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Non-Linear Effects of Built Environment on Cyclists' Perceived Safety and Comfort using Online Pairwise Voting

Abstract

Understanding how built environment (BE) features influence cyclists' perceptions is critical for designing human-centric and bike-friendly spaces. While previous research has largely focused on objective cycling conditions, this study addresses a key gap by investigating the non-linear relationships between BE features and cyclists' subjective perceptions of safety and comfort, through a novel integration of Street View Images (SVIs), computer vision (CV), and explainable machine learning (ML). Using a pairwise voting survey, 150 participants evaluated 300 SVIs, with the results extrapolated to 5,176 locations using CV and ML models. The Shapley Additive Explanations (SHAP) framework quantified threshold effects and highlighted asymmetries between perceived safety and comfort, revealing three key insights: (1) Over 80% of subjective perceptions are explained by spatial chaos, greenery, cycle lane type, feature entropy, perceived road width, and crowdedness, though their relative importance and thresholds vary; (2) Several BE features exhibit threshold effects, including notable inverted "V-shaped" trends, with safety demonstrating higher sensitivity and lower tolerance to BE features compared to comfort; (3) Comfort-oriented interventions are particularly effective in heritage areas where structural constraints limit safety improvements. These findings emphasize the need for localized and context-sensitive strategies that differentiate between safety-oriented and comfort-prioritized interventions, enabling more effective cyclist-friendly urban design.

Keywords: cyclists' perception, built environment, non-linear relationship, human perception, computer vision, street view image

1. Introduction

Cycling has emerged as a crucial component of sustainable urban mobility, offering multiple benefits including reduced carbon emissions, enhanced public health outcomes, and improved urban vitality (Gu et al., 2018; Ito and Biljecki, 2021). Cycling propensity depends strongly on a positive riding experience, for which safety and comfort are widely acknowledged as two essential prerequisites (Blitz, 2021; Fitch et al., 2022; Lim et al., 2025). Safety generally refers to perceived risks of traffic collisions and personal security (Cabral et al., 2018), while comfort covers the aesthetic appeal and pleasurability of the ride (Böcker et al., 2016). Both dimensions are shaped by moment-to-moment interactions with the street-level built environment (BE) and serve as robust predictors of cycling frequency and distance (Gan et al., 2021). Therefore, in street-level BE research, safety and comfort are not only fundamental measures of cycling environments but also proxies for complex perceptual mechanisms that require further investigation (Qi et al., 2025).

Although metrics characterizing BE, such as the green view index or the presence of cycle facilities, are commonly used as objective proxies to assess cycling safety and comfort, they often diverge from people's actual perceptions (Gao and Fang, 2025; Krenn et al., 2015). For instance, residents in areas deemed objectively conducive to cycling due to favorable infrastructure may still perceive the environment as unsafe or uncomfortable, and vice versa (Ma and Dill, 2017). Such discrepancies challenge the effectiveness of policy interventions in reconciling top-down planning strategies with bottom-up user needs (Cahyanti et al., 2022; Cain et al., 2014; Gullón et al., 2015). For instance, while cyclists may prioritize scenic routes through natural environments to avoid traffic, noise, and pollution, urban planners often emphasize direct routes with dedicated cycling

1 infrastructure, leading to potential misalignment in planning priorities (Marquart et al., 2020). This
2 tension highlights the need to include subjective perceptions when designing context-sensitive bike
3 environments (Delaney et al., 2017).

4 Traditionally, cyclists' perceptions of safety and comfort have been collected through
5 qualitative interviews or post-riding surveys (Costa et al., 2023; Ferreira et al., 2022). However,
6 these methods are labour-intensive and constrained in spatial resolution and data granularity, making
7 them untransferable for large-scale urban analysis (Koo et al., 2022; Liu et al., 2024). The collection
8 of street-level BE features faces similar limitations, as on-site audits require manual recording and
9 are difficult to scale (Ito and Biljecki, 2021). In response, recent advances in data collection
10 technologies and computer vision (CV) now enable the extraction of BE features from Street View
11 Images (SVIs). Machine learning (ML) models can then link these features to crowdsourced
12 perception survey data to predict subjective perceptions, for instance, whether a streetscape feels
13 "safe," "lively," "boring," "wealthy," "depressing," and "beautiful" (Dubey et al., 2016; Qiu et al.,
14 2022). This method has been extensively adopted in studies to explore the impacts of BE on
15 walkability, housing prices, and jogging (Kang et al., 2021b; Yang et al., 2024). However, most
16 existing studies adopt a pedestrian-oriented perspective, with limited exploration of cyclists'
17 experiences, revealing a significant research gap in the context of cycling.

18 To date, most studies investigating the relationship between BE features and cyclists'
19 perceptions of safety and comfort predominantly use linear models, such as linear regression or
20 geographically weighted regression (GWR) (Clark et al., 2021; Haustein and Möller, 2016; Ogawa
21 et al., 2024). While these approaches offer valuable insights, they frequently oversimplify the

1 complex, non-linear interactions that characterize human-environment dynamics (Ji et al., 2022).
2 For instance, visual complexity—a measure of the diversity and richness of BE elements—has been
3 shown to influence perceptions in non-linear ways, often following "U"- or "V"-shaped patterns
4 (Guan et al., 2022; Ma et al., 2023). Recent findings even suggest counterintuitive relationships; for
5 example, extremely high greenery may increase perceived danger by overwhelming cyclists with
6 too many visual elements (Ye et al., 2024). These non-linear dynamics highlight the need to move
7 beyond linear models to fully understand how BE features shape cyclists' experiences.

8 To address these gaps, this study examines the non-linear effects linking BE and cyclists'
9 perceptions by integrating SVIs, online surveys, ML techniques, and SHapley Additive exPlanations
10 (SHAP). Using Gusu District, Suzhou City, China—an area combining modern development with
11 historical preservation—as a case study, this research offers empirical evidence to inform policies
12 that better align with cyclists' perceptual needs through an innovative data acquisition and analytical
13 framework.

14 The remainder of this paper is structured as follows: Section 2 reviews prior relevant studies
15 and delineates the research gaps that this study aims to address. Section 3 details the study's context,
16 outlining the data sources and methodologies employed in the analysis. Section 4 reports on the
17 findings, presenting the outcomes of the subjective evaluations and discussing the relationships
18 between the BE features and cyclists' perceptions. Finally, Section 5 offers a conclusion to the
19 research, summarizing the key insights and implications of the findings.

2. Literature Review

2.1. Built environment features and their non-linear influences on cyclists' perceptions

The built environment (BE) at street level refers to the physical features that people can directly observe and experience in urban space (Koo et al., 2022). As these features immediately shape individuals' in-situ experiences, they represent a critical scale for investigating cycling safety and comfort (Gao and Fang, 2025; Xu et al., 2025). In traditional transport studies, numerous BE features have been identified as significantly associated with cycling safety and comfort, including building height variability, street wall continuity, cycle lane category, greenery, perceived road width, sky ratio, crowdedness, and the presence of waterfronts (Gu et al., 2018; Tran et al., 2020; Wu et al.; Xu et al., 2025; Zhou et al., 2022; Zhu et al., 2017).

Beyond studies focusing on the individual functionality of BE features, Lynch (1964) emphasized that the visual impression of a street depends not only on the presence of such elements but also on how they are organized. Streets containing similar types of BE features may evoke very different visual expressions when their spatial distribution, color, and texture vary (Ma et al., 2023). In computer vision (CV) research, this organizational dimension is often captured by the concept of "visual complexity," which quantitatively measures compositional characteristics: texture reflects edges and fine details, color contributes to visual diversity, and the richness and coherence of BE features convey impressions of legibility (Ma et al., 2023; Zhou et al., 2022). Furthermore, advances in CV have enabled the measurement of spatial chaos, which reflects street maintenance and cleanliness conditions (Chen et al., 2023). This feature captures signs of disorder such as damaged

1 infrastructure, neglected façades, litter, and obstacles, which reflect not only the deterioration of
2 individual elements but also the breakdown of spatial organization, implicitly signaling weakened
3 social norms (Chen et al., 2023; Wilson and Kelling, 1982). Empirical studies show that spatial
4 chaos reduces cycling frequency (Xu et al., 2025), yet its impact on perceived safety and comfort
5 remains insufficiently explored.

6 When explaining how BE influences cyclists' perceptions, most research has assumed linear
7 relationships. For instance, taller buildings, continuous street walls, and protected cycle lanes are
8 often treated as straightforward enhancers of safety and comfort, reinforcing enclosure and legibility
9 while reducing crowdedness (He and He, 2023; Hu et al., 2022; Ito and Biljecki, 2021; Koo et al.,
10 2022). However, a growing body of contrasting findings highlights the importance of considering
11 non-linear relationships. A higher sky ratio, for example, often enhances safety by creating open,
12 visible streetscapes that reduce blind spots and mitigate the “urban canyon” effect produced by
13 skyscrapers (Koo et al., 2022). However, the negative impacts are also observed, as excessive
14 openness may diminish the sense of enclosure and protection, leading to heightened vulnerability
15 (Harvey et al., 2015; Zeng et al., 2024). Similarly, perceived road width does not follow a simple
16 “wider is better” pattern but instead shows a U-shaped relationship with safety: moderate widths
17 strike the optimal balance, whereas very narrow or excessively wide roads are associated with
18 higher crash risk and reduced perceived safety (Ewing and Handy, 2009; Scheepers et al., 2016;
19 Ugan et al., 2022). Non-linear effects are also evident in visual complexity: moderate levels foster
20 perceptual fluency and positive emotions, while excessive visual information induces cognitive
21 overload and a sense of crowding, reducing perceived safety and comfort (Franěk and Petružálek,

2025; Jiang et al., 2021; Kawshalya et al., 2022). Although such dynamics of visual complexity have been documented in emotional responses (Van den Berg et al., 2016), driving behavior (Jiang et al., 2021), and walkability (Ma et al., 2023), their influence in cycling contexts remains underexplored.

