

The association of subjective physical disorder and pedestrian volume: A big urban data and machine-learning approach

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ABSTRACT

Physical disorder in an urban area is characterized by visible damage, decay, and deterioration in its built environment, such as broken windows, graffiti, and litter. While its adverse effects on mental health, crime rates, and life satisfaction are well-documented, its impact on pedestrian volume—an essential indicator of urban vibrancy and livability—remains poorly discussed. Moreover, previous studies have predominantly relied on objective measures of physical disorder, overlooking subjective perceptions and potentially leading to biased interpretations. To address these crucial research gaps, we developed an online visual survey to evaluate the perceived physical disorder in Shanghai, China, across five dimensions: architectural disorder, commercial disorder, road disorder, greenery disorder, and infrastructure disorder. Then, we leveraged diverse machine learning algorithms to predict citywide spatial patterns of physical disorder based on both high-level street elements and low-level features. Finally, we examined the associations between urban physical disorder and pedestrian volumes, categorized by age and gender. Our findings reveal disparities in the influence of different types of subjective physical disorder on pedestrian volumes by demographic groups. Moreover, the subjective physical disorder provides a valuable supplement to existing built environment factors in explaining collective walking behavior. Notably, greenery disorder exhibits a significant negative association with walking behavior among female, adult, and elderly pedestrians, whereas infrastructure disorder predominantly impacts young pedestrians. Leveraging big data, this subjective measurement framework enables demographically sensitive evaluation systems of physical disorder as well as targeted interventions to reduce perceived physical disorder and improve walkability for different population groups.

1. Introduction

Physical disorder (PD) in urban environments is characterized by high levels of decay and deterioration, such as abandoned houses and trash on the streets (Sampson & Raudenbush, 1999). This condition has been found to negatively impact residents' satisfaction, well-being, and health behavior (Hill et al., 2005; Ross et al., 2000; Wallace et al., 2019). Remarkably, exposure to PD often reduces residents' physical activity levels and can lead to adverse health outcomes such as obesity (Burdette & Hill, 2008). In that regard, walking constitutes the most prevalent form of physical activity, plays a pivotal role in maintaining human health (Lu, Chen, et al., 2018). While substantial research attention has

been committed to understanding how some built environment features such as the 5Ds (density, diversity, design, destination accessibility, and distance to transit) (Cervero & Kockelman, 1997; Kang, 2018; Lu, Chen, et al., 2018; Chen et al., 2022) facilitate walking behavior, researchers and city policymakers are increasingly interested in understanding how street environment features including PD may hinder on walking behavior (Kelly et al., 2007; Mendes de Leon et al., 2009). Consequently, examining the link between PD and walking holds profound significance towards creating a healthy and vibrant city.

Methodologically, PD has been assessed through subjective, objective, or combined approach (Ndjila et al., 2019). Objective measurements typically involve methods such as systematic social observation

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(SSO) (Sampson & Raudenbush, 1999) and virtual street audit (Mooney et al., 2014), while surveys and interviews that gather self-reported perception ratings (Ross & Mirowsky, 1999) constitute subjective measurements. However, prior literature on PD has increasingly favored objective measures due to the high cost, time consumption, and lack of standardized definitions associated with subjective survey instruments (Quinn et al., 2016; Mooney et al., 2017). More recently, with the advancement of big data and Machine Learning (ML) models, researchers have advocated scalable methods to detect PD elements (Chen et al., 2023; Li et al., 2024). For example, Chen et al. (2023) developed a deep learning framework leveraging street view imagery (SVI) to quantify PD across 264 cities in China, identifying distinct spatial patterns (e.g., scattered and linear-concentrated distributions). Li et al. (2024) proposed a standardized YOLOv8-based protocol for efficient PD assessment. Nevertheless, we posit that object detection-oriented approaches cannot effectively capture comprehensive and subtle human perceptions of the built environment (Ramírez et al., 2021; Song et al., 2024). This gap underscores the necessity for complementary while scalable subjective measures that can clarify how PD influences residents' perceptions and subsequently shapes their walking behaviors, thereby contributing to the ongoing discussions in the relevant discourse.

Recent studies have demonstrated the potential of integrating SVI, crowdsourcing surveys, and deep learning tools to achieve large-scale urban scene perception (Qiu et al., 2022; Rossetti et al., 2019; Zhang et al., 2018). Given the paucity of subjective perception data regarding PD, we proposed a novel assessment framework that integrates new urban data (i.e., SVI data), crowdsourced visual surveys, computer vision (CV) segmentation algorithms, and ML predictions. This approach is exemplified by collecting a dataset encompassing Shanghai's built-up area in the city core. The ML models trained in this study could be employed for large-scale perceived PD evaluation in other cities across China or high-density cities with similar contexts in other regions. Furthermore, we examined the association between perceived PD and pedestrian volume across different genders and age groups.

1.1. Subjective PD measures

Subjective assessments of PD are critical because objective PD influences resident behavior and health outcomes primarily through perceptual and emotional processes (e.g., fear, stress) (Hill et al., 2005). Meanwhile, subjective PD also serves as a critical lens to understand 'perception bias,' defined as the gap between subjective assessments and systematic observations, which reflects cognitive and social processes shaping lived experiences (Skogan, 2015). Conventionally, the subjective perceptions of PD are often assessed by multidimensional constructs, e.g., lack of maintenance, vandalism, graffiti, and social incivilities (Janssen et al., 2022; Ndjila et al., 2019; Perkins & Taylor, 1996). These perceptions are significantly moderated by sociodemographic disparities, for example, Gaub et al. (2021) found that female residents report higher levels of neighborhood disorder and view it as a more significant issue than male residents, while Plascek et al. (2021) showed that black adults with lower educational attainment perceive lower levels of disorder compared to their higher-educated counterparts. Hence, assessing subjective PD may capture the nuanced psychological and behavioral impacts of urban PD that objective assessments may often overlook (Mooney et al., 2014).

1.2. Leveraging ML in visual perception

The integration of ML algorithms, crowdsourcing visual surveys, and

SVI datasets has emerged as an innovative method to assess urban design qualities at a large scale, e.g., greenness, openness, enclosure, walkability, imageability, aesthetics, safety, and comfort (Chen & Biljecki, 2023; Porzi et al., 2015; Zhang et al., 2018). Typically, researchers utilize pairwise comparisons from survey respondents to derive image perception scores that can be subsequently trained using ML models to predict perceived scores on a larger geospatial scale (Qiu et al., 2022; Salesses et al., 2013; Zhang et al., 2025). Both high-level features (HLF) and low-level features (LLF) serve as essential variables in machine learning models, enabling the prediction of subjective perceptions by capturing the complex, nonlinear interactions among these visual characteristics (Rossetti et al., 2019). Furthermore, empirical studies show that perceived PD negatively impacts physical function and self-rated health, particularly among older adults, by discouraging outdoor activity and increasing fear (Millar, 2020; Velasquez et al., 2022). It also reduces perceived neighborhood safety (Velasquez et al., 2022). Thus, combining SVI with ML offers new pathways for large-scale PD assessments anchored in collective perceptions.

1.3. The impact of PD on walking behavior

A growing body of empirical evidence suggests that the built environment features may influence walking behavior (Hamidi & Moazzeni, 2019; Kelly et al., 2007; Koo et al., 2023; Jiang et al., 2024). Overall, people walk more in an environment with higher levels of density, diversity, and distance to transit (i.e., the 5Ds framework) (Lu, Chen, et al., 2018) at the meso-level and free from PD (Owen et al., 2004) at the street level. In contrast, visual manifestations of PD, such as graffiti, litter, and dilapidation, reduce residents' perceived safety and willingness to walk (Burdette & Hill, 2008). Additionally, hazard cues in disordered environments heighten fear, restricting outdoor activity (Ross et al., 2000). The detrimental effects of PD are particularly pronounced among vulnerable demographics, with age and gender potentially mediating this relationship. It is hypothesized that children and the elderly may experience increased vulnerability due to mobility constraints (Glass & Balfour, 2003), while women may exhibit greater sensitivity to safety concerns, which in turn may influence their daily walking patterns (Paydar et al., 2017; Řisová & Sládeková Madajová, 2020). However, findings on whether PD reduces walking remain rather mixed, with some studies reporting no evidence linking PD and reduced walking behavior (Ball et al., 2010; Caspi et al., 2013). The mixed findings may stem from methodological heterogeneity due to differing PD measures and contextual variations. This highlights the need for standardized, perception-oriented frameworks that incorporate key demographic moderators to better reconcile these discrepancies in measurement.

In light of previous literature, we identified two major research gaps to address in this study. First, current large-scale assessment methods for PD primarily rely on objective evaluations, such as object counts (Chen et al., 2023), and lack a cost-effective, automated approach for assessing perceived PD on a large geospatial scale, such as across a whole city, which is crucial for understanding the street environment comprehensively. Second, while a few studies have examined the impact of objective PD on individual walking propensities (Kelly et al., 2007), there is no research on how perceived PD affects collective walking behavior, e.g., pedestrian volume. By tackling these gaps, our research aims to enrich our understanding of the role of subjective PD in shaping urban walking behaviors, highlighting the importance of considering perceived PD in urban planning and design.

2. Data and methods

2.1. Research area and analytical framework

2.1.1. Study area

Shanghai, China is selected as the study area because it is one of the cities with the longest history in the country, offering a diverse urban landscape mixing old and new buildings. This unique environment provides ample research samples for varying degrees of PD. In this study, we selected the region within Shanghai Outer Ring Road as our study area and focused on all streets covered by Baidu Maps. There are 60,007 sample points for the research area (Fig. 1).

2.1.2. Analytical framework

The analytical framework consists of five steps (Fig. 2). First, we extracted Street View Imagery (SVI) from all sampling points and collected subjective ratings of five types of perceived PD from 300 randomly selected SVI locations across Shanghai. Second, high-level street elements and low-level image features were extracted utilizing Deep Learning algorithms as explanatory variables to train the ML model. Third, we selected ML models with the best predictive power and predicted the five subjective PD scores for all SVI samples within the study area. Fourth, we combined several deep learning algorithms to train a model capable of identifying the number of pedestrians with different age and gender attributes in SVI. We also collected built environment (BE) attributes potentially influencing walking behavior. Fifth, we explored the associations between perceived PD and pedestrian counts across different age groups and genders, after controlling potential covariates using spatial regression models. Notably, a 500 m × 500 m fishnet with 2746 grids was generated over the study area, serving as our study unit. This scale of 500 m × 500 m grid was chosen because it allows reliable assessment of both macro-scale and micro-scale built environment features, and commonly used in previous

studies (Chen et al., 2022; Jiang et al., 2021; Sung et al., 2014).

