used as baseline in the prediction of a numerical target feature based on other features of an instance and have shown effectiveness and robustness [5,8,27–29]. Using different algorithms to assess the prediction performance can better reflect real dataset applications.

The implementation processes related to machine learning algorithms and modeling are based on the Scikit-learn Python library [26]. Optimization and improvement at the

algorithm level are not in our research scope. Therefore, this paper does not introduce the theoretical and mathematical derivation processes of these algorithms.

The mean absolute error (MAE) was set as the loss function to evaluate the performance of the ML algorithms. It shows advantages in assessing the average model performance [30]. Assuming that n is the number of errors, x_i is the predicted perceived scores, and x is the true value. The MAE is calculated as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |x_i - x|$$

The lower MAE value implies the higher accuracy of a prediction model. We then applied the best performance models to all of the downloaded 14,274 Baidu SVIs and derived the four subjective scores for the Pudong Area.

3.3. Correlation Test and Cross-Reference Validation

The relationships within different human perceptions are subtle and could be correlated. Zhang et al. [5] indicated the high correlation between certain pairs of subjective perceptions measured from SVIs, such as “beautiful–wealthy” and “depressing–safe”. We applied Pearson correlation analysis to investigate the multicollinearity of the four perception scores. We also cross-referenced the subjective scores to the objectively quantified indicators with the external data, such as POI density, floor area ratio (FAR), etc. The goal was to test the effectiveness of the subjective measures in capturing more interpretable and objective urban metrics that have been proved to affect human perceptions of urban scenes.

3.4. Global Comparison with Other Cities

A high-quality environment stimulates urban innovation [31–33]. In recent years, the government has devoted considerable resources to improve the environmental quality of the Pudong area aimed at promoting innovative industrial and activities, especially in the Zhangjiang High-Tech area of Pudong [34]. To validate the generalizability of our framework and to inform what kind of perceivable environment facilitates urban innovation, we conducted a comparative analysis of the perceived scores between the Pudong Zhangjiang High-Tech area and five other global renowned innovative districts. Cambridge Kendall Square, Downtown San Francisco, Manhattan Wall Street, Seattle South Lake Union, and the London Knowledge Quarter were selected as the benchmarks. Perched next to the Massachusetts Institute of Technology, Cambridge Kendall Square is an internationally recognized innovation district that is propelled by innovative firms [35]. Neighboring Silicon Valley, Downtown San Francisco has one of the best innovation ecosystem where a large number of start-ups, business incubators, and leading-edge companies gather [36]. Located in New York, Manhattan Wall Street is the second leading high-tech hub in the United States [37]. Seattle South Lake Union is the hotbed of innovative companies including Amazon and Microsoft [38]. The London Knowledge Quarter (in the UK) has one of the leading clusters of innovation and research organizations in the world [39]. These five cities were listed in the World Top 20 Science and Technology clusters by the World Intellectual Property Organization (WIPO) [40]. These five districts have been widely studied as the leading global practices of innovational clusters [31,41,42].

The scores of the Zhangjiang High-Tech Park in the Pudong area were compared to those of the five benchmarks. Implications for urban design and renewal for Pudong and Zhangjiang were discussed based on the results of the comparison.

4. Findings & Discussion

4.1. Descriptive Statistics of the Classification and Significant Streetscape Features

Using a PSPNet pre-trained algorithm, more than 30 visual elements that appeared in sample SVIs were quantified based on the general formula, Formula (1), with large differences in their quantities and standard deviation. First, among these features, more ubiquitous elements (e.g., buildings, sky, trees, curbs, roads, and street walls) were re-

vealed to significantly affect human perceptions [2,5,10]. For example, sky, tree, and building views extracted from the SVIs have been tested to significantly affect perceived enclosure [4] as well as housing prices [15,20,43]. Second, less ubiquitous elements like people, proportion windows, signboards, and street furniture, such as outdoor dining and streetlights, have also been revealed to be important in affecting human behaviors and perceptions. For example, the presence of people, street squares, courtyards, parks, outdoor dining, landscape features, and identifiable building facades have been proved to affect the perception of “imageability” [2], while the proportion street walls, buildings, and the sky affected the perceived “enclosure” [2,18]. Therefore, we kept the 25 most vast visual elements, the mean view indices of which were greater than zero at 4 digits. Meanwhile, for individual features like people, using the absolute count makes more sense than using the pixel ratio. Therefore, we also replaced the view indices of the five features with their absolute counts, namely the people, cars, bicycles, motorbikes, and benches, which have been indicated to be important human activities indicators, along with street furniture objects [2,18]. In the end, these 30 features were the final explanatory variables fitting into ML models to the predict perceived scores. Table 1 provides a descriptive summary of either their view indices or absolute counts.

Table 1. Descriptive summary of 30 streetscape features.

