The Coherence and Divergence Between the Objective and Subjective Measurement of Street Perceptions for Shanghai

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Abstract. Recent development in Street View Imagery (SVI), Computer Vision (CV) and Machine Learning (ML) has allowed scholars to quantitatively measure human perceived street characteristics and perceptions at an unprecedented scale. Prior research has measured street perceptions either objectively or subjectively. However, there is little agreement on measuring these concepts. Fewer studies have systematically investigated the coherence and divergence between objective and subjective measurements of perceptions. Large divergence between the two measurements over the same perception can lead to different and even opposite spatial implications. Furthermore, what street environment features can cause the discrepancies between objectively and subjectively measured perceptions remain unexplained. To fill the gap, five pairwise (subjectively vs objectively measured) perceptions (i.e., complexity, enclosure, greenness, imageability, and walkability) are quantified based on Street View Imagery (SVI) and compared their overlap and disparity both statistically and through spatial mapping. With further insights on what features can explain the differences in each pairwise perceptions, and urban-scale mapping of street scene perceptions, this research provides valuable guidance on the future improvement of models.

Keywords: Street view imagery · Human perceptions · Subjective and objective · Coherence and divergence · Machine learning

1 Introduction

Street provides significant public space where people gather, meet, and interact [1]. How people sense and perceive the street environment directly influences human behaviors such as walking [2]. Therefore, it is essential to maintain consistency and efficiency in evaluating perceptions of the streets. Recently, SVI provides big dataset for micro-level human-perceived street characteristics [3] and studies have taken advantage of it to map the street environment perceptions [4–6].

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Using SVI, scholars were able to measure street perceptions objectively or subjectively [4, 5, 7]. However, to date there is little consensus on the measurement of perceptions. Objectively measured perceptions rely on complex math formulas by recombing extracted view indices using CV to proxy perceptions such as walkability [5]. Subjectively measured perceptions are typically collected through ML predicted scores based on crowd-sourcing visual survey results [6, 8]. However, previous study revealed it may exhibits different results even measuring the same perception concept [9]. Fewer studies have systematically compared the coherence and divergence between objective and subjective measurements of perceptions. Furthermore, it is largely unknown what street features can cause the disparities in pairwise objectively measured and subjectively measured perceptions.

To bridge these knowledge gaps, using Shanghai as case study site, we collected SVI to quantify five pairwise (objective vs subjective) perceptions [9], namely the enclosure, greenness, complexity, imageability, walkability. Our contribution is three-fold. First, we provide a comprehensive and high-throughput framework integrating Artificial Intelligence (AI) and SVI data that accurately reflects objective and subjective measurements. Second, we provide pairwise comparison (statistically and spatially) between objectively and subjectively measured perceptions to identify their overlap and divergence. Third, we investigate what physical features may explain the differences between two measures and further provide suggestions to help improve the measurement framework, which hasn't been studied in previous research.

2 Literature Review

The conventional methods to measure street perceptions rely on low-throughput questionaries or surveys, while this process is labor-intensive, time-consuming and challenging to deploy over larger territories [7]. Open-source SVI data such as Google Street Views largely overcomes these limitations and was increasingly used in urban studies regarding human-perceived street environment [10, 11]. Moreover, the rapid development in CV, deep learning (DL), and ML technology have enhanced efficiency and accuracy in processing SVI data. Combining SVI and computational frameworks, many studies have proved good robustness in mapping streetscape features and human perceptions [8, 12].

On the one hand, objective measure uses CV to extract pixels of various elements as view indices from SVI to describe the street environment [13]. Apart from simple indicator such as sky view factor, recent studies developed complex mathematical formulas to proxy the human perceptions. Specifically, Ma et al. [5] formulated equations deriving from operative definitions of each perception concept [14], and measured five perceptions (i.e., greenness, openness, enclosure, walkability, imageability) by recombining the view indices of key physical elements like sidewalk and tree. On the other hand, traditional subjective measures collect opinions from surveys and panel of experts [14]. Along this line, new studies emerged to integrate SVI and crowdsourced visual surveys [15]. Extensive studies have followed this approach and successfully predicted citywide subjective perceptions using ML algorithms [6, 12]. For example, Zhang et al. [6] mapped six subjective perceptions (e.g. lively) for different Chinese cities.