2.2. Distinguishing cycling safety and comfort

Although perceived safety and comfort are interrelated and often co-present in cycling experiences, some scholars revealed that they play hierarchical roles in shaping behavior: safety functions as the fundamental threshold that determines whether cycling occurs, whereas comfort differentiates the intensity and persistence of cycling once basic safety expectations are met (Alfonzo, 2005; Lim et al., 2025; Xu et al., 2024). This hierarchical relationship explains why a street may be perceived simultaneously as “somewhat safe yet less comfortable” or “comfortable yet still not safe”, but only when safety exceeds a minimum threshold can comfort’s positive influence translate into sustained cycling (Clark et al., 2019; Fitch et al., 2022). Within this framework, BE interventions can sometimes generate conflicting effects. Features that enhance safety, such as traffic separation, do not necessarily improve comfort, while comfort-oriented designs, such as greenery, can sometimes compromise safety (Guo et al., 2022; Lawrence and Oxley, 2019; Xu et al., 2024). For example, moderate roadside vegetation enhances visual comfort but can become a safety hazard if overgrown and obstructing sightlines (Asgarzadeh et al., 2012; Ye et al., 2024). This conflict arises not from direct interactions between safety and comfort but from diminishing returns or trade-offs within each dimension independently (Ye et al., 2024). As a result, composite indices that aggregate safety and comfort may lead to misinterpretations, such as

1 promoting greenery expansion without recognizing its potential safety risks (Yang et al., 2024).

2 Furthermore, a flexible analytical framework is essential to account for regional variations in
3 how safety and comfort are perceived and prioritized. Perceptual thresholds for safety and comfort
4 vary substantially across regions. For instance, pedestrian presence enhances cyclists' comfort in
5 many European cities but increases risk perception in some Asian urban contexts (Ferreira et al.,
6 2022). Even within high-cycling nations, urban priorities diverge: Netherlands's mature cycling
7 infrastructure focuses on comfort optimization through shaded routes and aesthetic continuity,
8 whereas safety-dominated interventions in emerging cycling cities often neglect these comfort
9 dimensions (Pucher and Buehler, 2008). Historic urban cores exemplify this tension, where safety
10 upgrades like widened bike lanes may unintentionally disrupt streetscape integrity – a key comfort
11 factor tied to cultural identity (Tyler et al., 2018). Despite evidence supporting the need to analyze
12 these two aspects separately, many studies continue to treat safety and comfort as a single combined
13 indicator, potentially oversimplifying their distinct roles in shaping cycling behavior (Fitch and
14 Handy, 2018).

15 **2.3. Advances in subjective perception collection and integration** 16 **methods**

17 Traditional perceptual data collection methods such as stated-preference surveys and post-ride
18 questionnaires require respondents to recall environments and rate safety and comfort on Likert
19 scales (e.g., 1–5) (Fitch et al., 2022; Wahlgren and Schantz, 2011, 2012, 2014; Wahlgren et al.,
20 2010). However, these approaches face limitations: scale ratings are vulnerable to response biases
21 (e.g., central tendency), which reduce reliability (Manton et al., 2016; Qiu et al., 2022; Salesses et

al., 2013); low spatial resolution obscures localized environmental variations (Koo et al., 2022); and large-scale field surveys are resource-intensive and impractical citywide (Han et al., 2023).

The rise of street-view imagery (SVI) and crowdsourcing has enabled more scalable alternatives. Pioneering datasets such as Place Pulse 1.0 and 2.0 datasets first introduced the SVI-based online pairwise voting method, where participants select one of two images rather than assigning absolute scores (Dubey et al., 2016; Salesses et al., 2013). This method reduces scale bias, enhances response consistency, and simplifies the decision-making process, making it more consistent with real-world perceptual comparisons (Qiu et al., 2022; Yao et al., 2021). Although SVIs capture static, two-dimensional views, previous studies confirm that visual cues strongly correlate with perceptions of three-dimensional spatial experience (de la Fuente de Val et al., 2005; Frank et al., 2013; Rossetti et al., 2019). By emphasizing relative judgments, pairwise voting further strengthens the alignment between image-based evaluations and in-situ experiences (Kang et al., 2021a; Rossetti et al., 2019).

Machine learning (ML) has gradually gained prominence in exploring the nonlinear relationships between BE and subjective perceptions (Table 1). Traditional nonlinear models, such as generalized additive models and polynomial regression, offer certain interpretability but remain constrained by pre-specified functional forms, limiting their capacity to capture complex interactions (Cheng et al., 2020; Ji et al., 2022; Kerr et al., 2016). These limitations are particularly evident in perception-related studies, where high-dimensional and heterogeneous data often result in estimation bias (SONG et al., 2022). With advances in computer vision (CV), large-scale semantic BE features can now be extracted from SVI, further challenging traditional approaches

1 (Ito and Biljecki, 2021). By contrast, ML, as a data-driven “black-box” approach, can capture
2 complex patterns in multi-source heterogeneous features extracted via CV without relying on pre-
3 assumptions (Gao and Fang, 2025). Recent advances in post-hoc explanation methods, such as
4 SHAP and LIME, enable interpretation of individual feature contributions and interactions, thus
5 complementing predictive power with interpretability (Liu et al., 2023). Furthermore, ML exhibits
6 stronger generalization capacity, enabling efficient extension from limited labeled data to citywide
7 applications and offering spatially contextualized insights for policy-making (Li et al., 2015; Ogawa
8 et al., 2024).

9 SVI-ML perceptual assessment has matured and been validated across a range of perceptual
10 dimensions that capture public impressions of the urban environment (Table 1), including urban
11 perceptions such as safety, liveliness, beauty, wealth, depression, and boredom (Dubey et al., 2016;
12 Salesses et al., 2013; Verma et al., 2020; Wang et al., 2019; Yao et al., 2019), as well as spatial
13 qualities such as imageability, enclosure, human scale, transparency, and complexity (Qiu et al.,
14 2022; SONG et al., 2022; Tang and Long, 2019; Xu et al., 2022). Recent work has extended these
15 approaches to cycling-specific contexts, confirming the reliability of SVI in assessing cyclists’
16 perceptions (Ito and Biljecki, 2021; Zeng et al., 2024). Nevertheless, most existing studies have
17 concentrated on general or pedestrian-based perspectives, and the non-linear effects of BE on
18 perceived safety and comfort in cycling contexts remain underexplored, representing a key gap in
19 literature.

Table 1 Applications of SVI-ML perceptual assessment

Study	Year	Objective	Data size (SVI): scored/total	Machine learning (ML) model	Participants size	Scoring method
Place pulse 2.0 (Dubey et al.)	2016	Urban perception	110988 / 110988	Siamese CNN	81,630	Pairwise votes
(Yao et al.)	2019	Urban perception	25000/99440	Random forest	20	Scale 0-100
(Wang et al.)	2019	Urban perception	3000/134778	Random forest	30	Scale 0-10
(Verma et al.)	2020	Urban perception	200/600	Random forest	73	Scale 1-7
(Ito and Biljecki)	2021	Bikeability	800/12014	LightGBM	8	Scale 0-10
(Yao et al.)	2021	Urban perception	20000/128592	Random forest	20	Scale 0-100
(Qiu et al.)	2022	Space quality	300/25276	Random forest	43	Pairwise votes
(SONG et al.)	2022	Space quality	300/25276	Random forest	43	Pairwise votes
(Xu et al.)	2022	Space quality	300/25276	Random forest	45	Pairwise votes
(Han et al.)	2023	Restorative perception	1250/442252	Random forest	25	Scale 0-6
(Zeng et al.)	2024	Bike safety, security, beauty	25000/40776	Random forest	50	Binary rating: Good/Bad
(Costa et al.)	2024	Bike safety	4480/36700	PCS-Net	251	Pairwise votes
(Ogawa et al.)	2024	Urban perception	1000/610017	Siamese CNN	38525	Pairwise votes
(Zhang et al.)	2025	Urban safety perception	1000/69681	LLM (Multimodal Large Language Model)	50	Pairwise votes
(Zhu et al.)	2025	Urban perception	3000/15264	XGBoost	30	Scale 0-100

Note: “Data size (SVI): scored/total” indicates the dataset's scale used for training relative to the total dataset size in the context of SVI scoring.

“Urban perception”: perceived safety, liveliness, beauty, wealth, depression, and boredom.

“Space quality”: perceived imageability, enclosure, human scale, transparency, and complexity.

3. Methodology

This study utilizes a hybrid data collection framework, combining SVIs and OpenStreetMap (OSM) data as input, and employs multiple Computer Vision (CV) and GIS tools to extract BE features as independent variables. Data collection and feature extraction processes are detailed in our previous work (Xu et al., 2024; Xu et al., 2025), which utilize image classification and semantic segmentation to derive BE features from SVIs. The dependent variables are derived from online pairwise voting results, collected from 150 participants who rated their subjective perceptions of "safety" and "comfort", respectively. By leveraging the Shapley Additive Explanation (SHAP) model, the non-linear relationship between streetscapes and cyclists' perceived safety and comfort is illustrated. Figure 1 presents the workflow for this study.