FID	Physical Feature	Mean	Std. Dev.	Min	Max
View Index using PSPNet					
1	Sky	32.57%	17.61%	0.00%	76.20%
2	Buildings	22.71%	19.60%	0.00%	96.37%
3	Trees	18.63%	16.26%	0.00%	81.10%
4	Roads	10.74%	5.21%	0.00%	22.33%
5	Sidewalks	2.21%	2.48%	0.00%	17.57%
6	Walls	1.86%	6.42%	0.00%	75.05%
7	Fences	1.65%	2.26%	0.00%	13.13%
8	Overpasses	1.58%	7.67%	0.00%	57.10%
9	Plants	1.24%	2.05%	0.00%	14.91%
10	Grass	1.10%	2.05%	0.00%	13.94%
11	Signs	0.65%	1.06%	0.00%	7.41%
12	Bridges	0.37%	2.80%	0.00%	36.87%
13	Railings	0.34%	1.01%	0.00%	7.89%
14	Skyscrapers	0.32%	1.67%	0.00%	19.95%
15	Earth	0.20%	1.02%	0.00%	13.89%
16	Vans	0.14%	0.68%	0.00%	7.00%
17	Columns	0.13%	0.86%	0.00%	13.00%
18	Streetlights	0.07%	0.13%	0.00%	0.93%
19	Awnings	0.04%	0.25%	0.00%	2.87%
20	Ashcans	0.01%	0.07%	0.00%	1.05%
21	Windows	0.01%	0.05%	0.00%	0.80%
22	Booths	0.01%	0.03%	0.00%	0.66%
23	Sculptures	0.01%	0.07%	0.00%	1.26%
24	Mountains	0.01%	0.00%	0.00%	0.03%
25	Fountains	0.01%	0.02%	0.00%	0.41%
Absolute counts using MASK R-CNN					
26	People	3.11	4.17	0.00	37.00
27	Cars	5.56	5.91	0.00	39.00
28	Bicycles	0.13	0.46	0.00	3.00
29	Motorcycles	0.21	0.78	0.00	10.00
30	Benches	0.25	0.84	0.00	6.00

Ranked by their GI scores [25], the top 15 five most important visual elements that contribute to pedestrians’ perception of street design qualities are reported in Figure 5. The values of sky, trees, people, buildings, and cars ranked highest based on the sum of

their GI scores in predicting four qualities, which is consistent with prior studies [2,5,44,45]. However, street furniture that have been proven to be important by prior urban design studies [2], such as streetlights and benches, are not highly ranked. Another interesting finding is that with a same feature, its importance scores in predicting different perceptions have a large amount of variance. For example, sky is much more important in predicting enclosure than aesthetics, trees are almost equally important in predicting all four perceptions, while the presence of people is more important to predict complexity.