Nevertheless, few studies have compared the overlap and divergence of the two perception schemes but revealed mixed results. Xu et al. [9] compared six pairwise objectively and subjectively measured perceptions and found that objective measures outperform subjective measures in explaining housing price variances for self-evident concepts such as greenness. While Song et al. [16] demonstrated that subjectively measured perceptions have a higher correlation with social inequality. However, previous research needs to better capture spatial differences and the underlining mechanism behind the discrepancy between the two frameworks.

Previous empirical studies attempted to understand the correlation between perceptions and the street features [14]. Zhang et al. [6] investigated the correlations between visual elements and six subjective perceptions (e.g., lively) and detected the negative impact of wall on all perceptions and the positive influences of natural features. Similarly, Qiu et al. [4] revealed that less typical features like signboard are important in affecting urban design perceptions. Nevertheless, prior studies only focused on the impact of visual elements on subjective perceptions. Acknowledging the difference between subjectively and objectively measured perceptions, it is crucial to further analyze and evaluate what features can potentially explain the discrepancies in measuring the same perception concept.

3 Methods and Process

3.1 Analytical Framework

With the research gap identified, this research is set to investigate the coherence and divergence systematically and spatially between subjective and objective measures of perceptions. It proposes high-throughput quantification and analysis methods with AI and big data. Furthermore, it is the first study which sheds light on the features that lead to differences of the two measurement streams (Fig. 1).

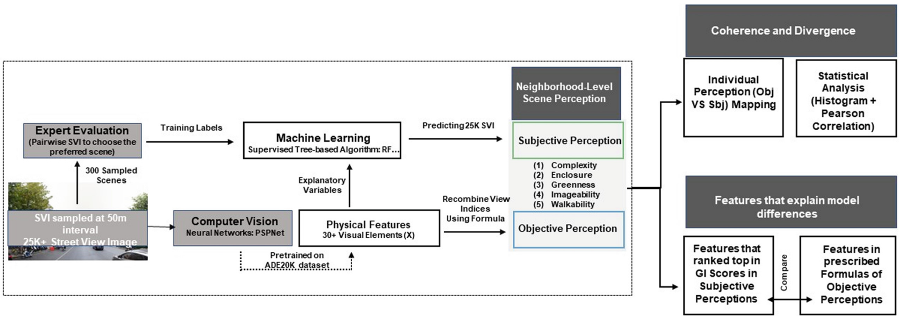

Fig. 1. Analytical framework.

3.2 Site Investigation and Data Preparation

As one of China's major financial, trade and shipping hubs, a city-wide analysis of the street perceptions in Shanghai using both measures across neighborhoods can provide meaningful comparisons and draw conclusions for the urban planning. The data are collected from (1) SVI: Baidu Street View API, and (2) shapefile of road networks: Open Street Map (OSM).

3.3 Quantifying Objective and Subjective Perception Scores

Extracting Physical Elements from SVIs. SVIs can reflect the human-centric perspectives of pedestrians or cyclists [10].We followed steps from previous studies [9] and sampled SVIs at 50 m intervals in QGIS along the road networks and requested SVI data from Baidu Street View Static API, and we retrieved 25,276 valid SVIs. Previous studies have used View Index to denote the ratio of the visual feature's total pixels to the full image [5, 9]. We applied Pyramid Scene Parsing Network (PSPNet) [17], to extract the view indices of physical elements from SVIs efficiently. The example semantic segmentation results are shown in Fig. 2. The process provided quantifiable view indices of 33 types of physical street elements from the dataset.

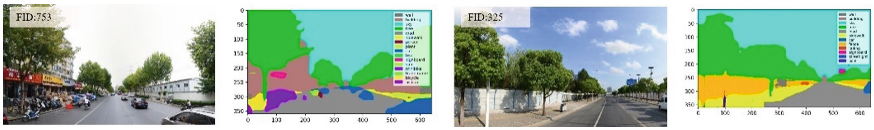

Fig. 2. Example of CV parsing raw SVI inputs and results.

Calculating Objective Perception Scores. Objective perceptions are calculated based on their operative definitions [14]. Following previous objective measurement framework [5], we calculated each perception using complex equations (Table 1) by recombining view indices. The results is then normalized to a 0–1 scale (worst to best) and obtained objectively measured perception scores.

Table 1. Measurements of objective perceptions.