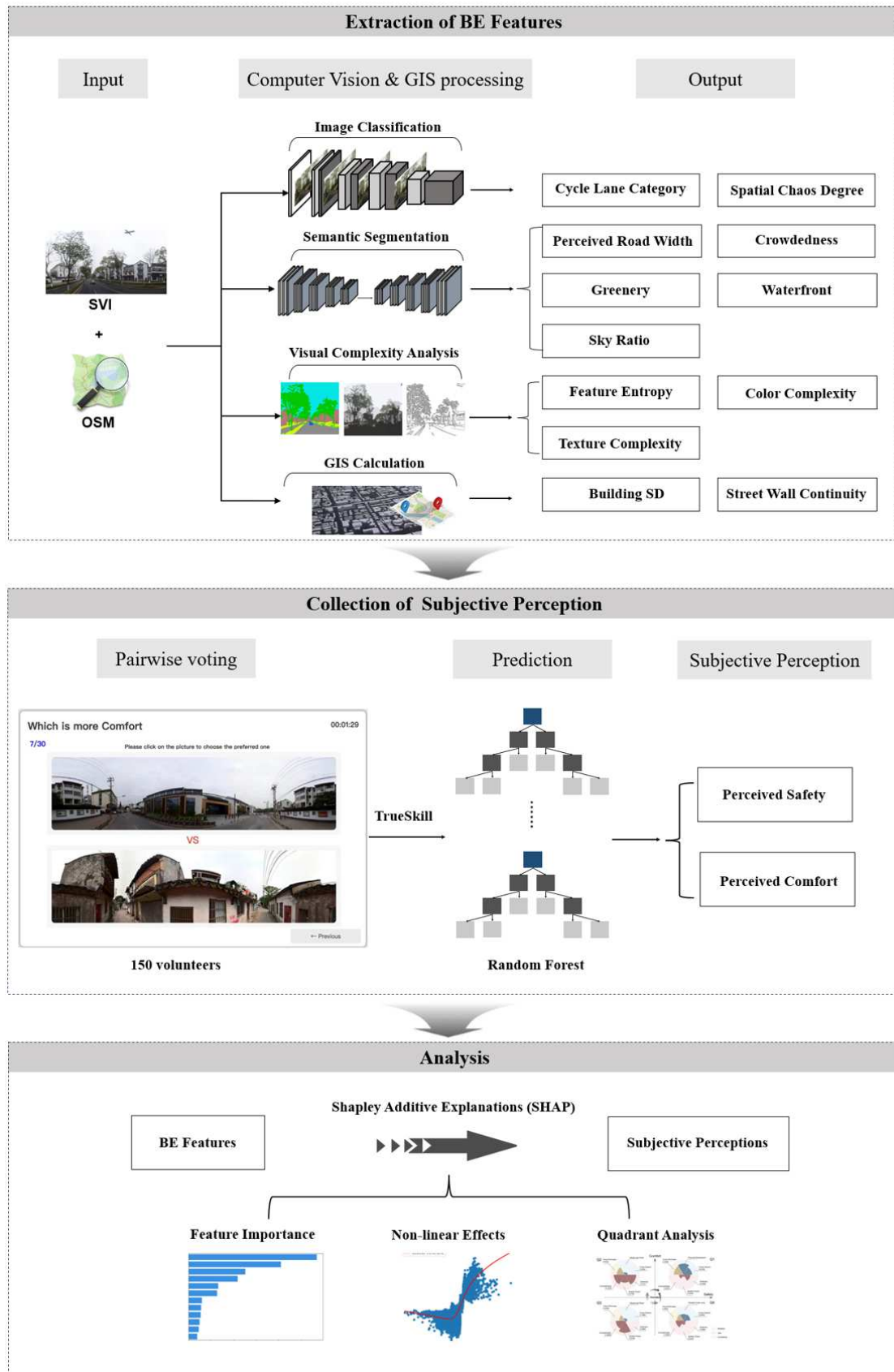


Figure 1 Technical Framework

3.1. Study area

Gusu District (83.4 square kilometers) in Suzhou City, China, includes both a new town area with a modern space layout and an old town area with heritage conservation and has been chosen for research due to the contrasting spatial structures of these regions (Figure 2). The old town is carefully preserved as a historical site, maintaining its unique layout, while the new town features wide roads with bike lanes (Yun et al., 2021). In contrast, the old town retains its unique "checkerboard pattern" layout, with mixed-use branch roads constituting 75.1% of the road network, adding both complexity and cultural significance to the area (Ryan, 2012; Yun et al., 2021). The old town serves as a cultural and leisure center, with government initiatives aimed at transforming "car-centered" spaces into "human-centered" ones to maintain the vitality of the historic city and encourage bike usage (Suzhou Planning Bureau, 2022). In contrast, the new town is structured into distinct functional zones (Figure 2), including the Ecological Innovation & Logistics Park, Traffic Hub & Business Center, Administrative & Business Center, and Residential zones (Suzhou Gusu District People's Government, 2024). This spatial heterogeneity makes Gusu District a compelling case for examining cyclists' perception within diverse urban contexts.

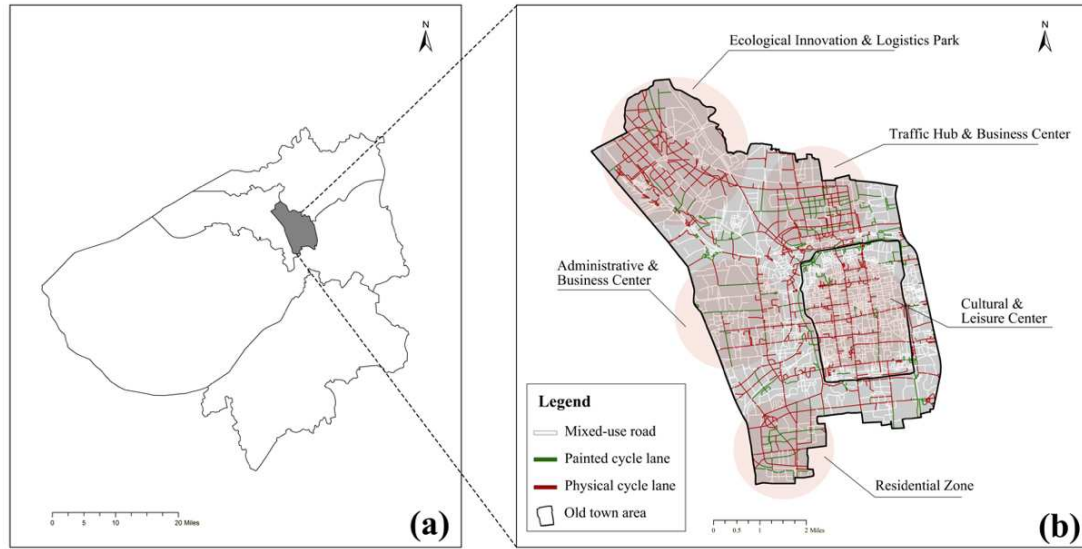


Figure 2 Study Area (a) Suzhou city (b) Gusu district

3.2. Hybrid data collection approach integrating SVI with online pairwise voting

SVIs were obtained from Baidu Street View service. Sampling points were generated every 100 m along the road centerlines, following the road topology provided by OpenStreetMap (OSM). (Wei et al., 2023). At each point, four directional images (0° , 90° , 180° , 270°) were retrieved via Baidu's API and stitched into 360° panoramas, ensuring comprehensive coverage and preservation of the complete BE features (Ito and Biljecki, 2021). After excluding unsuitable areas like highways and expressways, a total of 5176 panoramic SVIs were considered for further analysis.

An online survey for pairwise voting was developed (<http://47.242.149.177>) with participants recruited through social media. A total of 150 volunteers participated in July 2023, comprising 61 females (40.67%) and 89 males (59.33%). Participants' ages ranged from 24 to 42, with a median age of 27 (IQR = 25–29). The group included master's students, PhD students, and professionals in urban planning, landscape architecture, and transportation planning. All participants had recent

1 cycling experience (having ridden at least once in the week before the study) and were familiar with
2 living in Suzhou. Prior to the main experiment, participants were given an introduction to the
3 different types of cycle lanes depicted in the SVIs and instructed to imagine themselves cycling in
4 the scenes. Because the cycle facilities implemented in the cross-section of the study area are similar
5 and the participants were familiar with the area, guiding the cyclists to imagine their cycling
6 experience helped minimize experimental error from view occlusion issues. This approach aimed
7 to ensure that participants focused on the experience of cycling rather than merely scoring the
8 images from other perspectives, such as walking or driving. A complete version of the guideline
9 provided to participants is included in Appendix 7.3.

10 Before the survey, 300 panoramic SVIs were drawn from the full pool of 5,176 images using
11 stratified random sampling, with the number from each functional zone proportional to its share of
12 the dataset (Figure 2). This approach ensured randomness while controlling for geographic
13 clustering, making it suitable given the pronounced heterogeneity in the study area's urban form
14 and street environments (Xu et al., 2025). To statistically assess whether the sample was
15 representative of the population, a Maximum Mean Discrepancy (MMD) with permutation test was
16 employed (Gretton et al., 2012). The observed MMD² between the sample and full dataset fell within
17 the 95% confidence interval of the null distribution ($p = 0.0898 > 0.05$), confirming that the sample
18 adequately represents the spatial and feature distributions of the entire image pool.

19 In the experiment, participants were presented with two randomly selected SVIs (Figure 1) and
20 asked to choose the image they believed better represented either "Safety" or "Comfort." To ensure
21 consistent understanding among participants, qualitative definitions were provided for each concept

before voting. "Safety" was defined as concerns related to traffic risks, the possibility of crashes or conflicts while cycling, and worries about personal security or crime (Böcker et al., 2016). In contrast, "Comfort" was described as the overall enjoyment and pleasantness of the cycling experience, including visually appealing elements that positively impact the rider's mood (Lawrence and Oxley, 2019).