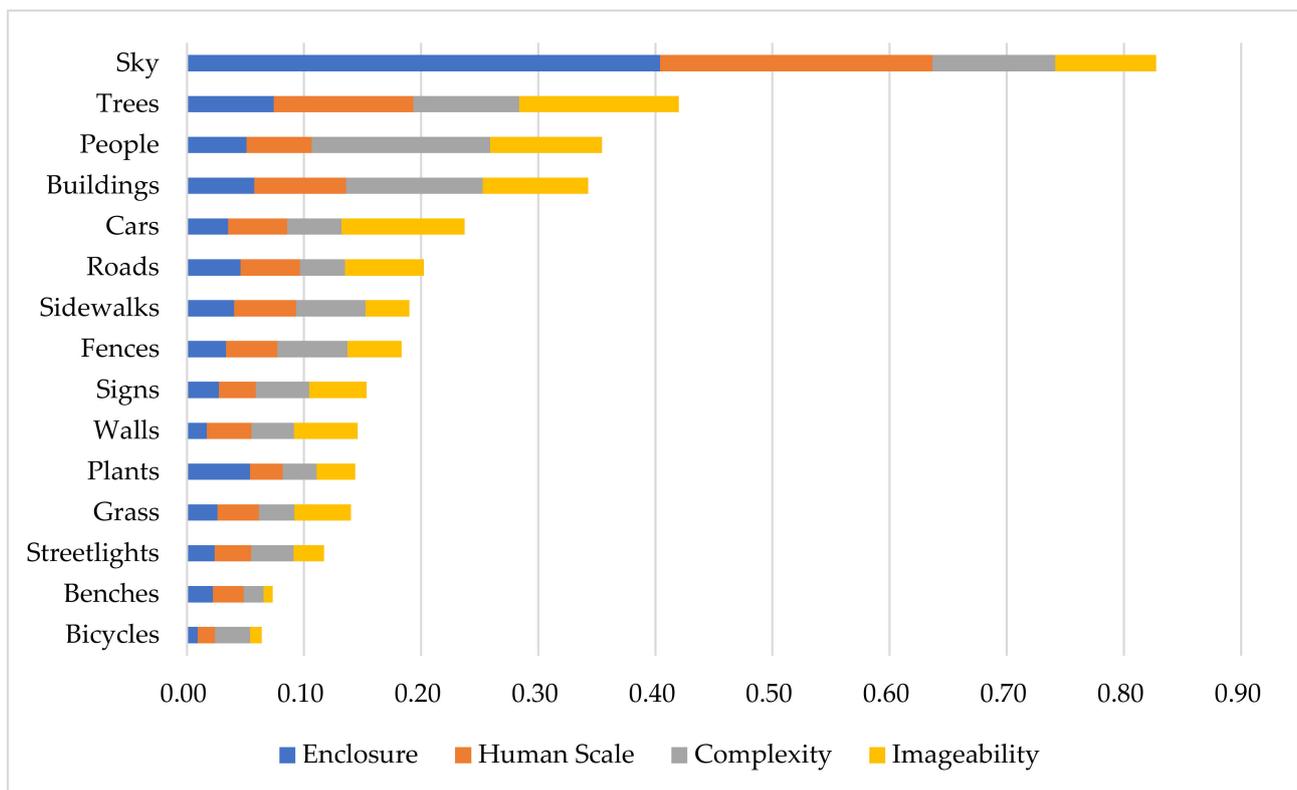


Figure 5. Top 15 important features in predicting four subjective scores.

4.2. ML Prediction Performances

Different ML models' prediction accuracies in terms of R^2 and MAE varied across four perceptual scores. SVM outperformed the other ML models in predicting complexity and imageability scores (Table 2). SVM uses kernel tricks to solve complex solutions. It contains a convex optimization function that can perform well when there are limited training data and many features [46]. Gradient boosting (GB) outperformed other ML models in the human scale score, while RF performed the best in predicting the enclosure score compared to other models. RF can handle overfitting efficiently and shows advantages in processing data with outliers [47]. As shown in Table 2, the enclosure score has a greater standard deviation (std.), which means that the value of the enclosure has higher dispersion and contains more outliers. This could explain why RF performed better in the enclosure score. Moreover, the MAE of the RF model for predicting imageability was 1.19, being much smaller than that of the remaining three perceptual scores, which could be the result of the online rater variations during image ranking [5].

Table 2. Performance of machine learning algorithms.

Model	Enclosure		Human Scale		Complexity		Imageability	
	R ²	MAE						
Linear Regression	0.38	1.31	0.22	1.81	0.15	1.69	0.19	1.82
K-Nearest Neighbors (KNN)	0.34	1.31	0.07	1.81	0.36	1.70	0.21	1.77
Support Vector Machine (SVM)	0.41	1.25	0.24	1.79	0.48 *	1.51 *	0.49 *	1.50 *
Random Forest (RF)	0.47 *	1.19 *	0.29	1.73	0.43	1.55	0.27	1.63
Decision Tree (DT)	0.18	1.58	0.05	2.36	0.26	2.29	0.08	2.14
Voting Selection (VS)	0.43	1.26	0.26	1.78	0.35	1.60	0.31	1.60
Gradient Boosting (GB)	0.47	1.21	0.51 *	1.62 *	0.41	1.52	0.14	2.01
Adaptive Boost (ADAB)	0.26	1.53	0.20	1.84	0.41	1.52	0.32	1.63

* Denotes best performance models for each perception score prediction.

The training resulted in best models with MAE being between 1.19 to 1.62 and with R² from 0.47 to 0.51. Compared to the R² scores achieved by Naik et al. (0.38 to 0.57) [8] and that of Ewing and Handy (e.g., 0.36 for imageability, 0.43 for enclosure, 0.36 for human scale, and 0.38 for complexity) [2], our results are therefore acceptable, considering the small training sample. Meanwhile, an error of 1.19 to 1.62 will not alter the interpretation of predicted quality with a 0–10 scoring system. For example, in the worst case, a true score of 7.5 could be predicted to a value between 6.31 to 9.12, which would be interpreted as good to very good quality. Therefore, for all of the downloaded 14,274 Baidu SVIs, the best models were selected to predict perceptual scores accordingly. Specifically, as Table 2 reported, SVM was selected to predict “complexity” and “imageability”, GB was selected to predict “human scale” while RF was selected to predict “enclosure”.

4.3. Correlations between Four Perceptions

The pairwise coefficients between imageability and the other three scores have a moderate (between ± 0.30 and ± 0.50) degree of correlation, while the correlations between enclosure, human scale, and complexity are high (between ± 0.50 and ± 1) (Table 3). The positive association between the pair of “enclosure–human scale” is particularly strong. Intuitively, this is reasonable because these two perceptions, by definition, overlap in many ways. Both of their operationalized measures have been proved to relate to streetscapes that construct a vertical and horizontal street scene, such as sky, buildings, trees, and street furniture. Our finding is consistent with the literature, for example “enclosure” and “complexity” were positively correlated in affecting walkability [2]. In addition, the strong correlations also indicate that future studies could investigate the divergence and coherence between these subjective measures, especially to define and differentiate their definitions more explicitly. Otherwise, the use of subjective measures could be restricted by its ambiguity, and the results could raise confusion in interpretation when making policy implications.

Table 3. Pearson correlation of four subjectively measured perceptions.