Perceptions	Qualitative definition	Objective score equations
1. Complexity	The visual richness of a place [14]	$O1\_Cmplx_i = \frac{VI_{persn}+VI_{signb}+VI_{strlgh}+VI_{tree}+VI_{chair}+VI_{windwp}}{VI_{bldg}+VI_{road}}$ (1.1)

(*continued*)

Table 1. (*continued*)

Perceptions	Qualitative definition	Objective score equations
2. Enclosure	The degree to which streets are visually defined [14]	$O2_{Encls_i} = \frac{VI_{bldg}+VI_{tree}}{VI_{road}+VI_{sidewlk}+VI_{earth}+VI_{grass}}$ (1.2)
3. Greenness	Visual urban greenery [5]	$O3\_Green_i = VI_{tree}$ (1.3)
4. Imageability	The quality of a place that makes it distinct [14]	$O4\_Imgbl_i = VI_{bldg} + VI_{skycrp} + VI_{signb}$ (1.4)
5. Walkability	The psychological walking experience [5]	$O5\_Walkb_i = \frac{VI_{sidewlk}+VI_{fence}}{VI_{road}}$ (1.5)

Notes: VI_{tree}, $VI_{sidewlk}$, VI_{fence}, VI_{road}, VI_{persn}, VI_{signb}, VI_{strlgt}, VI_{windwp}, VI_{skycrp}, VI_{earth}, VI_{grass}, and VI_{chair} denotes the view index of tree, sidewalk, fence, road, person, signboard, streetlight, windowpane, skyscraper, earth, grass, and chair, respectively.

Calculating Subjective Perception Scores. Following Qiu et al. [4]'s method to quantify subjective perceptions, we sampled 300 SVIs across Shanghai, covering urban center to countryside and a visual survey website was developed. Participants were shown randomly paired SVIs side by side to choose preferred image to reply to each perception. And we further adopted the Microsoft TrueSkill algorithm to convert the collected pairwise preferences into interpretable scores [18]. Since our explanatory variables encompass roughly thirty physical features, 300 samples are sufficient because scholars mentioned ten times the number of variables could attain reasonable results [8]. We split 300 SVIs by 80% for training and 20% for testing. The five perceptions of 300 SVIs are used as training labels and the view indices are used as independent variables for prediction. Five tree-based algorithms are selected for prediction, the balance performance of R-squared (R2) and Mean Absolute Error (MAE) were used to judge the results (Table 2).

Overall, Gradient Boosting (GB) had best performances (lowest MAE) in predicting four qualities. And Random Forest (RF) performed the best in predicting 'complexity'. The five models had R2 values (0.41–0.51) which explain around half of the variance, and they partially or entirely outperformed previous research outcomes by Ito & Biljecki [19] and Naik et al. [8]. And MAEs range from 1.2 to 1.51, indicating that the prediction errors would not offset fitted value away from true scores in the 0–10 scale. Results revealed that people exhibit more similarities in evaluating complexity, greenness and imageability perceptions. The best-performed model is selected for each perception to predict subjective scores for the entire SVIs.

Verifying Perception Scores. Zhang et al. [6] reported high correlations in 'beautiful-wealthy' and 'depressing-safe', presenting multicollinearity issues. We applied Pearson correlation analysis to the five perceptions within each framework. We found that

Table 2. Performance of ML algorithms.

Model criterion	S1_ Cmplx		S2_Encls		S3_Green		S4_Imblt		S5_ Walkb	
	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE
Random Forest (RF)	0.49*	1.21*	0.43	1.55	0.41	1.43	0.29	1.73	0.46	1.36
Decision Tree (DT)	0.08	2.14	0.26	2.29	0.12	1.96	0.05	2.36	0.13	1.94
Voting Selection (VS)	0.31	1.60	0.35	1.60	0.35	1.53	0.26	1.78	0.36	1.55
Gradient Boosting (GB)	0.14	2.01	0.41*	1.52*	0.49*	1.39*	0.51*	1.62*	0.48*	1.33*
ADA Boost (ADAB)	0.32	1.63	0.41	1.52	0.31	1.57	0.20	1.84	0.48	1.33

Notes: S1_Cmplx, S2_Encls, S3_Green, S4_Imblt, S5_Walkb represents Complexity, Enclosure, Greenness, Imageability and Walkability, respectively. And * denotes the best performance model

within the subjective perceptions, enclosure-complexity, walkability-complexity, and walkability-enclosure indicated relatively high (between ± 0.50 and ± 1) degree correlations, other pairs showed moderate correlations (between ± 0.30 and ± 0.5). Comparing to subjectively measured perceptions, objective perceptions in general reveal low or moderate correlations except one pair (greenness-imageability). This indicates that choosing objective perceptions help reduce the multi-collinearity issues.