Participants made a cumulative total of 4,516 pairwise comparisons, spanning the two evaluation criteria of safety and comfort. For each evaluation criterion, a minimum of 15 comparisons were made for every image, indicating whether it was selected (win) or not selected (lose) in each comparison. A transitivity test was conducted to assess the reliability of the pairwise voting results, with the detailed procedure documented in Appendix 7.2. This test ensured logical consistency: if Image A was preferred over Image B, and Image B over Image C, then Image A should logically be preferred over Image C (West, 2001). The transitivity percentage for perceived safety measures is 87.43% (p-value 0.92), and for perceived comfort 85.25% (p-value 0.633). These results indicate that violations of transitivity were not statistically significant, thereby confirming the robustness and reliability of this experiment, which outperforms the Place Pulse benchmark. The experiment was approved by the university's Human Research Ethics Committee.

3.3. BE features extraction combining multiple CV models

Table 2 summarizes the BE features considered in this study. The selection of these features was informed by previous bicycle-related studies that employed Computer Vision (CV) techniques, in which these variables have been empirically shown to correlate significantly with cycling safety and comfort. CV and Geographic Information System (GIS) approaches were integrated to extract

1 street-level features. For CV, two tasks were conducted. The first was image classification, where
2 the Swin Transformer model (<https://github.com/microsoft/Swin-Transformer>) was applied to
3 identify cycle lane categories and spatial chaos. The second was semantic segmentation, carried out
4 using the PSPNet model, which combines ResNet50-dilated as the encoder with PPM_deepsup as
5 the decoder (<https://github.com/CSAILVision/semantic-segmentation-pytorch>). This pre-trained
6 model, widely adopted in related studies, provides an efficient and reproducible approach for BE
7 feature extraction (Han et al., 2023; Koo et al., 2022; Xu et al., 2025). In addition, GIS tools were
8 employed to calculate street wall continuity and building height variability from OpenStreetMap
9 (OSM) data, with all features aggregated within 100 m buffers centered on each SVI sampling point
10 (Ito and Biljecki, 2021).

11 For the image classification task of identifying cycle lane categories, three categorized cycle
12 facilities (mixed road without cycle facilities, painted lines and physical segregations) and spatial
13 chaos were identified by image classification method (Figure 3). Each cycle lane category was
14 assigned approximately 400 SVIs as training data, with data augmentation (rotations and brightness
15 adjustments) applied to mitigate dataset limitations (Perez and Wang, 2017). Using an 8:1:1 split
16 for training, testing, and validation (Tian and Liao, 2021), the model achieved an accuracy of 0.859,
17 effectively classifying cycle lane types.

18 Spatial chaos (Figure 3) was quantified using an image classification framework introduced by
19 Chen et al. (2023), which identifies categories of environmental disorder within Chinese urban
20 settings. From this framework, four dimensions were selected relevant to the context of Gusu district:
21 (1) architectural disorder: illegal or temporary structures, damaged facades (e.g., graffiti, peeling

1 walls), and unauthorized advertisements; (2) commercial disorder: cluttered signage, vacant or
 2 pending shops, and irregularly placed advertisements; (3) road disorder: damaged pavements,
 3 personal belongings left on roadsides, and accumulated waste; and (4) construction disorder: poorly
 4 managed construction site fences. To identify these dimensions, separate classifiers based on Swin
 5 Transformer model were developed for each dimension, trained on about 200 positive and 200
 6 negative SVI samples with data augmentation to enhance generalization. The models achieved an
 7 overall accuracy of 0.918, and for each SVI the predicted probabilities of the four disorder categories
 8 were generated. The composite spatial chaos index was subsequently calculated as the arithmetic
 9 mean of these probabilities.



Figure 3 Cycle lane category and spatial chaos

12 Visual complexity was assessed and calculated in terms of color, texture, and feature entropy,
 13 each extracted from SVIs. The results in Figure 4, presented with normalized values for clarity,
 14 illustrate the relationship between complexity values and SVIs.

Color complexity was calculated by spatial entropy of grayscale (Equation 1) given that lighting conditions may vary between different SVIs (Guan et al., 2022):

$$vis_color = - \sum_{i=0}^{255} \left(p_i \log_2 p_i + \sum_{j=0}^{255} p_{ij} \log_2 p_{ij} \right) \quad (1)$$

where p_i represents the proportion of pixels with grayscale value i in the panoramic SVI ($0 \leq i \leq 255$), p_{ij} indicates the proportion of pixels with grayscale value i surrounded by neighboring pixels with an average grayscale value j in the panoramic SVI ($0 \leq i, j \leq 255$).

Texture complexity was measured using a fractal-based box-counting method (Jiang et al., 2021). After applying Canny edge detection, the edge maps were analyzed to estimate the fractal dimension, defined as the slope of the log-log relationship between the number of occupied boxes and the box size, as shown in Equation 2:

$$vis_texture = \lim_{\varepsilon \rightarrow 0} \frac{\log N(\varepsilon)}{\log \left(\frac{1}{\varepsilon} \right)} \quad (2)$$

where $N(\varepsilon)$ represents the number of boxes required to cover the edge map at box size ε .

Feature entropy (Ma et al., 2023) was calculated by Shannon entropy, captures the pixel-level diversity and distribution uniformity of BE features extracted from SVIs (Equation 3):

$$vis_entropy = - \sum_{i=1}^N p_i \log p_i \quad (3)$$

where N represents the number of features of SVI segmented by deep learning model, p_i indicates the proportion of the i_{th} feature pixels for each SVI.

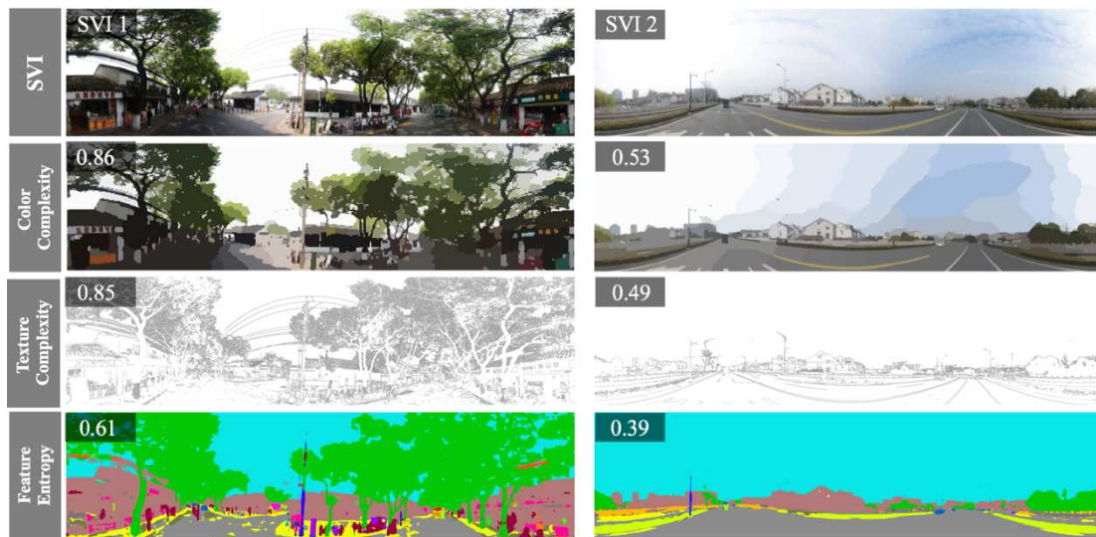


Figure 4 Result of visual complexity

1 **Table 2 Overview of BE features applied in this study**

BE feature	Data source	Extraction	Calculation
Building height variability (Zhou et al., 2022)	OSM	GIS: Aggregation (100m)	Standard deviation of building heights on both sides of the street with the 100m buffer
Street wall continuity (Gu et al., 2018)	OSM	GIS: Aggregation (100m)	The ratio of street edges intersecting buildings to total street length within the 100m buffer
Cycle lane category (Wu et al.)	SVI	CV: Image classification	Mixed-use road; Painted cycle lane; Physical cycle lane (segregated by fence and green belt)
Spatial chaos (Zhu et al., 2017)	SVI	CV: Image classification	Arithmetic mean of detection probabilities for architecture, commerce, road, and construction disorder
Greenery (Arellana et al., 2020)	SVI	CV: Semantic segmentation	$GR = \frac{Pixel_{plants} + Pixel_{trees} + Pixel_{shrubs} + Pixel_{flowers}}{Pixel_{SVI}}$
Perceived road width (Zhu et al., 2017)	SVI	CV: Semantic segmentation	$RW = \frac{Pixel_{road} + Pixel_{pavement}}{Pixel_{building}}$
Sky ratio (Xu et al., 2024)	SVI	CV: Semantic segmentation	$Sky = \frac{Pixel_{sky}}{Pixel_{SVI}}$
Crowdedness (Tran et al., 2020)	SVI	CV: Semantic segmentation	$Crowd = \frac{Pixel_{vehicle} + Pixel_{cyclist} + Pixel_{pedestrians}}{Pixel_{SVI}}$
Presence of waterfront (Ito and Biljecki, 2021)	SVI	CV: Semantic segmentation	Waterfront present/not present
Feature entropy (Zhou et al., 2022)	SVI	CV: Visual complexity analysis	Shannon entropy of BE features derived from semantic segmentation
Color complexity (Kawshalya et al., 2022)	SVI	CV: Visual complexity analysis	Spatial entropy of grayscale
Texture complexity (Jiang et al., 2021)	SVI	CV: Visual complexity analysis	Fractal dimension

2

3.4. Subjective perceptions forecasting through TrueSkill algorithm and Random Forest

Since the pairwise voting results were recorded in binary (win or lose) form, a preliminary procedure was taken to convert the binary record to a continuous perceived comfort and safety score. The TrueSkill system, based on the Bayesian skill system, refines image performance evaluations by mitigating the influence of evaluator characteristics (e.g., age, gender) through iterative updates using Gaussian density filtering (GDF) and Gaussian dynamics factors. Detailed explanations of the algorithm theory applied in pairwise voting were provided in the appendix (Section 7.1). This study adopted the TrueSkill algorithm developed by Microsoft Research (2005) following the rule of the Bayesian skill system (<https://github.com/sublee/trueskill>). The key process procedures are as follows (Equations 4-10).