	Enclosure	Human Scale	Complexity	Imageability
Enclosure	1.00	0.91 ***	0.84 ***	0.51 ***
Human scale	0.91 ***	1.00	0.82 ***	0.51 ***
Complexity	0.84 ***	0.82 ***	1.00	0.34 ***
Imageability	0.51 ***	0.51 ***	0.34 ***	1.00

*** $p < 0.01$.

4.4. Validation of Complexity Score

The results show that the degree of “imageability” is significantly and positively correlated with “enclosure” and “complexity” (Table 3). Furthermore, we crossed referenced the complexity score to the POI density (using food and beverage, entertainment, and recreation). A higher complexity score was correlated with more POIs, indicating the

predicted complexity score effectively captures the impacts of urban amenities and services (Figure 7a).

4.5. Uneven Spatial Distribution of Perceptual Qualities

Figure 6b provides the first comprehensive cognitive maps for Pudong District. The distributions of the four perceptual qualities are heterogeneous, with the downtown area (i.e., Lujiazui area) being perceived as having the highest concentrations of these qualities. The results indicate that more efforts could be invested into the periphery residential areas and new industrial parks. For example, Zhangjiang High-Tech Park, where street qualities are perceived as low but with a large residential population and employment. Urban renewal resources such as greenifying the streets and policy and regulation changes such as changing zoning codes from mono to multi and mixed land use could effectively improve the street quality as it is perceived by residences.

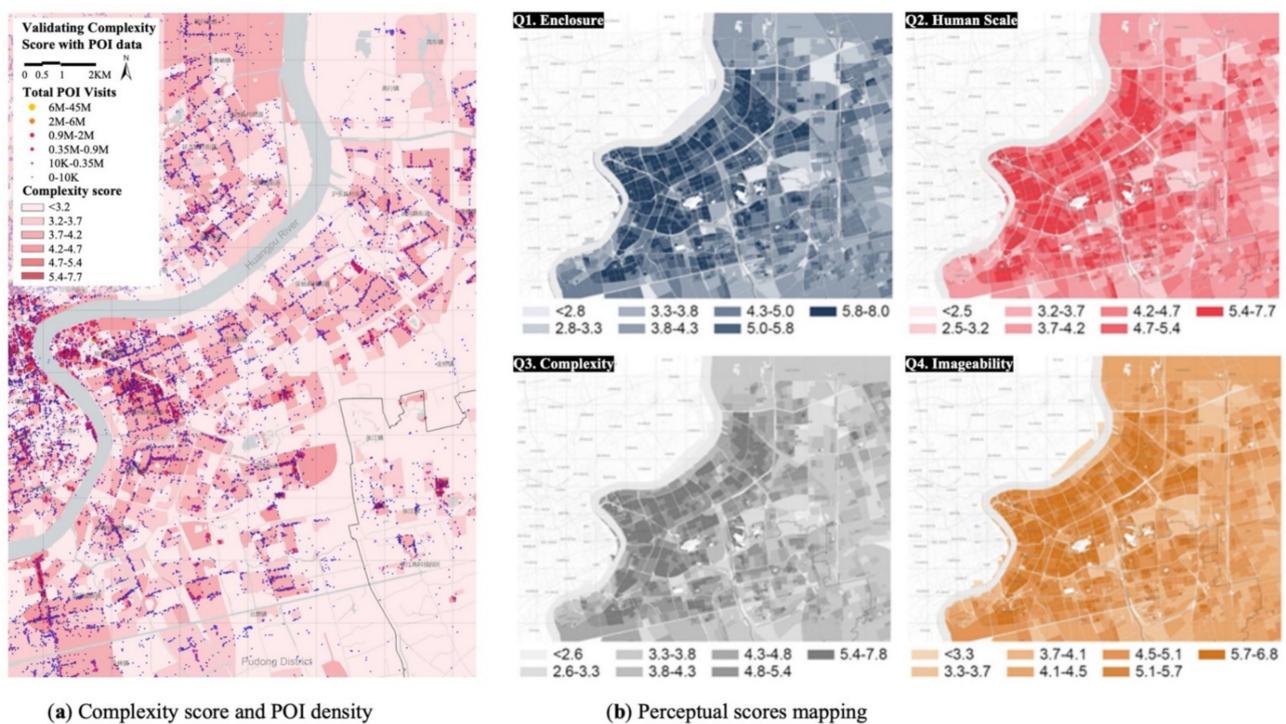


Figure 6. Mapping of (a) correlations between complexity score and POI density. (b) Cognitive maps of four subjectively predicted perceptual qualities.

4.6. Comparison with Other Cities

Averaging the four perception scores and comparing Pudong to other five global best practices (Figure 7a), we found the uneven distribution of the perceived quality in Pudong prevails. Taking the same sized area (3km radius) of the urban core as the one used in the study areas, Pudong has the lowest average score (Figure 7b), indicating that more design implementation should be taken into account to improve the overall appreciation of the street environment if the government's goal is to make Pudong a globally leading district for urban innovation. Good street environment quality has been identified to facilitate innovation and quality of life [10].