2.2. Predicting subjective physical disorder (SPD)

2.2.1. Collection of SVIs

This study extracted the road network of the Shanghai metropolitan area from Baidu Map (<https://map.baidu.com>), employing QGIS software to sample SVIs at a 100-m interval. Subsequently, SVIs were downloaded using the Chinese Baidu Street View API (<https://lbs.baidu.com/>) from January 2020 to December 2022. To ensure the visibility and reliability of street element identification, we retained daytime images in which street features were clearly visible, regardless of whether the sky was clear or overcast. Dark, blurry, or indistinguishable images due to severe overcast or backlighting were excluded. After removing indoor and invalid images, 60007 SVIs were downloaded, with all images acquired at the size of 600 × 410 pixels facing perpendicularly to the road network to proxy the pedestrians' experience along streets.

This study adapted the PD indicators from a 15-item scale (Ross & Mirowsky, 1999), and further excluded indicators uncommon in the Chinese cities and added some new indicators, such as illegal constructions and street vendors following prior established PD research focusing on Chinese contexts (Chen et al., 2023). This study aggregates the indicators into five aspects of subjective PD perceptions: (1) architectural disorder, (2) commercial disorder, (3) road disorder, (4) greenery disorder, and (5) infrastructure disorder (Table 1).

To collect subjective PD scores, an anonymous online survey (<http://node.ystary.cn/#/>) was used and participants were presented with randomly paired SVI and asked to determine which image exhibited higher levels of disorder in one of five aspects of PD (Table 1). Regarding SVI sample sizes, we chose 300 randomly sampled SVIs (covering different geolocations to increase the data representativity) from Shanghai, comparable to previous studies (Chen & Biljecki, 2023;

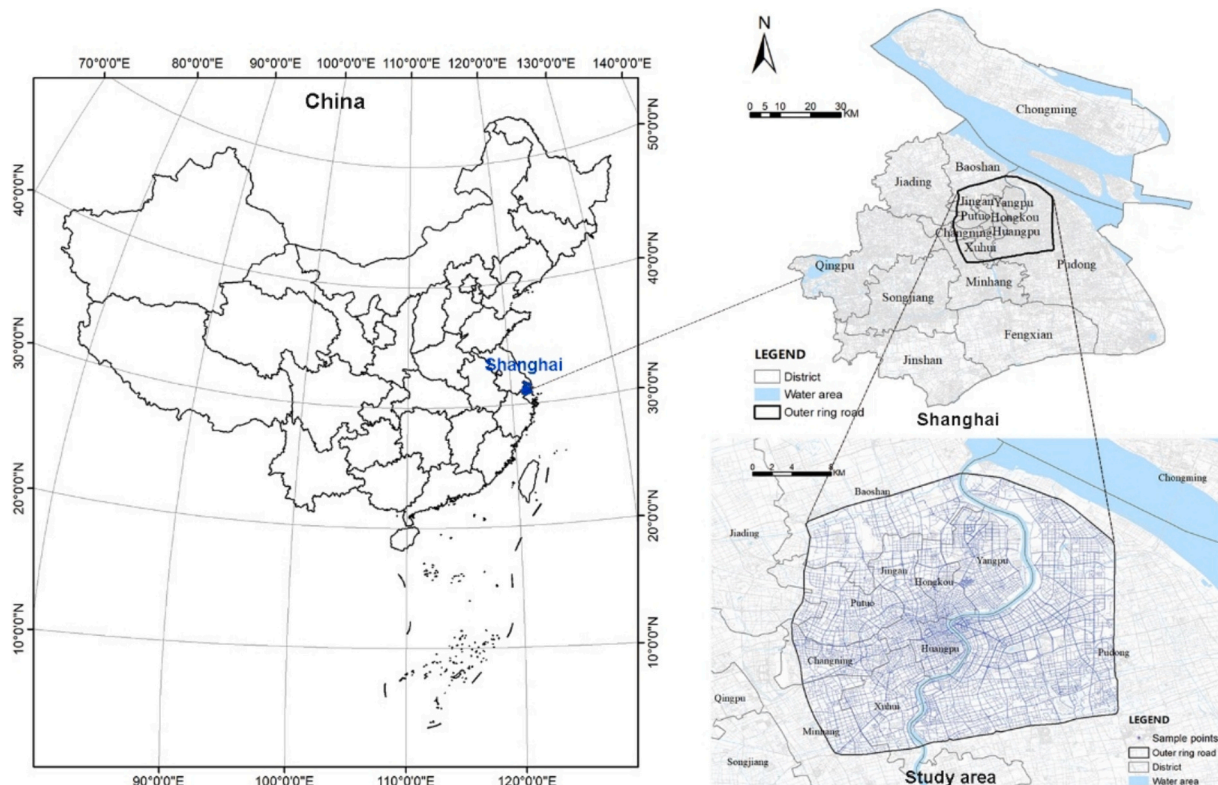


Fig. 1. The study area and the distribution of SVI sampling sites.

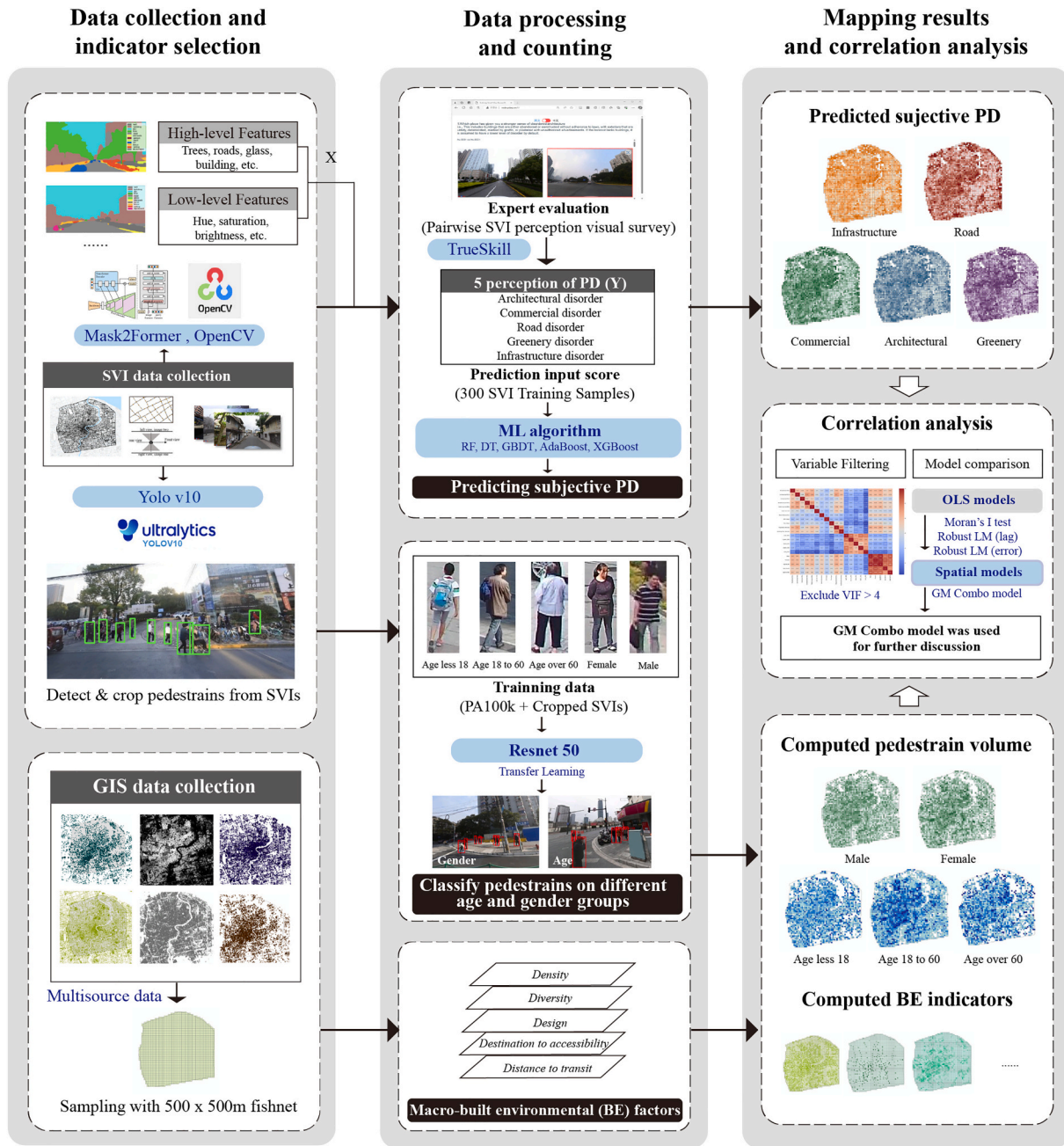


Fig. 2. Analytical framework for assessing the association between subjective PD and pedestrian volume using urban big data and machine learning.

Qiu et al., 2022). Our survey recruited over 50 respondents, maintaining a balanced gender ratio, aged between 20 and 40 years. Then, the TrueSkill algorithm was employed to convert votes into continuous scores (0 to 10, with 10 indicating the highest PD).

2.2.2. Obtaining high-level and low-level features of SVIs

Computer vision algorithm was utilized to extract 150 high-level physical features and 9 low-level image features from SVI. These features are critical indicators for identifying perceived PD (Rossetti et al., 2019).

High-level physical features pertain to specific physical elements in images, such as the sky, tree, and road. In this study, these features are quantified by the percentage of pixels they occupy in the total SVI (Fu

et al., 2019), as outlined in Formula (1). These high-level features were extracted through the advanced Masked-attention Mask Transformer (Mask2Former) ML framework, demonstrating superior performance in extracting detailed feature information from low-resolution images (Cheng et al., 2022). The model was trained using the publicly available ADE20K dataset (Zhou et al., 2017), which provides extensive annotations for diverse outdoor scene elements.