$$V'_{winner} = V_{winner} + \frac{\eta_{winner}^2 + \delta^2}{c} \times f\left(\frac{V_{winner} - V_{loser}}{c}\right) \quad (4)$$

$$V'_{loser} = V_{loser} - \frac{\eta_{loser}^2 + \delta^2}{c} \times f\left(\frac{V_{winner} - V_{loser}}{c}\right) \quad (5)$$

$$\eta_{winner}^{2'} = [\eta_{winner}^2 + \delta^2] \times \left[1 - \frac{\eta_{winner}^2 + \delta^2}{c} \times g\left(\frac{V_{winner} - V_{loser}}{c}\right)\right] \quad (6)$$

$$\eta_{loser}^{2'} = [\eta_{loser}^2 + \delta^2] \times \left[1 - \frac{\eta_{loser}^2 + \delta^2}{c} \times g\left(\frac{V_{winner} - V_{loser}}{c}\right)\right] \quad (7)$$

$$c^2 = 2\alpha^2 + \eta_{winner}^2 + \eta_{loser}^2 \quad (8)$$

$$f(x) = \frac{N(x)}{\phi(x)} \quad (9)$$

$$g(x) = f(x) \times [f(x) + x] \quad (10)$$

where V is the perceived safety or comfort score of an SVI, with V' as its updated score after a

pairwise comparison; η^2 is the variance of rating reflecting uncertainty, where η'^2 is its updated value; $N(x)$ and $\phi(x)$ represent probability density and cumulative distribution functions, respectively; α^2 means dynamics variance controlling score adaptation while c^2 is the scaling factor determined by $2\alpha^2$ and the variances of both SVIs.

The processed set of 300 SVIs was utilized as a training set for predicting subjective perception across the entire study area, employing the Random Forest (RF) model. RF is an ensemble learning method based on decision trees, which can evaluate the significance of variables (BE features) through their frequency and position in the tree structure. This method was selected for its stability, high accuracy in classification and regression tasks, low computational cost, and widespread use in subjective studies (Table 2) (Qiu et al., 2022). The dataset was divided into training (80%) and testing (20%) subsets, with cross-validation applied during hyperparameter tuning, and separate models were developed for perceived safety and comfort (Beleites et al., 2013; Qiu et al., 2022). Model performance was assessed using R^2 (explained variance), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The RF models achieved R^2 values of 0.617 and 0.592, MAEs of 0.061 and 0.086, and RMSEs of 0.078 and 0.108 for safety and comfort, respectively, demonstrating acceptable performance compared to similar studies (Qiu et al., 2022; Yao et al., 2021).

3.5. Shapley Additive Explanation (SHAP) and Quadrant analysis

To investigate the local effects of BE features, the SHAP algorithm, derived from game theory was utilized to interpret the RF model. SHAP offers a method to elucidate the internal mechanics of the RF model by calculating and allocating the contribution of each feature to the model's output

based on its marginal impact (Han et al., 2024). The SHAP value for a feature j , denoted as Φ_j , was calculated as shown in Equation 11:

$$\Phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|! (n - |S| - 1)!}{n!} [f(S \cup \{j\}) - f(S)] \quad (11)$$

where Φ_j quantifies the average marginal contribution of feature j across all possible feature combinations. It can be negative, zero, or positive, indicating whether the feature decreases, has no effect on, or increases the prediction.

To quantify the overall importance of a feature across all predictions, the mean absolute SHAP value was calculated using Equation 12:

$$I_j = \frac{1}{n} \sum_{k=1}^n |\Phi_j^{(k)}| \quad (12)$$

where I_j represents the average absolute impact of feature j across all predictions. These metrics clarify the non-linear relationships between BE features and perceived safety and comfort, enabling a detailed interpretation of their effects.

To analyze the potential pathways for promoting cycling environment, all BE features were divided into four quadrants based on the median values of perceived safety and comfort scores: High Safety & High Comfort (HH), Low Safety & Low Comfort (LL), Low Safety & High Comfort (LH), and High Safety & Low Comfort (HL). The average SHAP contributions of each BE feature were developed to represent the most influential BE features in each quadrant. For each data point i , a weight ω assigned to the predicted safety and comfort scores, which were then used to aggregate the SHAP contributions I_{j,Q_k} within each quadrant Q_k , following the calculation defined

in Equations 13-15:

$$\omega_{safety}^{(i)} = \frac{safety_{pred}^{(i)} + \epsilon}{safety_{pred}^{(i)} + comfort_{pred}^{(i)} + 2\epsilon}, \omega_{comfort}^{(i)} = \frac{comfort_{pred}^{(i)} + \epsilon}{safety_{pred}^{(i)} + comfort_{pred}^{(i)} + 2\epsilon} \quad (13)$$

$$\Phi_{j,combined}^{(i)} = \omega_{safety}^{(i)} \Phi_{j,safety}^{(i)} + \omega_{comfort}^{(i)} \Phi_{j,comfort}^{(i)} \quad (14)$$

$$I_{j,Q_k} = \frac{\frac{1}{N_k} \sum_{i \in Q_k} |\Phi_{j,combined}^{(i)}|}{\sum_{j=1}^M (\frac{1}{N_k} \sum_{i \in Q_k} |\Phi_{j,combined}^{(i)}|)} \quad (15)$$

where $safety_{pred}^{(i)}$ and $comfort_{pred}^{(i)}$ indicate the predicted safety and comfort scores for data point i estimated through the random forest model; ϵ represents a positive smoothing term to prevent division by zero. $\Phi_{j,safety}^{(i)}$ and $\Phi_{j,comfort}^{(i)}$ represent the SHAP values of feature j for data point i in safety and comfort models, respectively. N_k represents the number of data points in quadrant Q_k .

4. Results and Discussion

4.1. Validation of TrueSkill convergence and effects of demographical bias

To ensure that the results were not influenced by participants' age or gender, the performance and convergence of the TrueSkill algorithm were systematically assessed (Figure 5). The convergence assessment involved tracking cumulative voting comparisons across iterations. During each iteration, TrueSkill dynamically updated the win-loss ratings of images. The updated average rating (μ_{new}) was compared with the previous iteration's average rating (μ_{old}), considering the confidence intervals ($\pm 3\sigma$) as measures of rating uncertainty. Convergence was identified by a reduction in the absolute difference between μ_{new} and μ_{old} ($|\Delta\mu|$), where values approaching

1 zero indicated effective convergence. In addition, shrinking confidence intervals ($\pm 3\sigma$) further
2 confirmed the reliability and stability of the final image rankings.

3 Moreover, participant gender and age biases were assessed following the Place Pulse
4 verification methodology (Salesses et al., 2013). Specifically, the dataset was divided according to
5 participant gender and age groups, and each subgroup was compared against a randomly selected
6 control group matched by sample size. Ratings were recalculated using TrueSkill for each subgroup,
7 and correlations were analyzed using scatterplots and Fisher's test to verify consistency.

8 Figure 5(A) demonstrates that TrueSkill exhibited effective convergence for both safety and
9 comfort ratings, as indicated by the smooth decline in rating fluctuations, thereby validating the
10 stability and reliability of rankings used in this study. These findings align with previous studies
11 suggesting that TrueSkill typically achieves convergence after approximately 15 comparisons per
12 item, although theoretical limits suggest that 5 to 10 comparisons per item may suffice for achieving
13 stable rankings (Herbrich et al., 2006; Salesses et al., 2013). Figure 5(B) presents scatterplots
14 illustrating the influence of gender and age on safety and comfort perceptions. The analysis revealed
15 no significant differences (R^2 values and Fisher's test), confirming that the final results were
16 unbiased concerning participant age and gender.

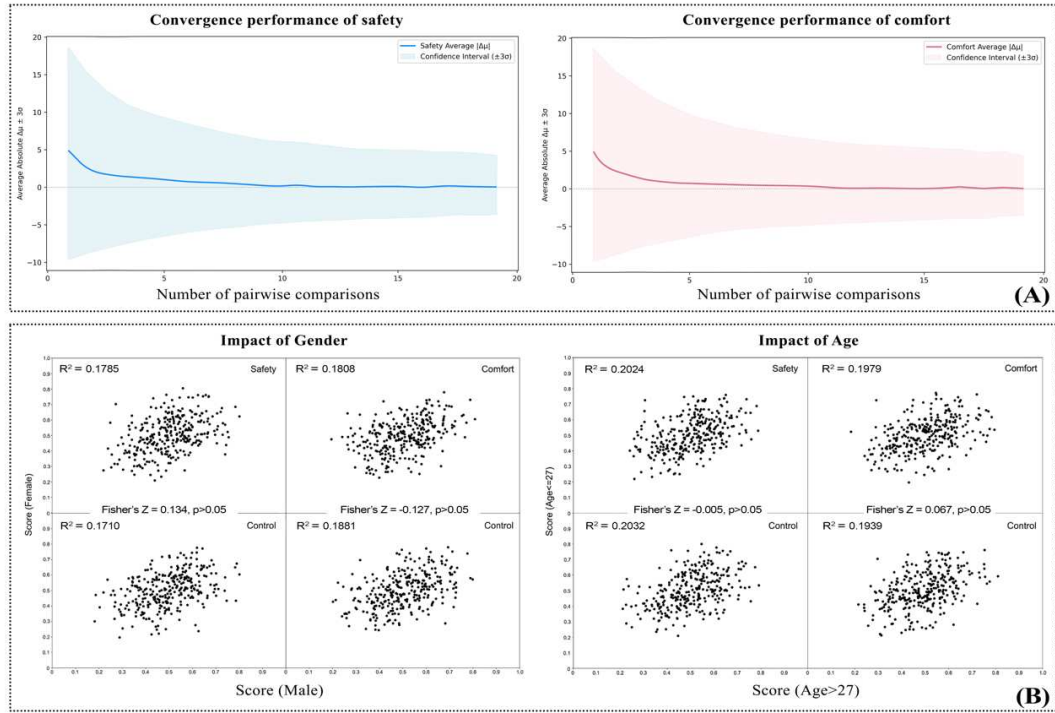


Figure 5 TrueSkill convergence performance (A) and test of demographical bias (B)