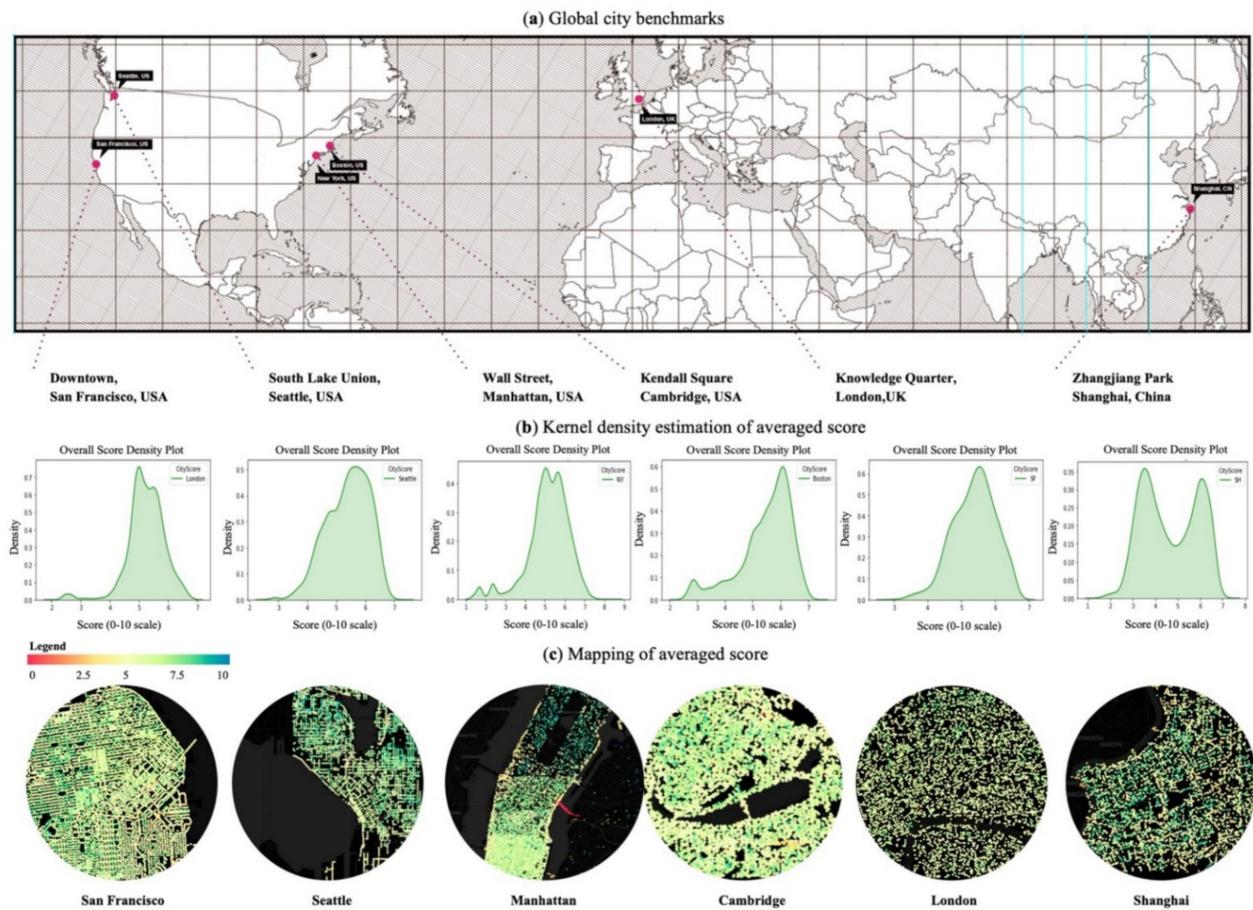


Figure 7. Comparing the perceptual qualities of six cities. (a) Locations. (b) Average score distribution. (c) SVI samples and study area mapping.

Specifically, depicted by Table 4, all five of the global districts have smaller variance (1.14 to 2.27) and standard deviation (1.07 to 1.51) in the average score, compared to that of Shanghai Pudong (3.38 and 1.84). Our findings suggest that the averaged street design quality of the Pudong area has large potential to increase. Meanwhile, the qualities in Pudong are highly polarized (Figure 8a), implying its biased and uneven urban development. It also suggests future study to investigate whether such uneven distribution has posed inequitable issues to specific population segments [9]. Moreover, the global comparison results confirm that our proposed method is applicable to a wide range of regions, and the results are reproducible and comparable.

Table 4. Average scores, standard deviation and variances.