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

where VI_{pf} represents the pixel ratio of the physical feature in an image, $\sum_{i=1}^n PIXEL_{pf}$ denotes the number of pixels linked to the physical feature

Table 1
Summary of factors for five subjective PDs.

Perception	Factors	Subjective visual survey
Architectural disorder	Abandoned buildings, buildings with damaged facades, buildings with unkempt facades, graffiti, illegal advertisement, illegal or temporary buildings.	Which place has given you a stronger sense of disordered architecture?
Commercial disorder	Stores with poor signboards, stores with poor facades, vacant and pending stores.	Which place has given you a stronger sense of disordered commerce?
Road disorder	Broken roads, roads stacked with personal belongings, garbage or litter on street.	Which place has given you a stronger sense of disordered roads?
Greenery disorder	Green spaces exhibit messiness and lack of maintenance.	Which place has given you a stronger sense of disordered green spaces?
Infrastructure disorder	Broken infrastructure, neglected wires, malfunctioning streetlights, unmaintained distribution boxes, damaged public interface, and construction fence remnant.	Which place has given you a stronger sense of disordered infrastructure?

in an SVI. $\sum_{i=1}^n \text{PIXEL}_{\text{total}}$ indicates the overall number of pixels comprising the complete SVI.

Low-level Image features refer to the fundamental elements of an image, including edges, spots, hue, saturation, etc., which have been proven to correlate with human perception of places (Rossetti et al., 2019). These features were extracted using OpenCV (cv2), which provides comprehensive tools for efficient image processing and analysis.

2.2.3. ML training and prediction

We selected five tree-based ML models (i.e., Random Forest, Decision Tree, Gradient Boosting, AdaBoost, and XGBoost) to train on five categories of PD perceptions using the selected explanatory variables (See Table A1). These models have effectively predicted continuous labels in previous urban scene perception tasks (Song et al., 2022; Yao et al., 2021). We split 300 SVIs into 80 % training and 20 % testing datasets.

Models were evaluated using metrics such as R-squared (R^2) and Mean Absolute Error (MAE) to select the optimal model for predicting perceptions. Finally, the optimal ML models were adopted to predict the PD scores for the Shanghai SVI dataset. The PD score of the study area is calculated as the arithmetic average of subjective PD at each sampling point within each 500 m × 500 m grid.

2.3. Calculating pedestrian volume

In this study, we counted pedestrians by age and gender using SVIs, as described in Section 2.2.1 for the methodology of SVI acquisition. Each sample point from Shanghai was associated with four SVIs representing different orientations: left, right, front, and back. For pedestrian detection, we focused on the left and right orientations, which are more likely to capture pedestrians along the streets. Previous studies have demonstrated that the effective integration of SVIs with computer vision (CV) technology presents a cost-effective approach for estimating pedestrian volumes at the street level (Chen et al., 2020). Building on the findings of Liu et al. (2023), which demonstrated the feasibility of using CV technology combined with SVIs to accurately count elderly pedestrians, we expanded our dataset to include diverse age and gender groups and implemented an optimized deep learning algorithm. This study employed detector models to identify pedestrians from SVIs and utilized a classifier algorithm to categorize them into several specific demographic groups: female pedestrians, male pedestrians, young pedestrians (under 18 years), adult pedestrians (aged 18 to 60 years), and elderly pedestrians (over 60 years).

Table 2
Model performance across varied model and training datasets.

Models	Attribute	Training dataset	Test dataset	Overall accuracy
Resnet50	Age (AgeLess18, Age18–60, AgeOver60)	PA-100 K	Cropped SVIs	35.6 %
Resnet50	Age (AgeLess18, Age18–60, AgeOver60)	PA-100 K and SVIs	Cropped SVIs	71.6 %
Resnet50	Gender (Male and female)	PA-100 K	Cropped SVIs	56 %
Resnet50	Gender (Male and female)	PA-100 K and SVIs	Cropped SVIs	78.5 %

2.3.1. Model selection and dataset preparation

Before pedestrian volume calculation, pedestrian detection was performed using the YOLO v10 model, a real-time object detection framework introduced in May 2024 (Wang et al., 2024). This model was utilized to crop pedestrians from the SVIs of the study area in Shanghai, where 28,463 sample points were identified with pedestrian presence. We further trained the Resnet50 (Koonce, 2021) model using the PA-100K dataset (Liu et al., 2017), which is specifically designed for human attribute recognition and comprises 100,000 pedestrian images annotated with 26 attributes (i.e., gender, age, and clothing type). For our study, we focused on five key attributes: ‘AgeOver60’, ‘Age18–60’, ‘AgeLess18’, ‘Female’, and ‘Male’. For gender recognition tasks, we utilized 45,336 images labeled as ‘Female’ and 54,664 labeled as ‘Male’. For age recognition tasks, our dataset included 5687 images of young pedestrians, 6910 images of adult pedestrians, and 1469 images of elderly pedestrians to ensure a reasonable balance of different labels.

To address the unique characteristics of SVIs, such as distortions and varied backgrounds, we created a supplementary dataset of 2000 selected SVIs. These images were annotated by three trained researchers, who labeled 2331 pedestrians based on non-facial features due to obscured faces. After excluding non-identifiable images due to small size or obstructions, the team successfully labeled a total of 2331 pedestrians, comprising 1231 females, 1100 males, 570 young, 1165 adult, and 596 elderly pedestrians.

2.3.2. Model training and evaluation

The ResNet50 architecture is deployed for both age and gender identification. To enhance its adaptability to SVIs, the model is first pre-trained on the PA-100K dataset and then fine-tuned on the customized SVI dataset. We evaluate its classification performance to validate the effectiveness of this two-stage training strategy. The accuracy of the models is presented in Table 2. The results indicate that for both age and gender classification tasks, the model that was pre-trained on the curated PA-100K dataset and subsequently fine-tuned using cropped SVIs exhibited superior performance, demonstrating significant improvements over the models trained solely on the PA-100K dataset. Specifically, the overall accuracy in the age classification task reached 71.6 %, with sub-category accuracy of 68 % for individuals under 18 years, 84 % for those aged 18 to 60, and 63 % for individuals over 60. In the gender classification task, the overall accuracy was 78.5 %, with accuracies of 73 % for males and 84 % for females.

2.4. The built environment factors

To control for the potential built environment factors influencing pedestrian walking behavior, this study assessed built environment variables based on the 5Ds framework: density, diversity, design, destination accessibility, and distance to transit (Lu, Chen, et al., 2018). Density was measured in terms of building floor area and population density in grid. Population density was derived from the 100-m gridded population dataset of China's seventh census in 2020 (Chen et al., 2024). Diversity was assessed using point of interest (POI) data obtained through the API of Amap (<https://lbs.amap.com/>). In this research, the original POI dataset was reclassified into five categories: residential, enterprise, commercial, public service, and entertainment, representing the key urban functionalities. Design variables included the number of street intersections. Destination accessibility was quantified based on the number of POIs in different categories in each grid. Finally, the distance to transit was assessed by the number of transits stops, including both subway and bus stops, present in each grid.

2.5. Statistical analysis

2.5.1. Variable selection

In this study, the relationship between subjective PD and total pedestrian volume was first analyzed. Subsequently, the pedestrian volumes of five different population groups (i.e., female, male, young, adult, and elderly pedestrians) were examined as dependent variables in subgroup analyses. Before the statistical analysis, the Pearson

correlation analysis was conducted between the pedestrian volume and the independent variables (Figure A1). Only those variables indicating statistically significant correlations ($p < 0.1$) with each group of pedestrian volume were selected for follow-up analysis. Then, we remove the irrelevant indicators. Besides, the Variance Inflation Factor (VIF) was calculated to examine variables with correlation problems (VIF value >4). Variables with VIF values exceeding 4 were removed, including architectural subjective PD.

2.5.2. Spatial effects and model selection

Previous research has established that walking activity exhibits spatial autocorrelation (Chen et al., 2022), potentially leading to biased estimates when using ordinary least squares regression. To address this issue, we first verified the presence of spatial dependence using Moran's I test (Moran, 1950). Further, robust Lagrange Multiplier (LM) tests (Anselin et al., 2010) were employed to identify specific spatial effects, revealing both spatial lag and error influences in our data.

To accurately model these effects, we utilized the GMM-based Combination of Spatial Autoregressive Models (GM COMBO) from the Python Spatial Analysis Library (PySAL) to address spatial autocorrelation and heterogeneity in the data. This model combines spatial lag and error terms to enhance the robustness of the estimations. Founded on the Generalized Method of Moments (GMM) approach, the GM COMBO model is particularly adept at handling endogenous variables within spatial contexts (Kelejian & Prucha, 1998, 1999). The model can be described as follows:

Table 3

The data sources and general descriptive statistics of all variables.