4.2. Descriptive result of predicted safety and comfort score

The predicted safety and comfort scores were spatially visualized using the Kriging interpolation method (Figure 6), enabling a standardized comparison of the two indices across the entire study area and revealing spatial patterns. The high-scoring areas of both indices largely coincide with the city's functional zones (Suzhou Gusu District People's Government, 2024): the Ecological Innovation & Logistics Park (Cluster a), the Traffic Hub & Business Center (Cluster b), the Administrative & Business Center (Cluster c), the Cultural & Leisure Center (Cluster d), and the Residential Zone (Cluster e). Safety hotspots are closely associated with the presence of cycling facilities, while comfort follows a more complex spatial pattern. Importantly, mismatches emerge between the two perception dimensions: safety is rated higher than comfort in the central part of Cluster b, whereas comfort exceeds safety in the ecological park of Cluster a, in Cluster c, and in

1 the historic old town of Cluster d.



2

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Figure 6 Visualization of perception forecasting results

4 4.3. Correlation structure among BE variables

5 A Pearson correlation test was conducted to avoid misinterpreting proxy or covariate
6 relationships as causal effects (Figure 7). Most variables showed weak to moderate correlations ($|r|$
7 < 0.5), and all VIF values were below 3, indicating low multicollinearity and supporting the
8 suitability for SHAP analysis.

9 Significant correlations underscore spatial contrasts in the cycling environment. The cycle lane
10 category is negatively associated with spatial chaos ($r = -0.444$) and crowdedness ($r = -0.23$), but
11 positively associated with perceived road width ($r = 0.453$). This reflects the divide between new
12 towns, where roads are wider, orderly, and often equipped with segregated facilities, and old towns,
13 where mixed-traffic branches dominate 75.1% of the network (Yun et al., 2021), yet still carry
14 approximately 43% of all bicycle trips within the district (Xu et al., 2025).

Visual complexity dimensions (feature entropy, color, texture) showed low intercorrelations, supporting their joint inclusion. Notably, spatial chaos and feature entropy exhibit a moderate negative correlation ($r = -0.35$). In highly chaotic environments, the streetscape tends to be dominated by monotonous hardscape surfaces (e.g., buildings, walls, pavements), while sky and greenery are compressed, resulting in a skewed pixel distribution and diminished diversity. By contrast, low-chaos scenes typically present a more balanced mix of roads, greenery, open views, and façades, which enhances visual variety and leads to higher entropy.

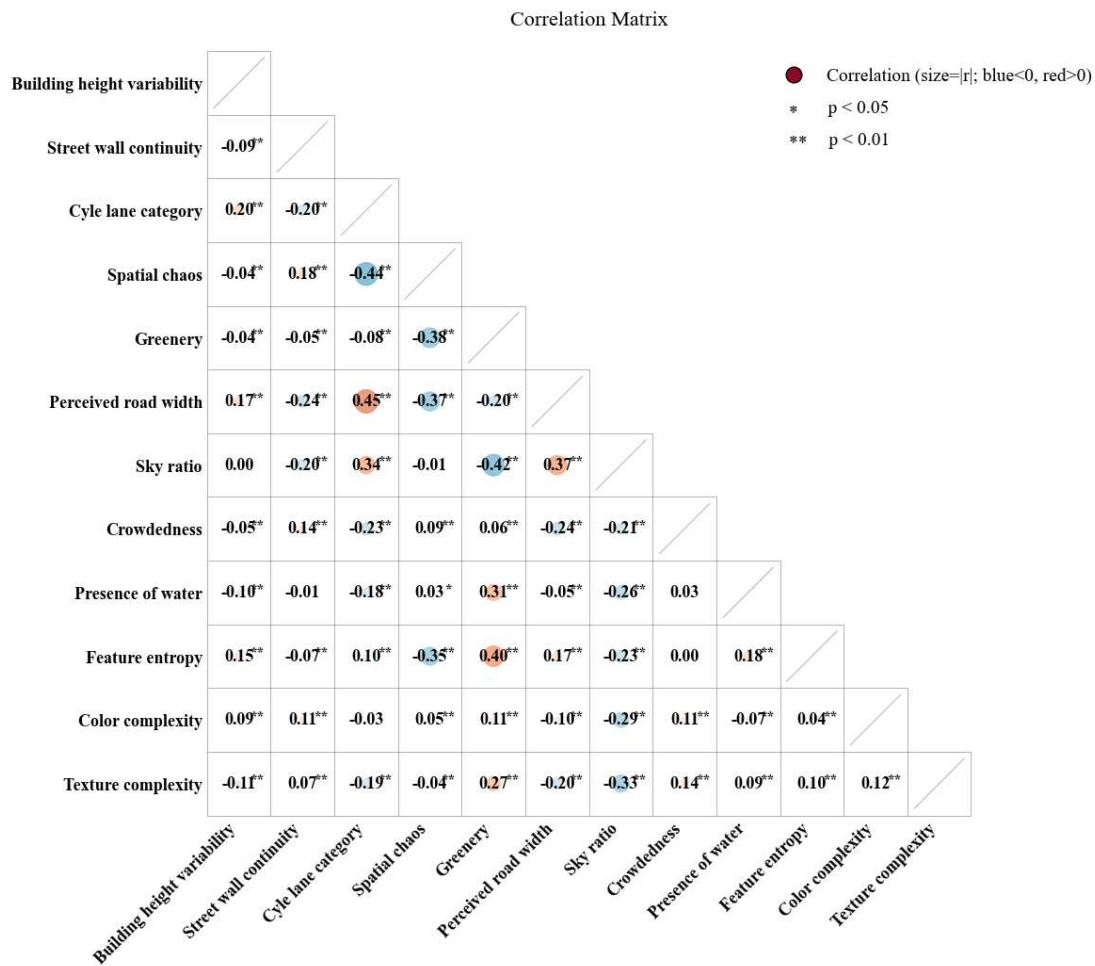


Figure 7 Correlation matrix

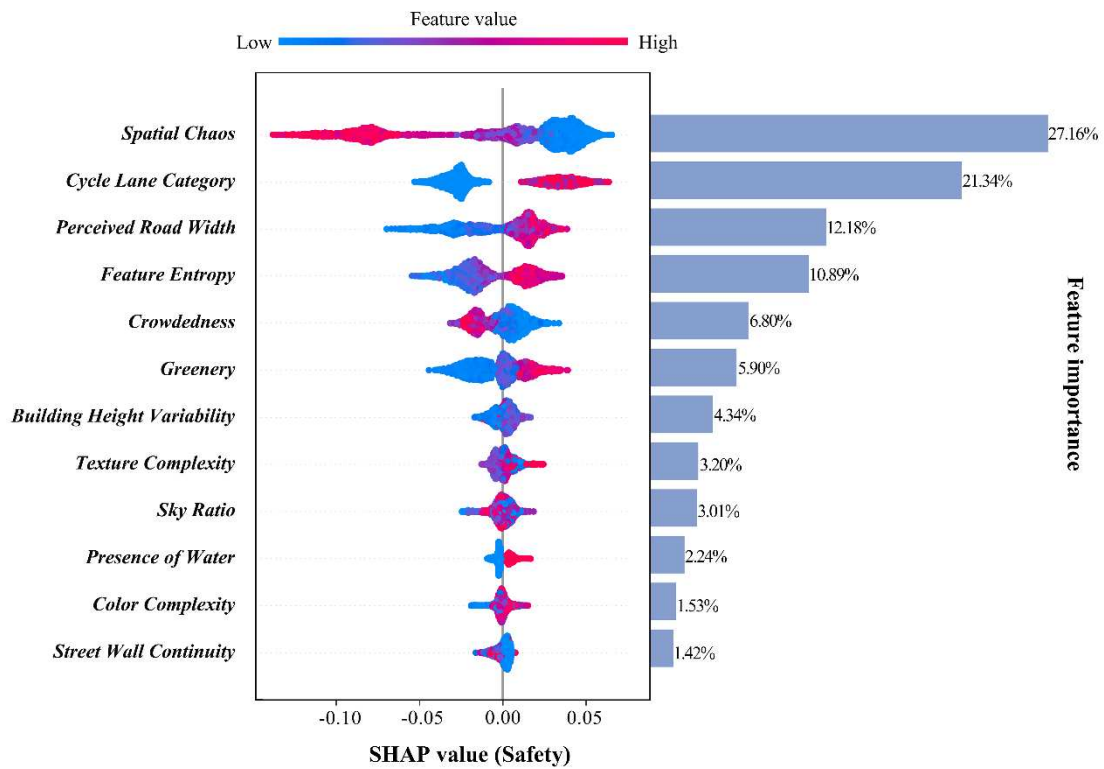
4.4. Feature importance of BE features

The beeswarm and feature importance plot (Figure 8) illustrates the relative importance and directional effects of BE features on cyclists' perceived safety and comfort. The top six features, including spatial chaos, cycle lane category, perceived road width, feature entropy, crowdedness, and greenery, each contribute more than 5% to relative importance, collectively accounting for over 80% of the predictive power for both perceptions. This threshold aligns with the approach adopted in prior interpretability practice (Han et al., 2024), in which features with lower contributions typically exhibit near-neutral and scattered SHAP distributions, indicating limited global influence.