3.4 Coherence and Divergence of the Subjective and Objective Perceptions

The descriptive statistics of perceptions are listed in Appendix. Their coherence and divergence are further examined statistically using histogram (Fig. 3). First, scores measured from both strands were close to normal distribution. Second, only imageability revealed more coherence in the mean value, variance, and data distribution. Though we discovered some overlap for enclosure and walkability, they have different variances. Third, complexity and greenness have the most evident differences. Lastly, all subjective scores are larger in mean value than objective counterparts. The overall low median values of objective perceptions manifested that simply recombining view indices might not comprehensively capture all indicators of visual experience, for example, the psychological emotions may contribute to how people sense a space [4]. Accounting for the overlap and divergence between the two measurement approaches, the neighborhood perceptions is represented by the average of scores withing 1km radius of each downloaded housing property [4, 7], and mapped subjective and objective perceptions using natural breaks (Jenks) to examine the spatial distribution and within-perception heterogeneity pattern of each perception.

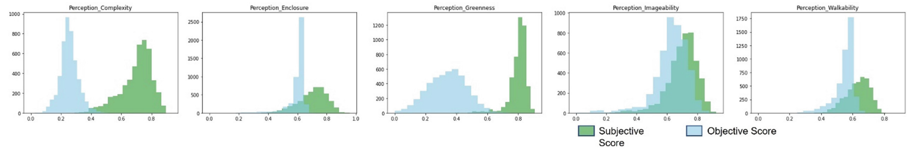

Fig. 3. Histograms of subjective and objective scores for five pairwise perceptions.

3.5 Features that Cause Differences Between Objective and Subjective Measures

Although pairwise perceptions exhibited similarities in subjective and objective scores, it exhibited more disagreements both statistically and spatially. This led to another unanswered question: what features in the streetscape can potentially lead to the divergence between subjective and objective perceptions?

Statistical inferences from prior studies revealed that visual elements have a different weighting in predicting subjective perceptions [6, 9]. On the one hand, for subjective perceptions, we chose tree-based algorithm models during prediction process as they can calculate Gini Importance (GI) score, which represents the importance of each explanatory variable [20] that contributes to the perception scores. We applied Tree-Based Regressor in the Python Scikit-learn package to calculate GI scores, ranking each physical feature in its impact. On the other hand, objectively measured perceptions are formula-derived by nature as framework was developed based on operative definitions [5, 14]. In essence, each perception is influenced by features prescribed in its formula. Hence, by comparing ranked physical elements from GI scores of subjective scores with features prescribed in their pairwise objective perception formula, we could identify elements that explain the disparity between the two measures for each perception.

4 Results and Discussion

4.1 Spatial Mismatch Between Subjective and Objective Perceptions

We mapped the distribution of subjective and objective scores of five perceptions in Shanghai (Fig. 4). For greenness, both streams have a strong consensus in identifying areas of bad or low quality. Regarding walkability and enclosure, higher subjective scores concentrate in sub-city centers in Lu Wan, Xu Hui, Zha Bei, Jing'An, Hong Kou and downtown Pu Dong. While higher objective scores scatter across districts, we see more areas are with high walkability and enclosure than their subject counterparts.

Both statistically and spatially, this research sheds new lights on the coherence and divergence of the two measurement frameworks. The mapping of each perception using both measures shows that street perceptions distribute unevenly. Subjective scores spatially exhibit a more uneven pattern. It is observed that districts with more urban and sub-city center areas show high complexity, enclosure, imageability and walkability while exhibit relatively lower greenness. This finding aligns well with our understanding that typically in densely populated downtown neighborhoods, the street interface is more complex (higher complexity), has more towers (higher enclosure), with its distinct identity (higher imageability) and is more walking-friendly (higher walkability).

However, due to the narrow street profile, trees are typically not lushly planted (lower greenness).

When making pairwise comparisons across measures, enclosure, greenness, and walkability seem to exhibit closer within-perception heterogeneity patterns. However, we find a significant discrepancy on pairwise perceptions regarding complexity and imageability. For example, most lands in downtown Pu Dong are rated as low quality in objective complexity, while subjective score shows them as high quality.

4.2 Key Urban Features for Variances Between Two Models

Figure 5 illustrates the feature importance of each subjectively measured score. Following prior research [4], the GI score was applied to assess the importance of various features contributing to the subjective scores, and we compared them with the prescriptive formulas of objective scores. This enabled us to derive preliminary assumptions on elements that can explain the differences between the two measurement frameworks for each perception.