Variables	Description	Count	Mean	S.D.	Max	Min
Subjective PD						
Architectural PD	Subjectively perceived disorder of architecture.	60,007	4.971	0.842	10.000	0.590
Commercial PD	Subjectively perceived disorder of commerce.	60,007	3.816	0.895	10.000	0.239
Road PD	Subjectively perceived disorder of road.	60,007	4.181	1.266	10.000	0.002
Greenery PD	Subjectively perceived disorder of greenery.	60,007	4.039	1.556	10.000	0.264
Infrastructure PD	Subjectively perceived disorder of infrastructure.	60,007	5.152	1.141	10.444	0.441
Pedestrian volume						
Female pedestrian	The count of female pedestrians.	28,463	1.533	1.727	15	0
Male pedestrian	The count of male pedestrians.	28,463	1.486	1.576	19	0
Young pedestrian	The count of pedestrians under 18 years.	28,463	0.378	0.717	8	0
Adult pedestrian	The count of pedestrians aged 18 to 60 years.	28,463	2.274	2.205	20	0
Elderly pedestrian	The count of pedestrians over 60 years.	28,463	0.368	0.7	11	0
Built environment factors						
<i>Density</i>						
Population density	The number of people per 25 ha.	2724	168.253	127.361	547.5	0.312
Building floor density	Average building floor density per square meter across 25 ha.	2724	1.451	0.858	6.629	0
<i>Diversity</i>						
Land use mix	Entropy for the diversity of land uses within the buffer area. Mix index = $-\sum p_i \ln(p_i)$, where p_i represents the proportion of i th of POI type.	2724	1.139	0.428	1.602	0
<i>Design</i>						
Density of road intersection	Number of road intersections in each 500 m $\times$ 500 m grid.	2724	5.477	7.205	133	0
<i>Destination to accessibility</i>						
Residential POIs (N)	Count of residential POIs (e.g., commercial house, residential building, residential community) in each 500 m $\times$ 500 m grid.	2724	13.265	18.298	237	0
Enterprise POIs (N)	Count of enterprise POIs (e.g., enterprise, company, factory) in each 500 m $\times$ 500 m grid.	2724	17.281	24.409	218	0
Commercial POIs (N)	Count of commercial POIs (e.g., food, beverage, shopping mall, market, store, theatre, commercial service office) in each 500 m $\times$ 500 m grid.	2724	24.046	27.938	207	0
Public service POIs (N)	Count of public service POIs (e.g., hospital, school, governmental organization, social group, management institution) in each 500 m $\times$ 500 m grid.	2724	16.009	22.343	212	0
Entertainment POIs (N)	Count of entertainment POIs (e.g., scenic spot, park, open square, tourist attraction) in each 500 m $\times$ 500 m grid.	2724	5.592	8.773	87	0
<i>Distance to transit</i>						
Bus stops (N)	Count of bus stops in each 500 m $\times$ 500 m grid.	2724	1.525	1.496	13	0
Subway stops (N)	Count of Subway stops in each 500 m $\times$ 500 m grid.	2724	0.467	1.301	11	0

Note: 1) All variables in this table are in their original forms. 2) The log transformed variables used in regression models in the latter sections will be depicted by prefix "Ln".

$$\begin{aligned} y &= \rho W_y + X\beta + u \\ u &= \lambda W_u + \epsilon \end{aligned} \quad (2)$$

where y is the vector of dependent variables influenced by both the spatial lag of y itself and a set of explanatory variables ρW_y . The spatial lag is represented by ρW_y , where ρ is the spatial lag coefficient and W_y is the spatial weights matrix, which is constructed using the K-nearest neighbors (KNN) method to define the interactions among spatial units. The coefficients for the explanatory variables are denoted by β . The error term u includes a spatial autocorrelation component λW_u and an independently and identically distributed random error vector ϵ , which accounts for unobserved influences.

In Model 1, only subjective PD variables were added into the GM COMBO model. In Model 2, both subjective PD and built environment variables were added into the model.

3. Results

3.1. Descriptive results

3.1.1. Subjective physical disorder scores

(a) ML model selection and prediction

During the perception prediction phase, the performances of different ML models varied across the five aspects of subjective PD. The XGBoost (Extreme Gradient Boosting) algorithm surpassed other models in predicting Commercial Disorder, Road Disorder and Greenery Disorder, while the Random Forest model demonstrated superior performance in Architectural Disorder. The Gradient Boosting model was particularly effective in predicting Infrastructure Disorder. As detailed in Table 4, specific predictive performance metrics show that the selected models achieved R^2 values ranging from 0.42 to 0.67 and MAEs ranging from 0.91 to 1.29, implying acceptable prediction accuracy compared to research utilizing similar ML models (Cui et al., 2023; Qiu et al., 2022; Zhang et al., 2018). Furthermore, the consistency between ML-predicted scores and human ratings is illustrated in Figure A3, confirming the validity of the prediction results.

(b) Spatial distribution of subjective PD indicators

We use selected 5 ML models to predict corresponding perception scores for 60,007 SVIs, as shown in Table 3. The five perceptions in descending order of average scores were Infrastructure, Architectural, Road, Greenery, and Commercial, indicating a higher perception of disorder in infrastructure within the Outer Ring Road of Shanghai. In addition, the higher standard deviations of the Greenery PD and Road PD scores implied that these two perceptions have a higher level of variation than the other three PD types.

After predicting Subjective PD scores for SVIs within the Outer Ring Road of Shanghai, the arithmetic mean of these scores was assigned to

corresponding streets using the spatial join function in QGIS. This process facilitated the visualization of the spatial distribution of five types of perceived PD scores across natural breaks, as illustrated in Fig. 3a. Meanwhile, the segmentation results and perception scores depicted by Fig. 4 were provided for six randomly selected SVI samples. Additionally, to ensure consistency in spatial analysis units, we created a grid of 2747 cells, each measuring 500 m by 500 m, and calculated the average Subjective PD scores within each grid cell for mapping and visualization, as shown in Figure A2.

The spatial mapping analysis reveals that the subjective PD levels in the old town areas on the Huangpu River's west bank are higher than those on the east bank. Specifically, in terms of architectural, commercial, and infrastructure PD, higher quantiles were observed in the eastern sections of Jing'an District, Hongkou District, Yangpu District, and Huangpu District. Conversely, the Pudong New Area and Baoshan District exhibit lower overall levels of greenery PD. However, greenery PD along the west bank of the Huangpu River is higher compared to other types of PD, indicating that green spaces in the older urban areas are more chaotic and disordered than those in the city's outskirts, implying that areas need to optimize the green space to improve the travel experience of pedestrians. Additionally, concerning road PD, significant levels are observed not only on the west bank of the Huangpu River but also in the southeastern corner of the Pudong District and along the south side of the Middle Ring Road.

3.1.2. Pedestrian volume

We obtained pedestrian volume data, including age and gender information, for each street in the outer road area of Shanghai covered by SVIs. In total, 85,934 pedestrians were detected, comprising 43,640 female pedestrians and 42,294 male pedestrians, with 10,755 young pedestrians, 64,716 adult pedestrians, and 10,643 elderly pedestrians. Fig. 3b presents the pedestrian counts on each street in Shanghai, divided by age and gender groups. Pedestrian counts ranged from 0 to 20, with detailed statistics provided in Table 3.

The spatial patterns are clearly visible, with most detected pedestrians concentrated on streets within the middle ring area. Pedestrian density is notably high in the Huangpu District. Specifically, the walking areas for male and female pedestrians largely overlap, although some localized differences were observed. The elderly pedestrians are more concentrated in specific areas, primarily on the west bank of the Huangpu River near the old city. For subsequent statistical analysis, the counts for each of the five pedestrian groups were aggregated within each grid.

3.2. Model results

The Moran's I test results for the residuals of GM COMBO models are presented in Tables 5 and 6. Compared to the OLS baseline models, the average Moran's I values for residuals significantly decreased. This indicates that the GM COMBO model has effectively mitigated the spatial autocorrelation. After incorporating built environment attributes into

Table 4
Performance of machine learning algorithms.

ML Model	Architecture		Commercial		Road		Greenery		Infrastructure	
	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE
Random Forest	0.44*	1.01*	0.38	1.35	0.52	1.17	0.63	0.99	0.49	1.41
Decision Tree	0.18	1.18	0.30	1.26	0.30	1.45	0.41	1.21	0.28	1.61
Gradient Boosting	0.35	1.05	0.40	1.31	0.51	1.20	0.64	0.96	0.55*	1.29*
AdaBoost	0.43	1.01	0.42	1.28	0.52	1.18	0.60	1.01	0.42	1.49
XGBoost	0.39	1.07	0.42*	1.24*	0.53*	1.18*	0.67*	0.91*	0.52	1.34

Notes: * denotes the best performance model.

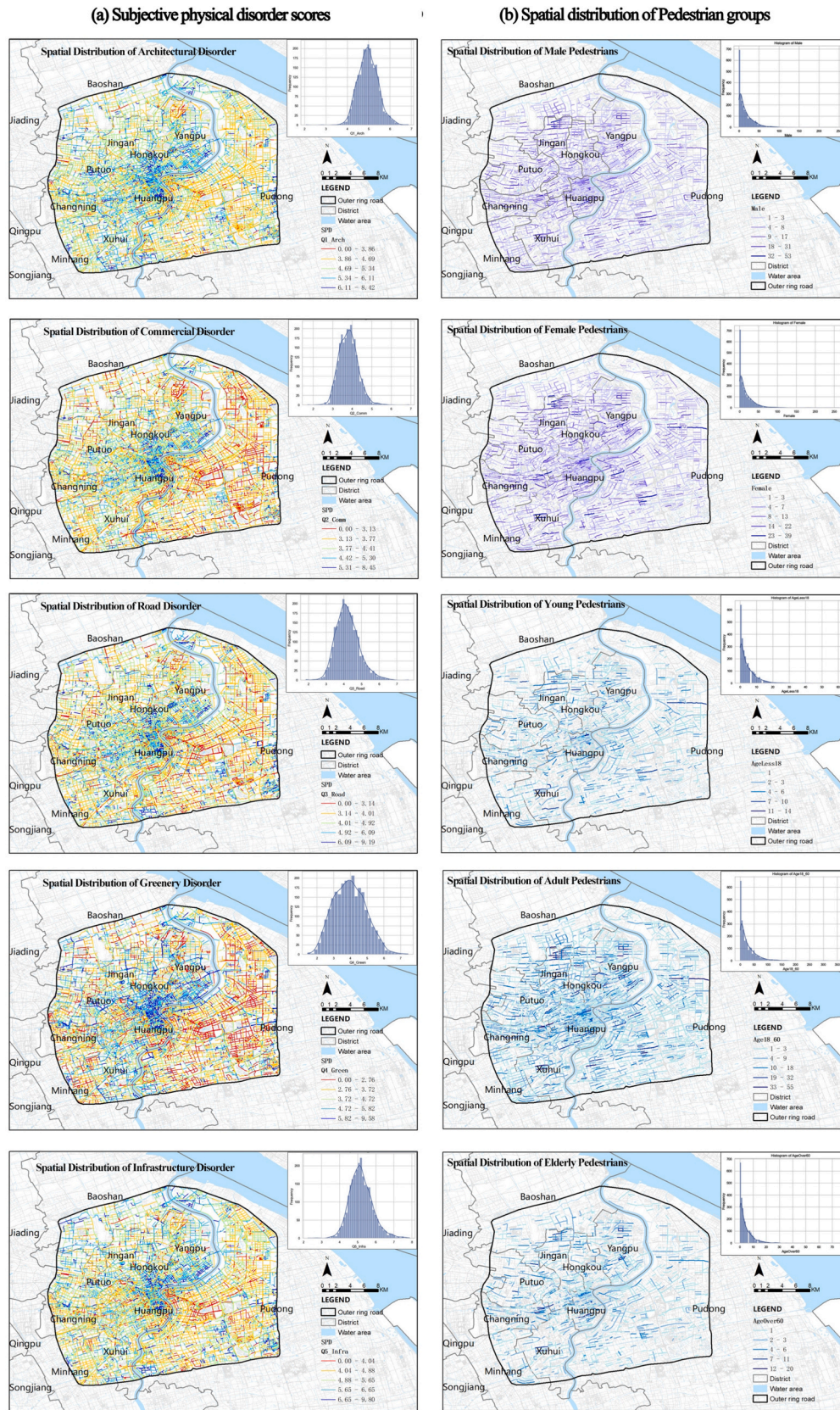


Fig. 3. Spatial distribution of subjective PDs and 5 pedestrian groups (a) Spatial distribution and histogram of five subjective PD scores (Architectural, Commercial, Road, Greenery, and Infrastructure disorder); (b) Spatial distribution and histogram of five pedestrian groups (Male, Female, Young, Adult, and Elderly).