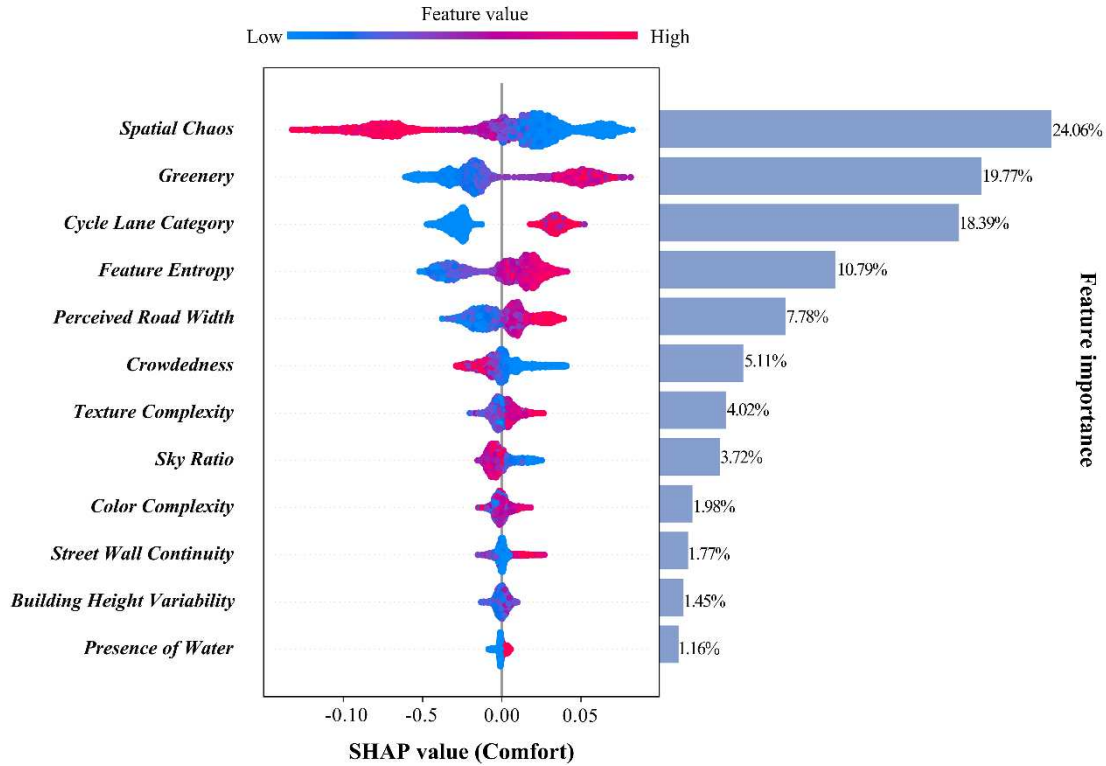
Spatial chaos emerges as the most significant predictor, contributing 27.10% to safety and 24.06% to comfort, with predominantly negative effects that lower both perceptions as disorder increases. This finding aligns with Wen et al. (2025) and Verhoeven et al. (2017), who demonstrated that environmental disorder conveys signals of potential risk and exhibits a notable negative correlation with bicycle use. Feature entropy demonstrates comparable importance across the two perceptions (10.89% for safety and 10.79% for comfort), but the plots reveal a non-linear pattern: moderate levels of diversity and balanced distribution enhance perceptions, while excessive complexity undermines safety, with comfort showing a broader tolerance range.

When comparing safety and comfort, cycle lane category and perceived road width play a more prominent role in safety (21.34% and 12.18%, respectively), with mostly positive effects, suggesting that higher-grade segregated facilities and wider roads significantly enhance perceived safety. In contrast, greenery exerts a much greater influence on comfort (19.77%) than on safety (5.90%), consistently showing positive effects and underscoring its role in promoting a more

1 pleasant and enjoyable cycling experience.



2



3

4 Figure 8 SHAP beeswarm plots and feature importance of perceived safety and comfort

4.5. Non-linear relationships between BE and perceived safety and comfort

The SHAP dependence plots in Figure 9, fitted with Locally Weighted Scatterplot Smoothing (LOWESS) smoothers, reveal the non-linear and threshold effects of key BE features on cyclists' perceived safety and comfort. Most BE features exhibit similar non-linear responses for both safety and comfort: the two perceptions tend to move in the same direction and display diminishing marginal returns with saturation around critical thresholds. For instance, crowdedness exerts a broadly negative influence on both perceptions, with effects stabilizing around median values. This similar pattern is supported by evidence that both safety and comfort originate from individuals' immediate cognitive processing of environmental cues and are closely tied to emotional valence and arousal, thereby producing comparable psychological responses to certain BE features (Lim et al., 2025).

It is noteworthy that the non-linear patterns of cycle lane category exhibit potential contextual dependencies. Painted lanes produced substantial improvements in both perceptions, with effects saturating rapidly, whereas physical segregation offered only limited marginal gains. This finding challenges the intuition that "physical separation is always superior" (Ito and Biljecki, 2021), and aligns instead with empirical studies conducted in low-speed, low-volume contexts where painted lanes afford sufficient lateral clearance and can perform comparably to or even better than segregated facilities in perceived safety (Almallah et al., 2024; Wall et al., 2016). Mertens et al. (2016) further emphasized that the effectiveness of painted lanes is strongly dependent on speed moderation: while the marginal utility of reducing speed is limited for segregated lanes, lowering

limits from 50 km/h to 30 km/h on painted lanes yields substantial gains in both safety and comfort perceptions. Although SVI-based measures fail to capture dynamic traffic conditions, this static framing emphasizes the visual salience of infrastructure and helps isolate its marginal contribution in idealized low-stress settings. Accordingly, painted lanes emerge as a context-sensitive and cost-effective intervention, particularly in areas constrained by space or heritage considerations.

A key divergence arises in the threshold effects between safety and comfort, especially for spatial chaos, greenery, feature entropy, and perceived road width. For spatial chaos, safety declines sharply once the index exceeds 0.28, while comfort remains relatively unaffected until about 0.40—representing a 43% higher tolerance. Safety plateaus at a greenery level of around 0.36, whereas comfort continues to rise until about 0.50. Feature entropy follows an inverted-U relationship: safety transitions from negative to positive at 0.42 and peaks near 0.54; for comfort, the turning point and peak are delayed to 0.50 and 0.62, respectively. For perceived road width, safety peaks at a ratio of 0.40 before saturating, while comfort experiences a secondary increase beyond 0.80.

These differing inflection points suggest a pattern wherein safety saturates earlier, while comfort requires more substantial environmental refinements such as wider roads, richer greenery, and more harmonious visual composition. This disparity may be explained by a hierarchical perceptual mechanism in decision-making: safety serves as a prerequisite influencing the initial choice to cycle, whereas comfort acts as a differentiating factor that shapes the intensity and sustainability of the cycling experience once basic safety expectations are met (Alfonzo, 2005; Xu et al., 2025).

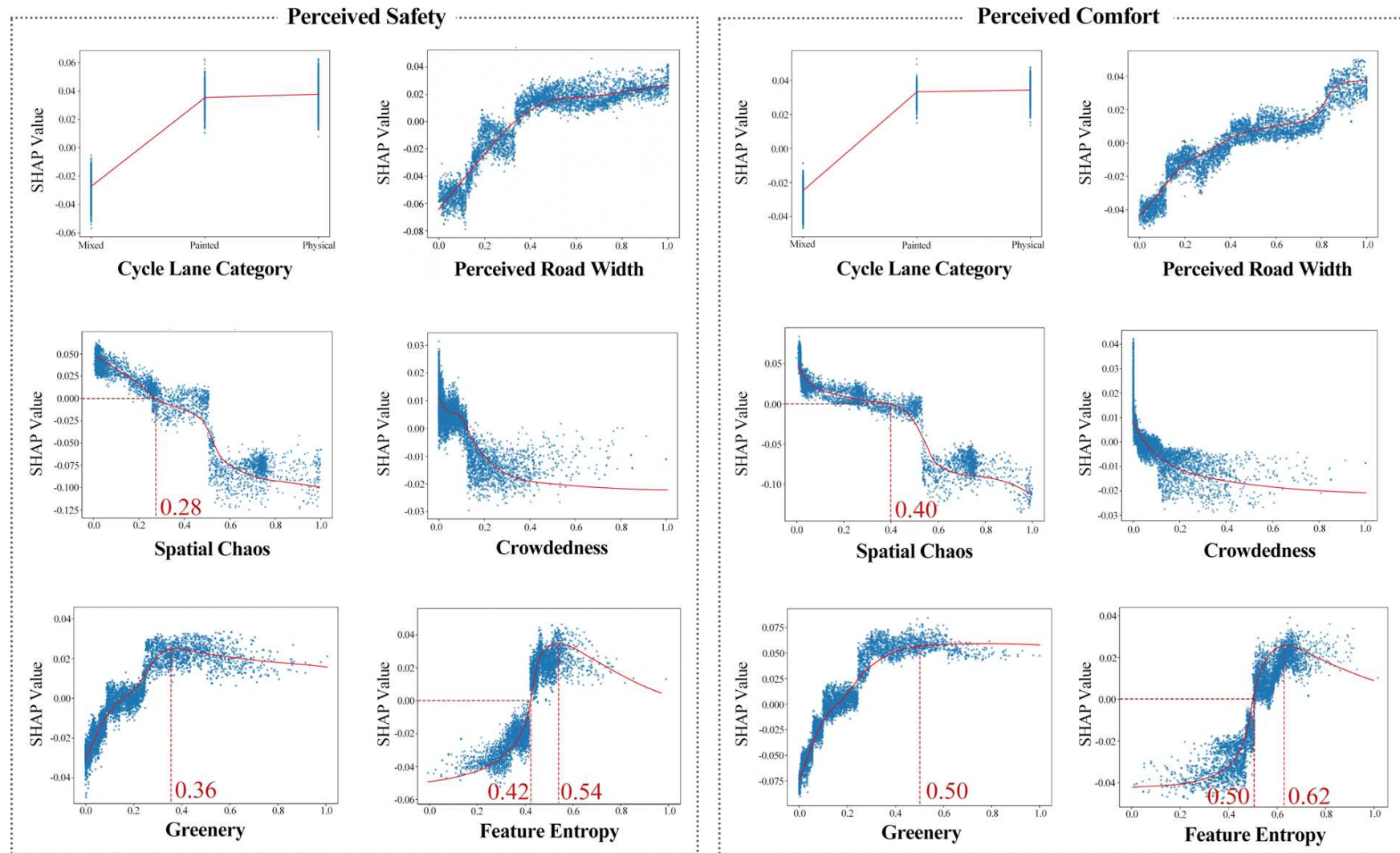


Figure 9 SHAP dependence plot of key BE features on perceived safety and comfort with highlighted inflection points

4.6. Quadrant analysis of perceived safety and comfort

Pie charts (Figure 10) illustrate the quadrant analysis by integrating BE features' weighted contributions to perceived safety and comfort (Section 3.5). Each chart presents the average SHAP contributions and median BE values for the quadrant, with percentages indicating relative importance.