Regarding the Complexity, besides sky, the top ten important features exhibit very close GI values in explaining subjective scores. For objective perception, complexity is affected by various elements such as the signboard. The low median value of objective complexity suggest it can further be improved by calculating the diversity of elements in the scene. The subjective measure of Enclosure seems to reveal people sense the enclosure predominantly by feeling the overall ratio of sky with its relationship with other vertical or horizontal features, thus the sky can be further added into the objective formula. Objective Greenness is solely dependent on 'tree'. Its scores show huge discrepancy from subjectively perceived greenness, which is determined jointly by trees, buildings, roads, cars, plants, earth, sky and wall. We speculate that greenness depends not only on quantity but on quality [21] and its structural composition of different types of greenery [22]. These assumptions need further verification in the future. Imageability represents the memorable quality of the site. The objective imageability clearly neglected the quality of softscape. For example, in Shanghai the lush row of London Plane trees along Heng Shan Road located in the French Concession Zone render the uniqueness of the neighborhood because of its cultural identity. This assumption is supported by examining the GI scores, of which the tree and grass rank 2nd and 3rd, respectively. The objective Walkability would benefit from incorporating additional elements such as the presence of cars and planting. However, regarding GI scores for subjective perceptions, some features that are important in previous research, such as street furniture and streetlights, were not among the top ten ranked GI scores. Current ML framework uses view indices of elements as explaining variables, this might cause some bias as the street furniture functions as street amenity and improves the walkability, but the limited pixel ratios of the furniture can mislead to a weak correlation. In the future it can be improved by counting object instances or judging its presence [19].

5 Conclusion

This study collected five urban design perceptions (i.e., complexity, enclosure, greenness, imageability, and walkability) using subjective and objective measures in Shanghai. It is