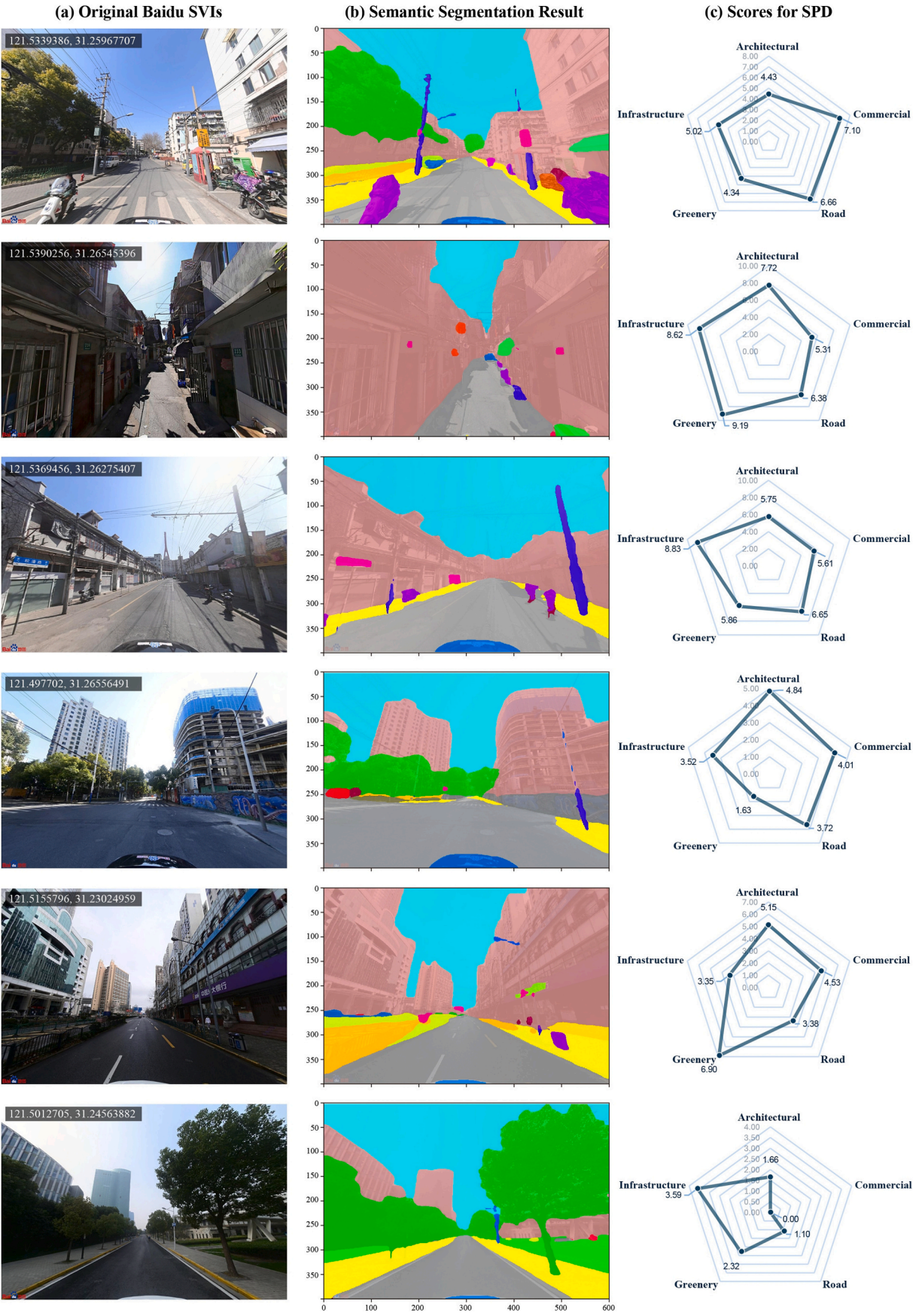


Fig. 4. Samples of (a) origin SVI, (b) semantic segmentation result, and (c) the corresponding predicted subjective PD scores.

Table 5

The results of GM COMBO models with subjective PD as variables.

Variables	GM COMBO Model 1 (Y = Male)		GM COMBO Model 1 (Y = Female)		GM COMBO Model 1 (Y = Young)		GM COMBO Model 1 (Y = Adult)		GM COMBO Model 1 (Y = Elderly)	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Constant	0.76050		2.0680		0.9693	**	2.4615		−0.6152	
Commercial PD	31.8838	***	29.6595	***	7.2621	***	44.6284	***	9.8028	***
Road PD	3.4502		2.0737		0.1588		3.4347		1.9449	*
Greenery PD	7.5478	***	7.4964	***	2.7806	***	10.5286	***	1.7275	**
Infrastructure PD	−30.0647	***	−30.2568	***	−8.5787	***	−43.9088	***	−7.898	***
Pseudo R-squared	0.583		0.580		0.445		0.596		0.507	
Moran's I on residual	−0.1055		−0.0995		−0.1266		−0.1048		−0.0971	

* $p < 0.1$.** $p < 0.05$.*** $p < 0.01$.**Table 6**

The results of GM COMBO models with subjective PD and built environment as variables.

Variables	GM COMBO Model 2 (Y = Male)		GM COMBO Model 2 (Y = Female)		GM COMBO Model 2 (Y = Young)		GM COMBO Model 2 (Y = Adult)		GM COMBO Model 2 (Y = Elderly)	
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Constant	−7.7852	***	−5.2913	***	−0.8417	*	−8.9978	***	−3.2170	***
Subjective PD factors										
Commercial PD	21.8770	***	20.6992	***	5.2736	***	29.4965	***	7.6910	***
Road PD	3.4122		1.0364		−0.0258		1.8101		2.5100	**
Greenery PD	−4.7483		−5.3880	**	−0.2009		−8.3284	**	−1.6082	**
Infrastructure PD	−4.7797		−5.7381		−3.1906	***	−5.6318		−1.4233	
Built environment factors										
Population density	14.4001	***	10.4198	***	2.0914	***	18.4452	***	4.0817	***
Building floor density	6.6563	**	5.4908	*	1.0027		10.0165	**	1.1443	
Land use mix	−4.7686	***	−5.0422	***	−0.5470		−8.4066	***	−0.9897	***
Density of road intersection	97.1779	***	96.1307	***	26.9296	***	138.4849	***	27.8846	***
Residential POIs (N)	22.2067	***	25.6737	***	1.2469		37.9155	***	8.3217	***
Enterprise POIs (N)	−13.0750	***	−11.8618	***	−3.0199	***	−17.1972	***	−4.5302	***
Commercial POIs (N)	12.1476	*	15.1057	***	4.3222	***	19.7797	*	3.0795	***
Public service POIs (N)	15.2564	***	16.8884	***	3.3720	***	28.2723	***	0.3311	
Entertainment POIs (N)	16.5101	***	22.4118	***	3.4889	***	30.2017	***	5.2457	***
Bus stops (N)	15.8386	***	19.5992	***	4.1115	***	28.4736	***	3.0624	***
Subway stops (N)	13.5465	***	17.7989	***	4.5325	***	22.9519	***	3.9456	***
Pseudo R-squared	0.697		0.692		0.553		0.712		0.595	
Moran's I on residual	0.0550		0.0819		0.0130		0.0655		0.0796	

* $p < 0.1$.** $p < 0.05$.*** $p < 0.01$.

the GM COMBO model, the explanatory power showed only a modest improvement, with the average pseudo- R^2 increasing from 0.607 to 0.697 (Model 1 vs. Model 2). This suggests that the effects of macro-level BE indicators may have already been partially captured by Subjective PD variables.

3.2.1. Effects of subjective PD

Regression analysis showed that total pedestrian volume was significantly associated with certain subjective PD indicators, particularly commercial and greenery physical disorder (Tables A2, A3, A4). However, aggregate-level results did not capture all patterns. Stratified analyses by gender and age group indicated that the effects of specific Subjective PD types were more pronounced for certain demographic groups, but these associations were less evident in the total sample.

Among all Subjective PD indicators, commercial PD had the strongest explanatory power, with consistently positive and significant effects across all pedestrian groups in Model 1 (e.g., coefficient = 31.883 for

males, 29.659 for females; Table 5) and Model 2 (e.g., coefficient = 21.877 for males, 29.496 for adult pedestrians; Table 6). This indicates that perceptions of commercial PD strongly influence walking behavior, suggesting that higher levels of perceived commercial PD encourage walking across all genders and age groups.