City	Sample	Enclosure	Human Scale	Complexity	Imageability	Avg. Score	Variance	Std. Dev.
Cambridge	6354	5.36	5.22	5.57	5.47	5.41	2.16	1.47
London	6019	5.45	5.10	5.50	5.24	5.33	1.22	1.10
Manhattan	6716	5.70	5.30	5.45	5.17	5.40	1.14	1.07
San Francisco	6410	5.40	4.79	5.28	5.38	5.21	1.41	1.19
Seattle	6517	5.51	5.23	5.64	5.40	5.44	2.27	1.51
Shanghai	14,274	4.57	4.33	4.21	4.68	4.45	3.38	1.84

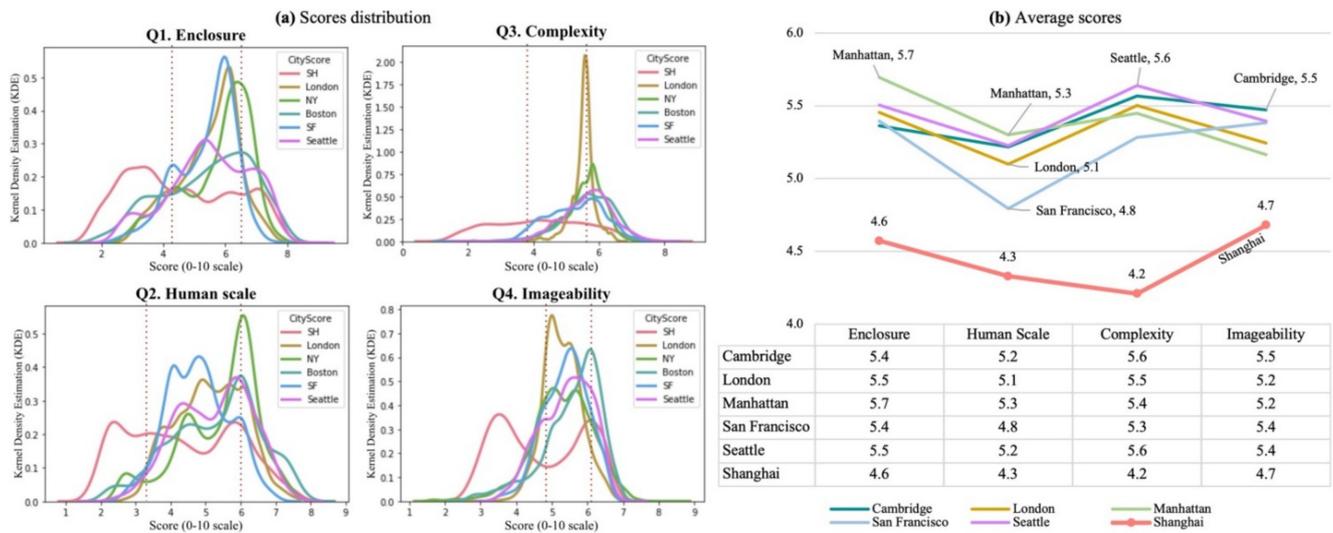


Figure 8. Comparing the perceptual qualities of six cities. (a) Score distributions. (b) Averaged scores.

Regarding individual quality perception, Pudong is still perceived the most unevenly and has a polarized distribution, with its mean score in all four dimensions being the lowest (Figure 8a and Table 4). Figure 8b depicts that the enclosure and complexity scores see the largest gap between Pudong and other best practice locations. Based on our previous analysis, sky, building, trees, and people significantly affect the quality of these two perceptions. Therefore, tailored urban design actions, such as adjusting zoning codes to increase the maximum FAR allowed and encouraging more transportation-oriented development (TOD), could potentially improve the perceived enclosure and complexity.

4.7. Cross-Reference to Zoning Metrics

To provide more actionable policy suggestions for urban renewal, we cross-referenced perception scores to several important objective metrics from urban form and density (Figure 9). The compared metrics, such as average block size, street width, and floor area ratio (FAR), all have significant implications for travel demand, pedestrian behavior, and urban design [3]. Zhangjiang has the widest roads but the lowest measured density, which explains why it has the lowest perceived enclosure, since lower building heights and wider streets lead to less enclosure [4]. Less enclosure limits the neighborhood walkability and results in less walking behaviors, which is confirmed by the pedestrian counts from the SVIs.

Regarding the number of POIs with amenities and services, Zhangjiang also has the least density (Figure 10). In addition, all amenity POIs are concentrated within a specific spot, which is the shopping complex next to a metro station. For other cities, such as London, Downtown San Francisco, or Cambridge, the distribution of amenities is more homogeneous and even. Figure 10 depicts that the amenities in urban cores of other global cities, and shows how they are all more reachable and within a reasonable walking distance. This finding is also consistent with our analysis that Zhangjian is perceived as the worst city regarding complexity score compared to the other studied areas.