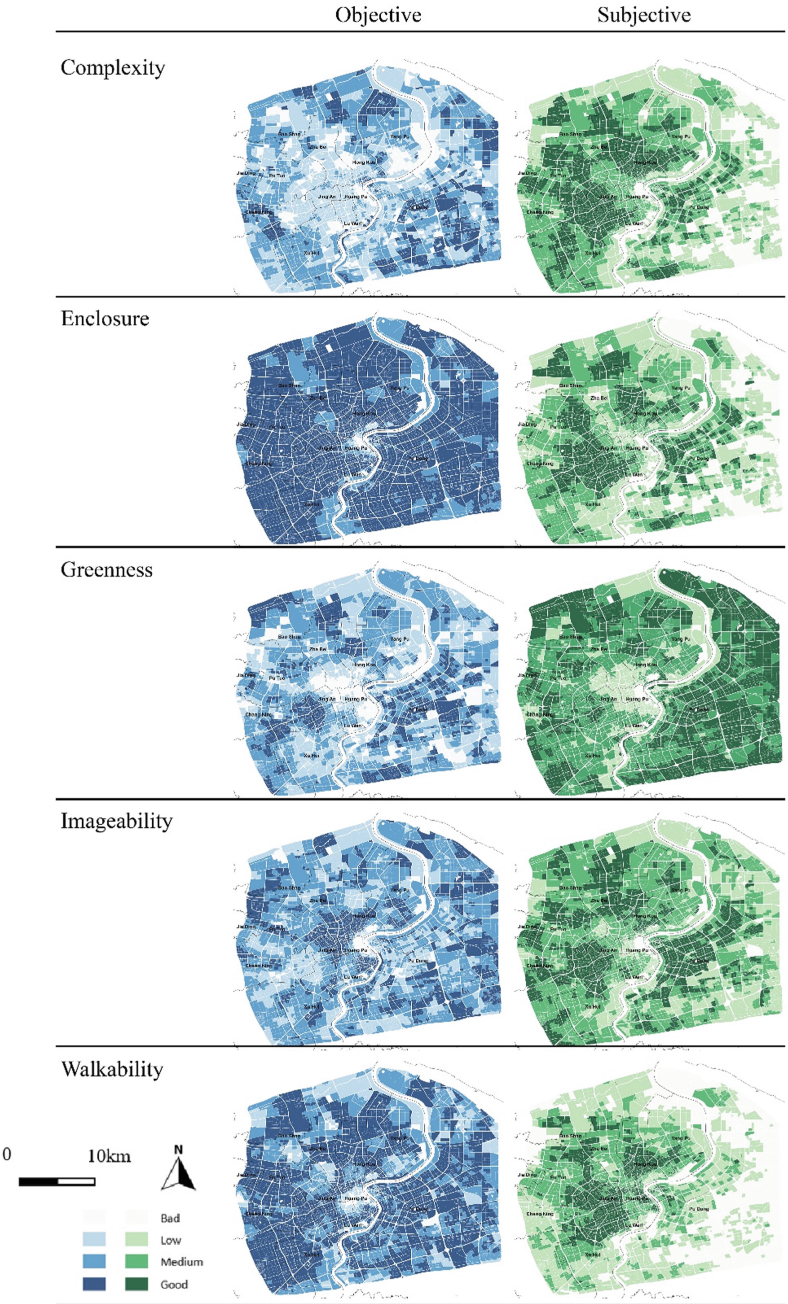

Fig. 4. Spatial distribution of subjective and objective perceptions. (Color figure online)

pioneering research that systematically compared their overlap and divergence between

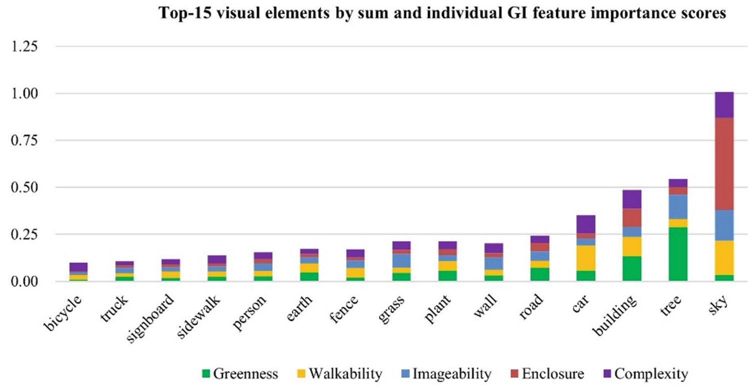

Fig. 5. Top 15 physical elements for each subjective score and their sum Gini importance.

the two streams. First, we identified both similarities and discrepancies between subjective and objective pairwise perceptions, they are reflected by statistical differences in variances and mean values. In general, subjective scores exhibit higher mean values than their objective counterparts. While objective perceptions can potentially help reduce the multi-collinearity issues identified in subjective perceptions. Second, we identified the disparity regarding within-perception heterogeneity across pairwise perceptions. It revealed clear spatial mismatch regarding the distribution pattern when mapping pairwise perceptions. It is observed in the findings that straightforward perceptions exhibit more similarities for the pairwise measurement, while complex qualities (e.g., imageability) show more discrepancies and even demonstrate contrary within-perception heterogeneity patterns. Third, it provides preliminary inferences on physical features that lead to the discrepancies of the two measures and provide advice on future model improvement. Finally, it overall provides a high-throughput measurement and comparison framework for subjective and objective perceptions, which can be applied to studies of other cities in the future as long as SVI data is available.

There are also limitations to the study. First, for subjective measure, the training samples were based on experts' preference selections on 300 images, the dataset can be further expanded. The prediction accuracy can be further improved by adding low-level features as explanatory variables [19]. Second, when comparing the pairwise concept, individual perceptions can be jointly analyzed by using other statistical models such as Principle Component Analysis to derive more interpretations [23]. Finally, our preliminary conclusions on improving the measurement models can be tested in future work.

Appendix

General descriptive statistics of perceptions.

Neighbourhood attributes		Count	Mean	Std. Dev.	Min	Max	Data source
Subjective streetscape attributes							
S1_CMPLX	Subjectively perceived complexity	40,159	0.6	0.0	0.5	0.9	Predicted by ML models from Baidu SVIs
S2_ENCLS	Subjectively perceived enclosure	40,159	0.7	0.1	0.3	0.9	
S3_GREEN	Subjectively perceived greenness	40,159	0.8	0.0	0.4	0.9	
S4_IMBLT	Subjectively perceived imageability	40,159	0.7	0.1	0.3	0.9	
S5_WALKB	Subjectively perceived walkability	40,159	0.6	0.1	0.4	0.8	
Objective streetscape attributes							
O1_CMPLX	Objectively calculated complexity	40,159	0.3	0.1	0.0	0.6	Recombined selected physical feature view indices
O2_ENCLS	Objectively calculated enclosure	40,159	0.6	0.0	0.1	0.7	
O3_GREEN	Objectively calculated greenness	40,159	0.4	0.1	0.0	0.8	
O4_IMBLT	Objectively calculated imageability	40,159	0.6	0.1	0.0	0.9	
O5_WALKB	Objectively calculated walkability	40,159	0.6	0.1	0.2	0.7	

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