Other Subjective PD indicators showed more varied effects for different pedestrian groups when built environment factors were incorporated in Model 2, especially considering greenery PD and infrastructure PD. For instance, greenery PD was negatively and significantly associated with walking among female pedestrians (coefficient = −5.388, $p < 0.05$), but not for male pedestrians, suggesting that highly level of perceived orderly greenery may promote walking for the female but not the male. For young pedestrians, infrastructure PD had a significant negative impact (coefficient = −3.190, $p < 0.01$). Among elderly pedestrians, walking behavior was positively associated with road PD (coefficient = 2.510, $p < 0.05$) but negatively with greenery PD (coefficient = −1.608, $p < 0.05$). For adult pedestrians, greenery PD also

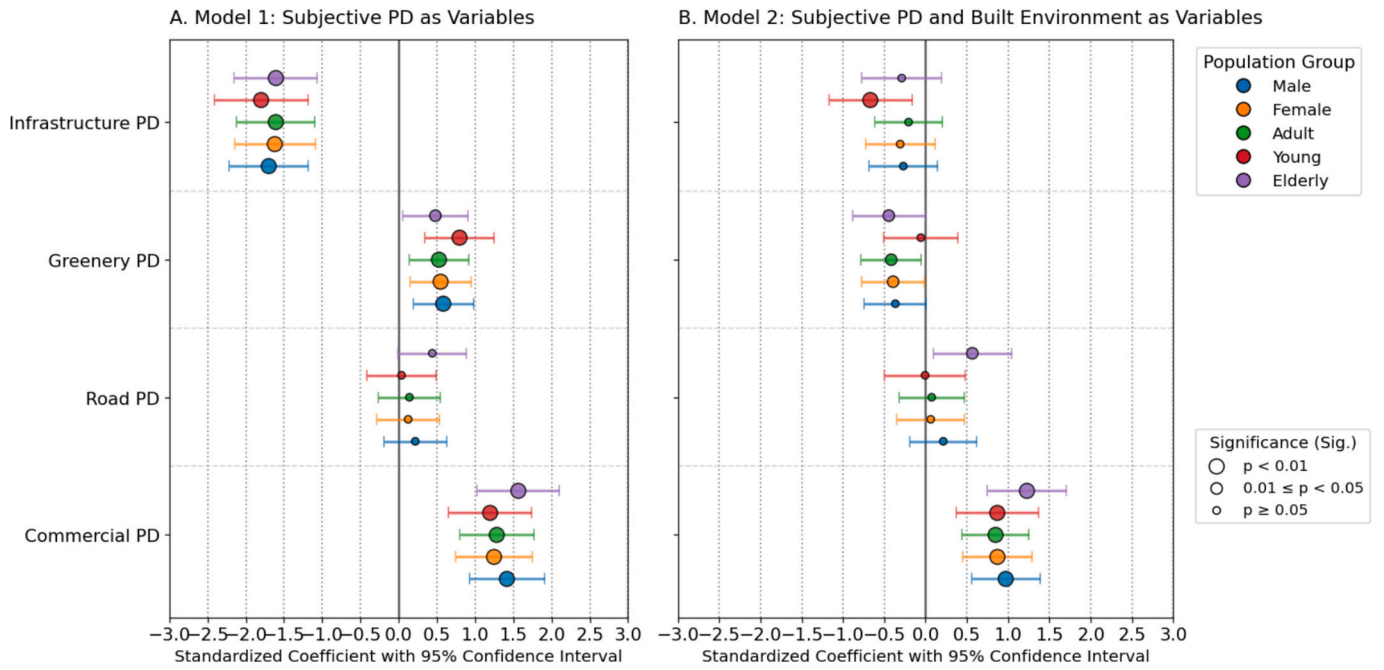


Fig. 5. Standardized coefficients of subjective PD variables on the outcome across population groups: (a) Model with subjective PD variables only; (b) Model adjusting for built environment variables. Error bars indicate 95 % confidence intervals.

had a significant negative association (coefficient = -8.328 , $p < 0.01$). To visually illustrate these findings, Fig. 5 presents the standardized regression coefficients of subjective PD indicators across population groups, both before and after adjusting for built environment factors.

3.2.2. Effects of built environment

Nevertheless, most built environment variables demonstrated significant associations with pedestrian volume. Population density, density of road intersections, Commercial POIs, Entertainment POIs, Bus stops, and Subway stops were consistently positively associated with walking across all groups, aligning with prior studies that highlight their role in facilitating pedestrian volume (Chen et al., 2022; Lu, Chen, et al., 2018). Conversely, Enterprise POIs exhibited significant negative effects across all groups, consistent with prior literature (Chen et al., 2022). However, land use mix also showed significant negative effects for all groups except the young group, highlights the varying relationship between land use diversity and walking behavior across different studies (Barnett et al., 2017; Boer et al., 2007), reflecting the context-specific nature of such interactions. Furthermore, while studies on how macro-level built environment factors influence pedestrian volume have rarely explored gender differences, prior research on age differences has established an inverted U-shaped relationship between urban density and pedestrian volume (Liu et al., 2024), whereas this study found a positive and statistically significant correlation.

4. Discussion

4.1. The significance of subjective PD

Subjective PD varies across demographic groups and potentially mediates the link between objective PD and active travel behaviors and public health outcomes. This study aims to develop a scalable ML

approach to predict PD perceptions by integrating expert-driven crowdsourced survey data, SVI, and CV algorithms. The ML models deliver robust predictions and reveal the heterogeneous spatial distribution patterns of five types of PD in Shanghai, China. Furthermore, applying the spatial model confirms that subjective PD significantly impacts pedestrian volume, indicating the importance of assessing subjective PD. In addition, this subjective measurement method offers a complementary perspective for urban research and future urban revitalization planning. It captures detailed and nuanced perceptions often overlooked when relying solely on objective measures.

4.2. The contribution of subjective PD to walking

The Subjective PD attributes demonstrated strong explanatory power in predicting pedestrian volume across different demographic groups, addressing gaps in previous studies that overlooked the impact of PD on collective walking patterns (Ghani et al., 2016; Liu et al., 2024). Our findings confirmed that Subjective PD features effectively complemented built environment factors in explaining pedestrian volume. Beyond the macro-scale built environment factors commonly discussed in previous research (Chen et al., 2020; Kang, 2018), subjective PD features proved equally significant, particularly in understanding pedestrian activity across diverse demographic groups.

Diverging from established associations between PD and reduced outdoor activity (Marco et al., 2017), our analysis revealed a positive association between subjective commercial PD and pedestrian volume. This apparent contradiction arises because the pairwise comparison method captures not only physical deterioration but also functional dimensions of disorder, including mixed land uses, business diversity, and economic informality. Consequently, Shanghai's organically evolved commercial districts with dense small enterprises registered higher PD scores than planned developments. Functional disorder dimensions

could enhance street vitality by facilitating economic accessibility and social encounters, potentially explaining the observed pedestrian attraction (Jacobs, 1961; Li & Pang, 2024; Ochoa et al., 2024; Spierings, 2023; Tiitu et al., 2024).

For gender differences, pedestrian volume among females showed a stronger negative correlation with greenery PD, suggesting that women tend to walk more in well-maintained green spaces due to safety concerns (Richardson & Mitchell, 2010). Regarding age differences, younger pedestrians were more negatively affected by infrastructure PD, possibly due to the limited range of destinations they visit, requiring more orderly street facilities. For elderly pedestrians, road PD was positively associated with walking, potentially due to their preference for older neighborhoods with vibrant commercial activities, despite higher perceived PD. Both adult and elderly groups exhibited negative associations between greenery PD and pedestrian volume, underscoring the importance of well-maintained green spaces. While the positive impact of green spaces on walking behavior has been widely validated (Chandrabose et al., 2024; Kaczynski & Henderson, 2007; Lu, Sarkar, & Xiao, 2018), this study specifically highlights the role of well-maintained and attractive greenery (i.e., quality of greenery) in promoting walking among women, adult, and elderly pedestrians.

4.3. Implications for urban planning and design

This research offers several implications for urban planning and design. First, our research reveals that subjective PD shapes walking behavior across different demographic groups differently. Moreover, it extends our understanding of walking determinants for various age groups. For instance, reducing greenery PD could encourage walking among women, adults, and elderly individuals, while addressing infrastructure PD may create safer and more convenient walking environments for children. Our findings support the notion that for urban authorities, enhancing streetscapes can serve as a cost-effective and practical approach to promoting urban vitality and pedestrian volume (Ewing et al., 2016). Additionally, our research findings enable urban designers to better understand urban conditions from PD dimensions and appending to the existing measurement of constructs like urban design quality, devise targeted design strategies, and foster healthy and inclusive urban environments, ultimately contributing to a more equitable society (Pineo, 2022).

4.4. Limitations and future research

The study contains several limitations. First, although our machine learning approach integrated both high-level and low-level visual features and demonstrated strong agreement with human auditors' evaluations, the explanatory power for specific categories of PD (e.g., infrastructure and commercial PD) remains moderate. The complex and dynamic mechanisms through which various visual features influence subjective PD also require further exploration. Future research could address these limitations by expanding the training dataset and refining algorithms to capture additional Objective PD indicators. Such improvements would enable a more comprehensive interpretation of how objective built environment attributes influence subjective perceptions of disorder.

Second, as a proof-of-concept research, this exploratory study focused on identifying general patterns among pedestrians across three age groups. Perceptions of PD may vary significantly across age subgroups within adults aged 18 to 60, suggesting that examining finer

demographic distinctions could be a valuable direction for future research. Additionally, interaction effects between demographic factors such as age and gender represent another important research perspective worthy of further investigation. Future studies could incorporate perception surveys from more diverse age groups, employ specific age categories, and systematically examine interactions between demographic factors. These investigations could be enhanced through expanded participant recruitment and complementary high-resolution SVIs captured in the field.

Third, although the concept of neighborhood disorder originated from Western urban studies, subtle yet meaningful cultural differences may exist in how specific environmental elements are perceived as disorderly and how these perceptions affect walking behavior. Future comparative studies conducted in both Chinese and Western cities could enhance the cross-cultural generalizability of our findings.

5. Conclusion

This research advances urban analytics by introducing a novel framework that predicts citywide subjective PD using SVIs. By systematically evaluating five subjective PD categories—architectural, commercial, road, greenery, and infrastructure—through perceptual surveys and machine learning algorithms incorporating high-level street elements and low-level visual features, we demonstrate that subjective PD measures offer critical insights into walking behaviors that complement traditional objective assessments.