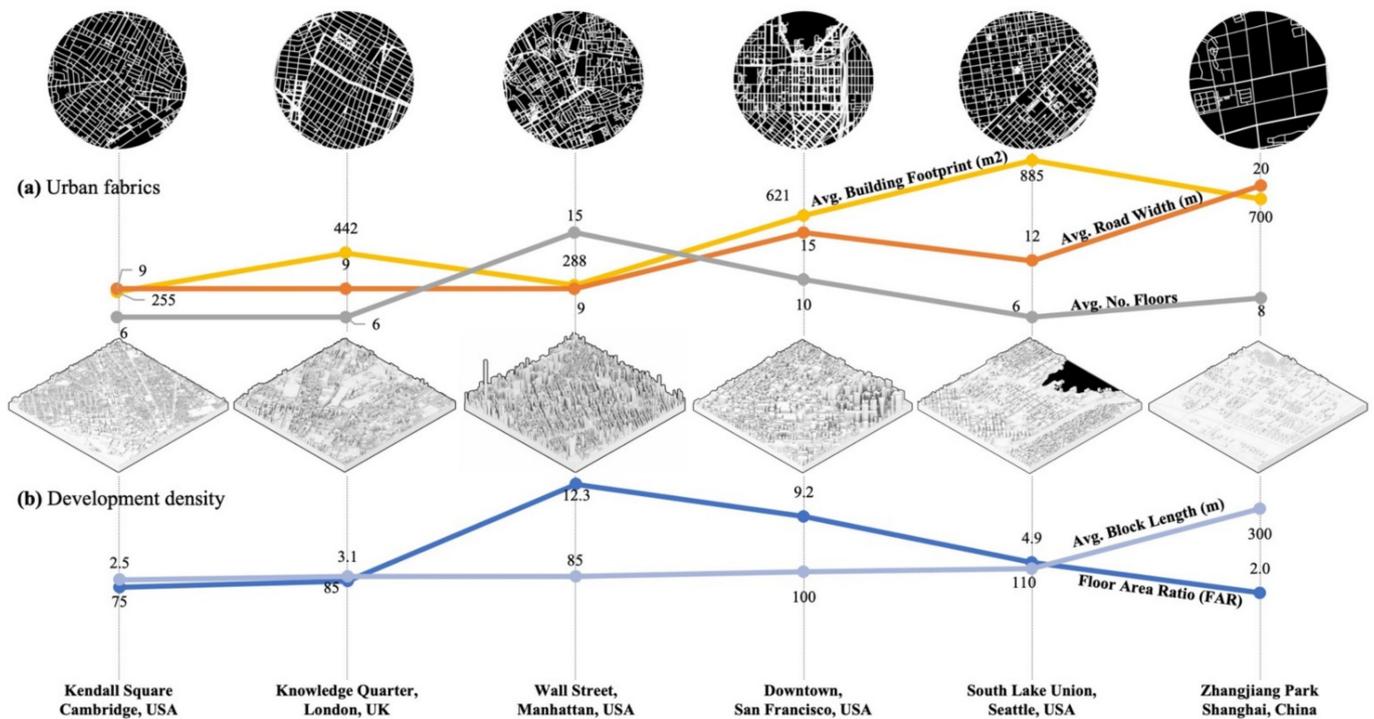


Figure 9. Comparing (a) urban fabrics and block metrics and (b) development density and metrics.

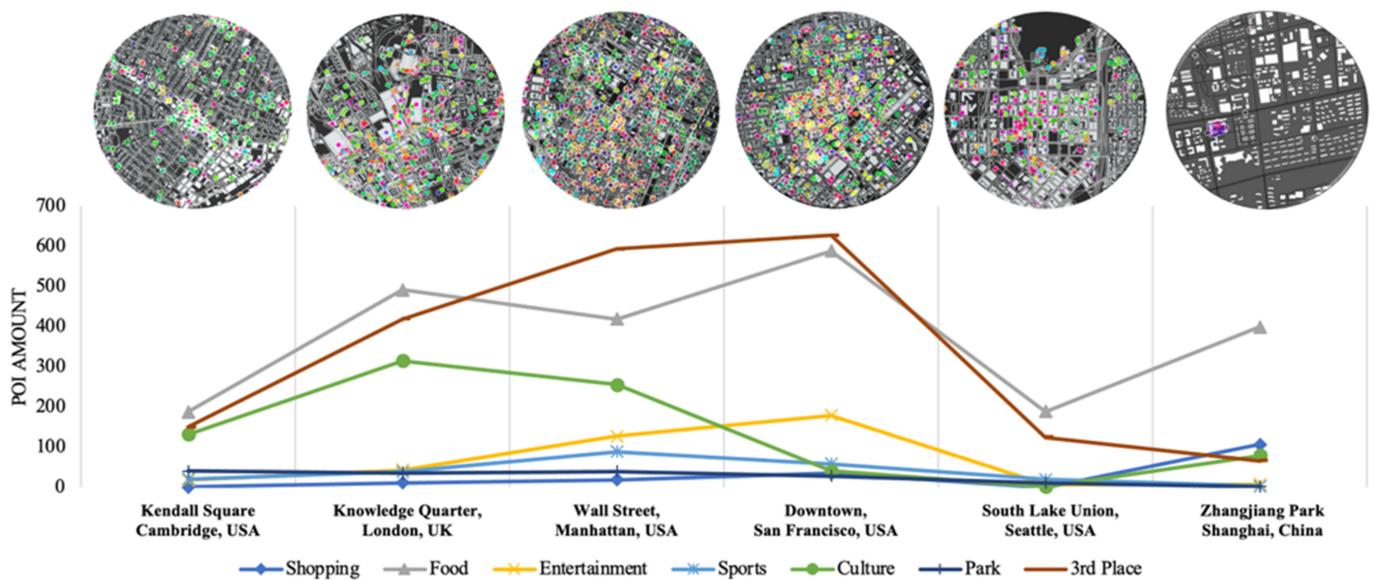


Figure 10. Comparing amounts of urban amenities and services especially the 3rd place.