Our findings contribute to the field in three key aspects. First, commercial and infrastructure PD exhibit contrasting associations with pedestrian volumes—while perceived commercial PD positively correlates with walking in the Chinese context, infrastructure deficiencies disproportionately deter young pedestrians. Second, greenery PD shows significant negative associations with walking patterns among female, adult, and elderly pedestrians, suggesting targeted vegetation maintenance as an equity-sensitive intervention. Third, our perception-integrated framework outperforms conventional methods in explaining pedestrian behavior variance through its capacity to capture nuanced human-environment interactions.

These insights underscore the importance for urban planners and policymakers to prioritize mitigating greenery PD to enhance walkability for vulnerable populations while maintaining appropriate levels of commercial vitality. The methodology developed offers municipalities a scalable tool for perceptual environment assessment using ubiquitous street view data. Future research should explore the specific mediating mechanisms behind demographic-specific PD impacts and validate these relationships across diverse cultural contexts. This work emphasizes the necessity of incorporating human perception metrics alongside traditional urban analytics to create inclusive, pedestrian-oriented cities.

CRediT authorship contribution statement

Fangqi Liu: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Yi Lu:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Qiwei Song:** Writing – review & editing, Software, Methodology, Formal analysis, Data curation. **Waishan Qiu:** Resources, Methodology. **Dongwei Liu:** Writing – review & editing, Software.

Appendix A

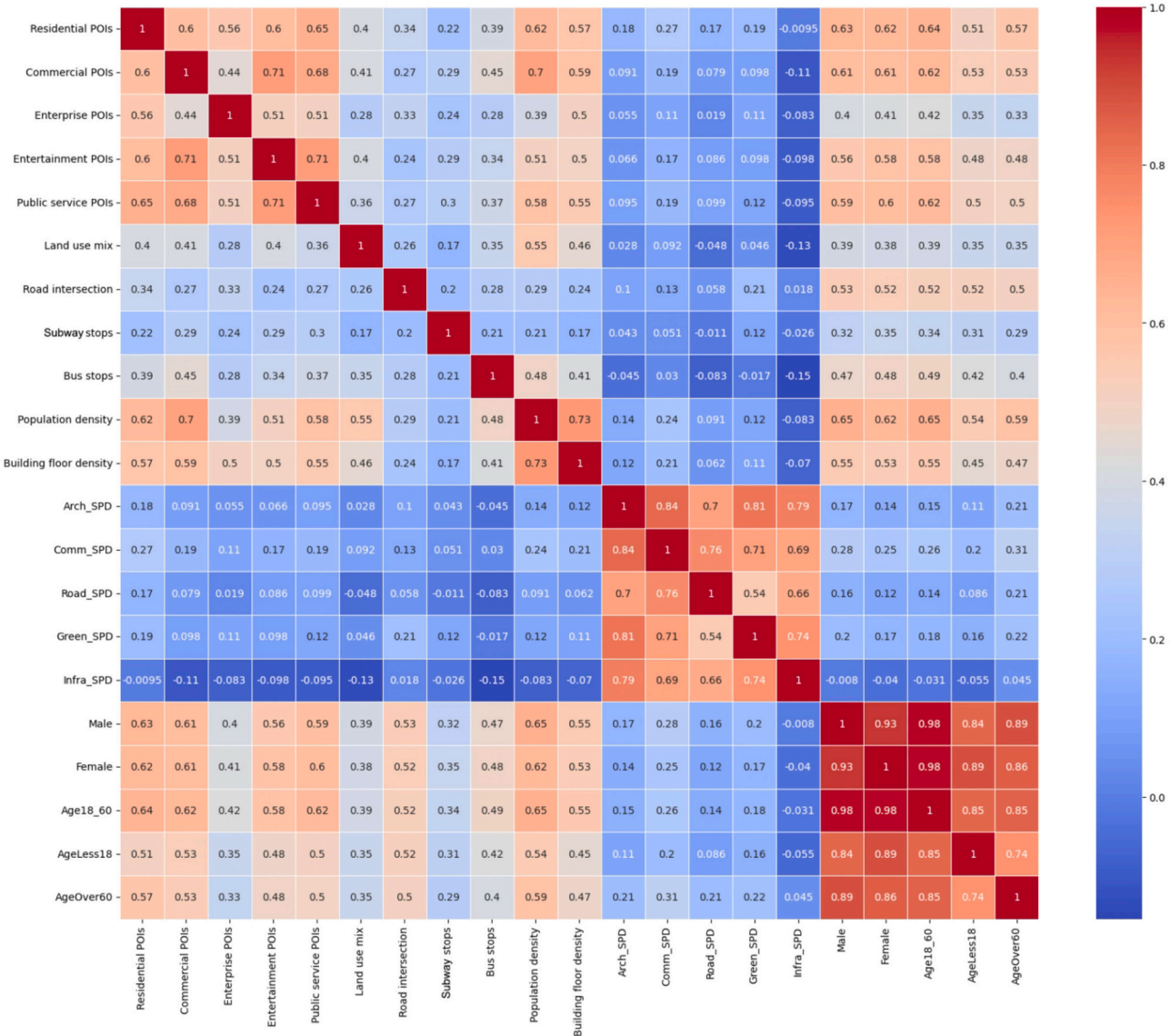


Fig. A1. The pairwise correlation analysis for all variables.

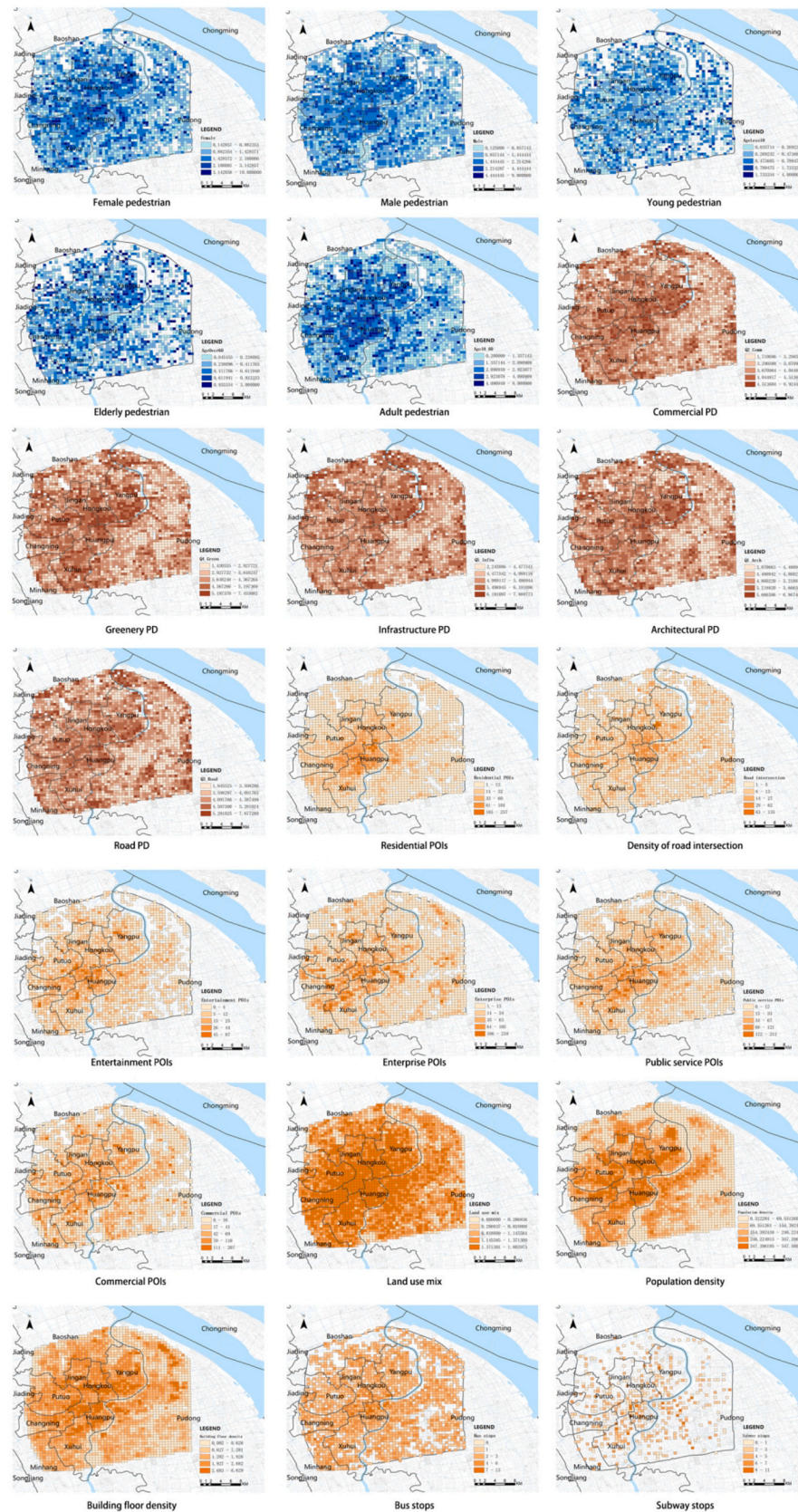


Fig. A2. Spatial distributions of all variables using grid-based statistical units in the study area.