5. Conclusions

5.1. The Effectiveness of Proposed Subjective Measure Framework

While this method may not immediately replace the long-existing techniques in urban environment auditing, it offers many merits. For example, it is closely related to the pedestrians' perspective, has a low-cost, requests nothing from proprietary software or methods, and can be commonly applied to where an SVI dataset is available. The proposed method provides a useful alternative for planners and policymakers.

First, the cross-study of six global urban cores including the Pudong district confirms the generalizability of our proposed framework. Our proposed framework is viable to consistently predict perceptions from open-source SVI datasets that widely exist. The results are reproducible and are therefore comparable for cross-study purposes. All of the four important human perceptions suggested by urban design theory have been successfully operationalized in our study. Notably, we improved the accuracy rates regarding R^2 after comparing it to prior work [2], largely owing to capability of pre-trained CV models in accurately extracting more kinds of street features at a large-scale compared to collecting this information through human labor. Our results are also better because ML models perform better in predicting tasks with higher dimensional feature space when they are compared to conventional regression models used by Ewing and Handy [2].

Second, subjective measures capture more comprehensive and subtle human perceptions than using individual view indices. On the one hand, our findings that “enclosure” and “complexity” are positively correlated are consistent with the literature [2]. On the other hand, we found seriously correlated associations between human scale and enclosure, which indicates future studies to more explicitly investigate the divergence and coherence between subjective measures. Furthermore, more streetscape features were found to be significant in affecting human perception compared to the literature, while some elements that are conventionally perceived important, such as the streetlights and the signboards, were not highly ranked in our study.

Third, although they were simply measured from images, perceptual scores capture many urban space qualities and characteristics that have only been accessible when using objectively measured urban metrics. For example, the perceived “complexity” exhibits a strong correlation with the POI density of urban amenities and services. When cross-referencing “enclosure” and “human scale” to urban density and urban form metrics like FAR, street width, building height, block size, we also found a significant correlation.

Fourth, while objective metrics must be measured using massive POIs and urban 3D model data with complicated workflows with ArcGIS and Rhino, our framework can stand alone without any licensed programs and software. All of the information that is needed is open-source. Therefore, compared to other objective measures of urban form, our proposed framework is more accessible and has higher throughput. Furthermore, unlike deep learning frameworks [8,9] that predict perceptual scores directly from generic image features, our approach follows fundamental urban design theory and identifies a wide range of streetscape features affecting different perceptions. Therefore, it provides more actionable policy implications for urban designers and planners.

Finally, the cross-study indicates that the polarized and uneven urban development in the Pudong District is prevailing, especially compared to global best practices. Unlike other benchmark cities, Pudong has the largest score variances and the lowest average scores within all four perceptions. Particularly, the perceived “enclosure” and “complexity” see the largest gap. On the one hand, our findings suggest the need for a more equitable and wise allocation of urban design efforts and resources invested to improve periphery areas, especially in residential and innovative industrial parks like Zhangjiang. Street qualities are vital to the quality of life to urban residents as well as to facilitate urban innovation. On the other hand, since sky, buildings, trees, and people significantly affect these two perceptions, more tailored urban design actions should be applied. For example, adjusting zoning codes to increase the allowed FAR and encouraging more transportation-oriented development (TOD) and mixed-use development could potentially improve the perceived enclosure and complexity in Pudong.

5.2. Limitations and Next Steps

Our studies have several limitations. First, limited by time and resourced, our SVI segmentation only used pre-trained CV models on the most common streetscape classifications. Future studies could train specific classification models to fulfil more tailored tasks, such as to extract building façades and windows and to identify façade styles, which

significantly affect many design quality related human perceptions [2,18,48]. Second, our training data size was limited by the scarcity of volunteer raters. Only 23 raters were involved, and 300 sample SVIs were rated. A larger sample size and more participants could potentially increase the accuracy and reliability of perception predictions. Meanwhile, the subjective perceptual scores were not randomly selected. They were collected from a very specific and small study group consisting of only designers. In the future, inputs from volunteers with other areas of knowledge such as those working in real estate or home buyers will be more desirable, which would likely shed light on more unbiased civic preferences. Third, thanks to our reviewers, our data might provide more convincing and reliable information on streetscape feature importance if the experiment design performs the feature classification first and asks raters to not only compare street scenes, but to also select the most attractive features from the scene. Fourth, further investigation could be done to address the divergence and coherence between subjective perceptions and the objective metrics of urban forms. Last, the data source could be further improved. Although the acquired street-level images could help us understand the quality of public streets, the impacts of the private streets of inner blocks remained unknown due to the lack of SVI data.

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