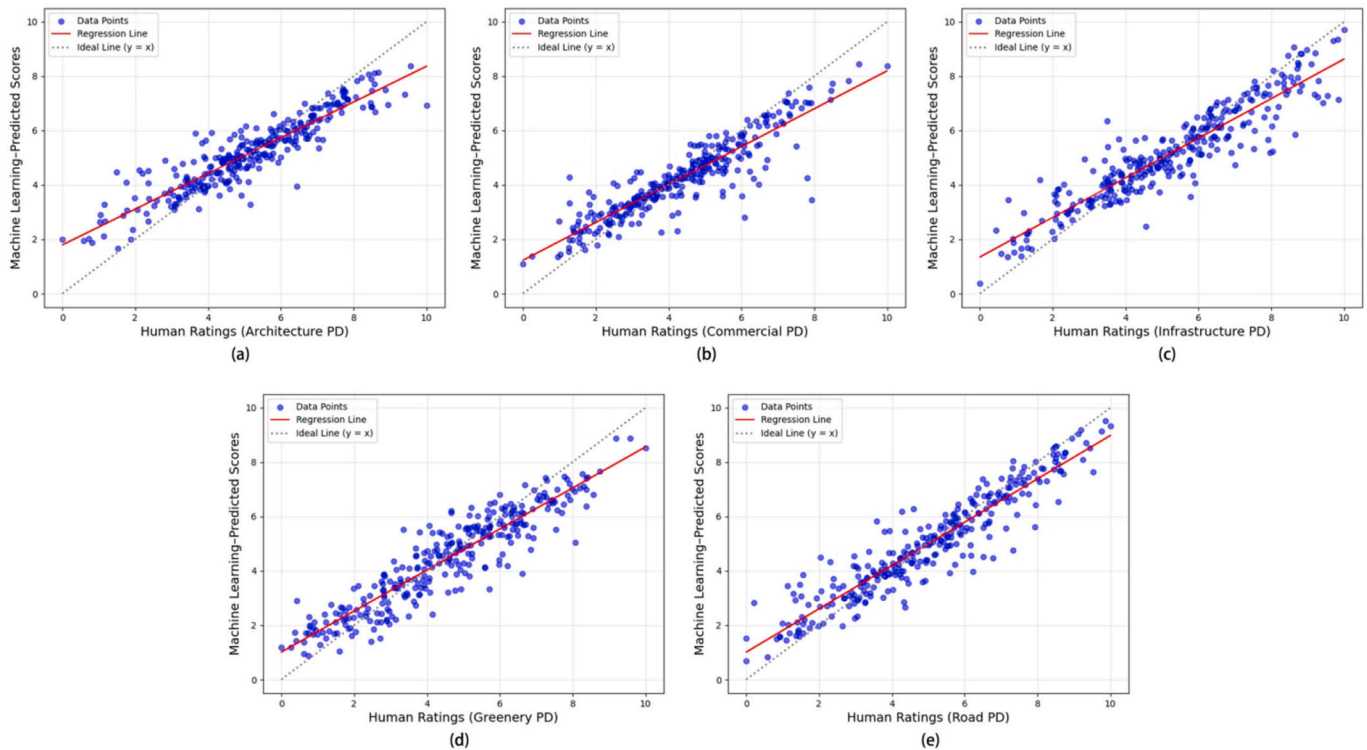


Fig. A3. Comparison between machine learning-predicted scores and human ratings.

Table A1

Feature selection of subjective PD explanatory variables.

Perception	Predictors of high-level physical features	Predictors of low-level image features
Architectural disorder	Wall, tree, road, grass, person, earth, table, plant, car, house, mirror, box, path, stairway, blind, bench, bus, truck, streetlight, pole, plaything, bag, minibike, bicycle, traffic, ashcan, bulletin.	Mean hue, Hue standard deviation, Mean saturation, Saturation standard deviation, Mean brightness, Brightness standard deviation, Number of blobs, Number of edge pixels.
Commercial disorder	Wall, tree, road, windowpane, grass, person, door, table, mountain, plant, painting, mirror, fence, railing, box, column, sand, stairs, palm, truck, awning, streetlight, apparel, pole, poster, plaything, barrel, bag, minibike, bicycle, traffic, ashcan.	Mean hue, Hue standard deviation, Mean brightness, Brightness standard deviation, Number of edge pixels.
Road disorder	Wall, tree, road, grass, person, earth, door, table, mountain, plant, car, painting, house, fence, rock, railing, base, box, column, signboard, skyscraper, stairs, stairway, bench, bar, truck, awning, streetlight, booth, apparel, pole, banister, van, plaything, bag, minibike, step, trade, pot, bicycle, sculpture, traffic, ashcan.	Mean hue, Hue standard deviation, Brightness standard deviation, Number of blobs, Number of edge pixels.
Greenery disorder	Tree, road, grass, earth, table, mountain, plant, chair, railing, box, sand, stairway, flower, streetlight, poster, plaything, barrel, bag, minibike, trade, traffic, ashcan, plate.	Mean hue, Hue standard deviation, Mean saturation, Saturation standard deviation, Brightness standard deviation, Number of edge pixels.
Infrastructure disorder	Sky, tree, road, grass, earth, door, table, plant, chair, railing, box, stairs, bus, awning, apparel, pole, banister, plaything, bag, pot, bicycle, traffic, ashcan, plate.	Mean hue, Hue standard deviation, Mean saturation, Saturation standard deviation, Mean brightness, Brightness standard deviation, Number of blobs, Number of edge pixels.

Table A2

The results of OLS models with SPD as variables.

Variables	OLS Model (Y = Total)		OLS Model (Y = Male)		OLS Model (Y = Female)		OLS Model (Y = Young)		OLS Model (Y = Middle aged)		OLS Model (Y = Elderly)		vif
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
Constant	25.9451	***	10.9430	***	15.0020	***	4.5992	***	20.3248	***	1.0211	*	
Commercial PD	195.1927	***	96.8739	***	98.3187	***	21.5137	***	147.8948	***	25.7842	***	3.37
Road PD	7.7439		5.5812		2.1628		-0.2625		4.9168		3.0896	**	2.68
Greenery PD	69.0668	***	33.4440	***	35.6228	***	9.8129	***	51.2384	***	8.0156	***	2.71
Infrastructure PD	-198.0278	***	-95.5143	***	-102.5135	***	-25.1098	***	-150.0012	***	-22.9167	***	2.84
R-squared	0.185		0.186		0.173		0.147		0.179		0.174		
Adj. R-squared	0.184		0.185		0.172		0.145		0.178		0.173		
Moran's I on residual	39.035	***	37.833	***	37.732	***	28.977	***	38.959	***	32.103	***	

(continued on next page)

Table A2 (continued)

Variables	OLS Model (Y = Total)		OLS Model (Y = Male)		OLS Model (Y = Female)		OLS Model (Y = Young)		OLS Model (Y = Middle aged)		OLS Model (Y = Elderly)		vif
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
Robust LM (lag)	343.251	***	336.963	***	322.713	***	238.091	***	343.246	***	255.966	***	
Robust LM (error)	0.624		1.234		2.065		13.776	***	1.302		3.979	**	

* p < 0.1.
 ** p < 0.05.
 *** p < 0.01.

Table A3

The results of OLS models with subjective PD and built environment as variables.

Variables	OLS Model (Y = Total)		OLS Model (Y = Male)		OLS Model (Y = Female)		OLS Model (Y = Young)		OLS Model (Y = Middle aged)		OLS Model (Y = Elderly)		vif
	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.	
Constant	−15.2099		−9.1893		−6.0206		−0.6803		−10.7705		−3.7591		
Subjective PD factors													
Commercial PD	56.0493	***	28.0684	***	27.9808	***	6.9836	***	39.6611	***	9.4045	***	3.77
Road PD	2.6677		3.3142		−0.6466		−0.3557		0.5679		2.4555	**	2.79
Greenery PD	−9.3904	*	−4.3943	*	−4.9961	*	0.3711		−8.1887	**	−1.5728	*	3.02
Infrastructure PD	−14.1659	*	−6.2851		−7.8808	*	−4.6716	***	−8.1134		−1.3809		3.47
Built environment factors													
Population density	38.3192	***	21.4370	***	16.8822	***	3.5682	***	28.8365	***	5.9145	***	3.48
Building floor density	16.5780	***	8.7746	***	7.8035	**	1.4981		13.7984	***	1.2815		2.51
Land use mix	−10.5520	***	−5.0227	***	−5.5293	***	−0.4607		−8.9557	***	−1.1356	***	1.56
Density of road intersection	234.0045	***	116.6649	***	117.3396	***	33.4551	***	167.9146	***	32.6348	***	1.28
Residential POIs (N)	84.7746	***	40.9170	***	43.8576	***	5.0077	***	67.4043	***	12.3626	***	2.47
Enterprise POIs (N)	−31.6741	***	−17.0228	***	−14.6513	***	−3.5835	***	−22.8511	***	−5.2395	***	1.77
Commercial POIs (N)	13.0408	**	5.3160	*	7.7248	**	2.8800	***	8.4226	*	1.7381	*	3.11
Public service POIs (N)	41.5873	***	19.7532	***	21.8340	***	4.5195	***	36.0994	***	0.9684		2.71
Entertainment POIs (N)	53.7629	***	23.3345	***	30.4284	***	5.1177	***	42.3361	***	6.3091	***	2.81
Bus stops (N)	41.0725	***	18.2018	***	22.8707	***	4.6129	***	33.1095	***	3.3501	***	1.44
Subway stops (N)	34.9198	***	15.0726	***	19.8471	***	4.7521	***	25.8147	***	4.3530	***	1.17
R-squared	0.673		0.658		0.646		0.508		0.671		0.552		
Adj. R-squared	0.671		0.656		0.644		0.505		0.669		0.549		
Moran's I on residual	18.533	***	16.393	***	18.491	***	13.481	***	17.302	***	16.361	***	
Robust LM (lag)	60.129	***	55.925	***	54.077	***	38.887	***	63.396	***	23.877	***	
Robust LM (error)	51.841	***	31.115	***	48.424	***	6.297	**	37.569	***	34.158	***	

* p < 0.1.
 ** p < 0.05.
 *** p < 0.01.

Table A4

Results of GM combo models using total pedestrian count as the dependent variable.*

Variables	GM COMBO Model 1 (Y = Total)		GM COMBO Model 2 (Y = Total)	
	Coef.	Sig.	Coef.	Sig.
Constant	2.9364		−13.0273	***
Subjective PD factors				
Commercial PD	61.3100	***	4.5968	***
Road PD	5.4708		0.7003	
Greenery PD	15.3446	***	−2.0181	**
Infrastructure PD	−60.5144	***	−1.5326	
BE factors				
Population density	/		6.1735	***
Building floor density	/		2.1518	**
Land use mix	/		−4.1240	***
Density of road intersection	/		19.7072	***
Residential POIs (N)	/		4.9774	***
Enterprise POIs (N)	/		−4.7567	***
Commercial POIs (N)	/		4.8701	***
Public service POIs (N)	/		4.8217	***
Entertainment POIs (N)	/		5.3944	***
Bus stops (N)	/		7.8582	***
Subway stops (N)	/		8.3552	***
Pseudo R-squared	0.6031		0.692	
Moran's I on residual	−0.914	***	0.0819	***

* p < 0.1.
 ** p < 0.05.
 *** p < 0.01.

Data availability

Data will be made available on request.

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