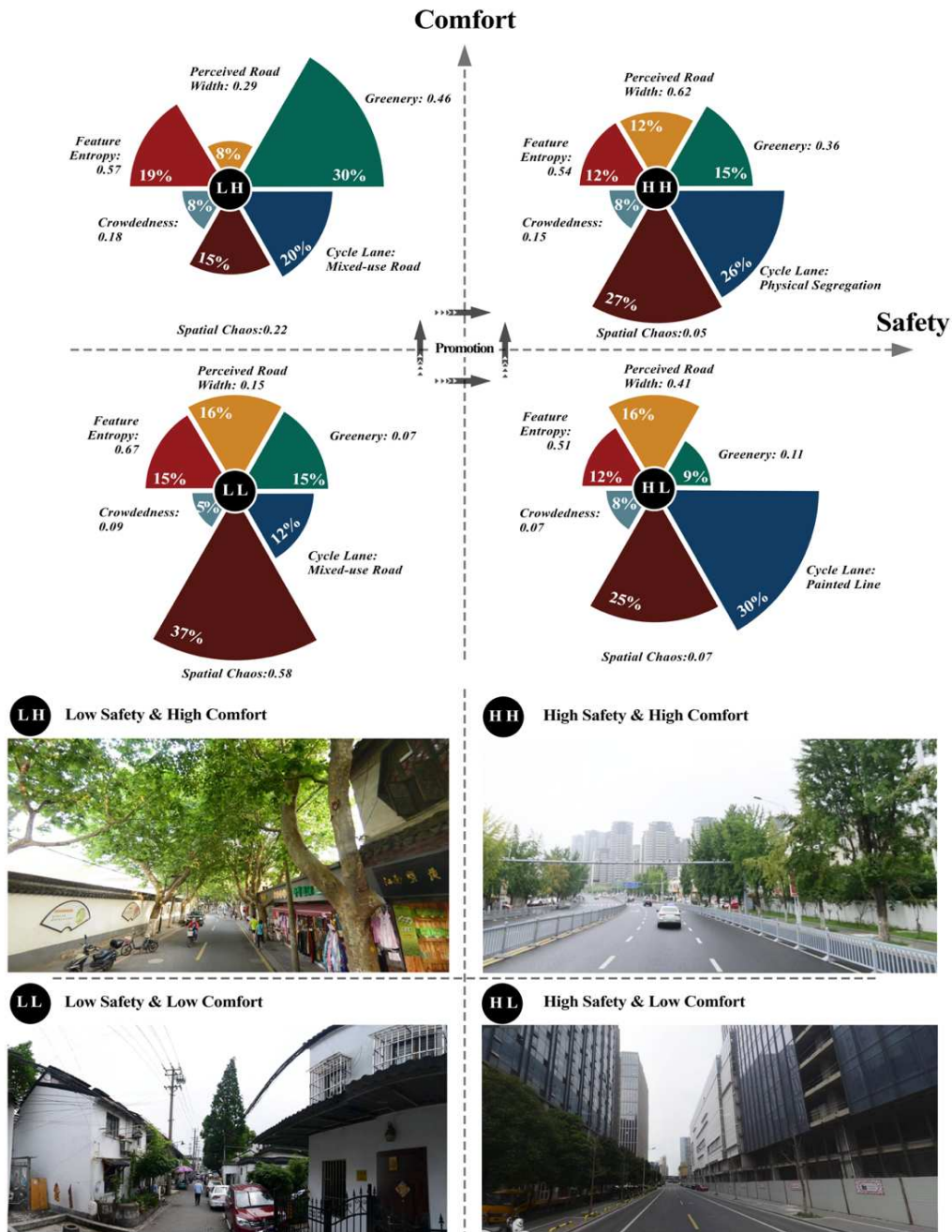


Figure 10 SHAP contribution of BE features across four quadrants based on safety and comfort

1 Cross-quadrant analysis reveals a consistent foundational pattern that supports all subsequent
2 strategic trade-offs: perceived road width and cycle facility, together with spatial chaos, form the
3 structural foundation of perceived safety, while greenery and visual complexity further shape
4 comfort experience. In contrast, crowdedness shows generally low contributions across all
5 quadrants, particularly in the LL-3rd quadrant (low safety and low comfort). Two explanations are
6 plausible: first, the marginal effects of crowdedness may become negligible when more fundamental
7 issues emerge, such as the absence of cycling facilities and spatial chaos falling below minimum
8 thresholds. This suggests that in such low-quality environments, improving facilities and reducing
9 chaos yields greater returns than focusing solely on traffic management; second, static SVI may fail
10 to capture dynamic aspects such as traffic flow and speed, potentially leading to an underestimation
11 of its contribution. Therefore, the role of crowdedness warrants further investigation.

12 Although the ideal objective is to move all areas toward the HH- 1st quadrant (high safety and
13 high comfort), characterized by physical segregation, high greenery coverage, a favorable, wide
14 perceived road width, and low spatial chaos, the practical approach requires tailoring interventions
15 to the specific shortcomings of other quadrants.

16 The LH- 2nd quadrant (low safety but high comfort) and the HL-4th quadrant (high safety but
17 low comfort) share the common trait of a single dominant shortcoming: safety in LH and comfort
18 in HL. Strategies should therefore avoid overinvesting in already strong dimensions and instead
19 adopt targeted, minimal interventions to bolster the weaker aspect. LH areas, typically found in old
20 town leisure zones (cluster d) and administrative & business centers (cluster c in Figure 6) with
21 compact layouts, abundant greenery, and vibrant activities. In such areas, safety can be improved

1 by adding painted bike lanes, implementing traffic-calming measures, and addressing visible signs
2 of disorder such as dilapidated facades and cluttered signage. At the same time, it is important to
3 maintain a degree of visual diversity in the streetscape to preserve the neighborhood's lively
4 character. In contrast, HL areas, primarily located in traffic hubs and business centers (Cluster b in
5 Figure 6) with adequate facilities but insufficient greenery and aesthetic experience, should
6 prioritize comfort by introducing greenery and diversifying street interfaces, avoiding over-
7 investment in already saturated safety infrastructures. Increasing feature entropy to around 0.62—
8 the optimal range for comfort—can help achieve “ordered diversity” instead of monotony or chaos.

9 In the LL- 3rd quadrant (low safety and low comfort), which primarily includes heritage
10 preservation regions in old town (cluster d in Figure 6), high spatial chaos, extremely narrow
11 perceived road widths, and elevated feature entropy negatively impact cycling perceptions. These
12 challenges are particularly pronounced in historic districts, where heritage conservation goals often
13 conflict with sustainable mobility objectives (Zhao et al., 2025). Preservation laws limit physical
14 modifications and entrenched car culture resists road reallocation, making it difficult to introduce
15 dedicated cycling infrastructure (Parajuli and Pojani, 2018). In our study area, 75.1% of roads are
16 mixed-traffic lanes averaging only 8 meters in width, the 2.5-meter regulatory minimum for bicycle
17 lanes makes physical upgrades highly challenging, often leading to political inertia and limited
18 short-term gains (Suzhou Planning Bureau, 2022; Szell et al., 2022).

19 Under such constraints, legal frameworks create a “ceiling” on the effectiveness of BE-based
20 interventions for improving safety in heritage regions. A more viable pathway is to prioritize
21 comfort, which has been shown to enhance vibrancy and stimulate cycling frequency in cultural-

leisure centers (Gao et al., 2018). Rather than emulating the HL-4th quadrant, where geometric attributes such as bicycle facilities and perceived road width contribute heavily to SHAP values (46%), heritage districts should shift toward the LH-2nd quadrant as a more feasible reference. Efforts should focus on comfort-related enhancements: increasing greening coverage toward comfort-saturation thresholds (approximately 1.4× safety saturation levels), optimizing feature entropy to around 62% of cyclists' viewpoints, controlling spatial chaos, and improving building facade quality. On the safety dimension, the focus should shift from static interventions toward systemic traffic governance, adopting strategies that flexibly reallocate street space and traffic priority between cars and bicycles at different times of the day (Qiu et al., 2025). While safety and comfort exhibit a perceptual hierarchy in shaping cycling behavior, prioritizing comfort-oriented BE strategies in heritage settings remains both relevant and pragmatic. Empirical evidence suggests that some cyclists negotiate routes by privileging aesthetic or experiential qualities over broader safety considerations, thereby legitimizing a “comfort-maximization” approach under high regulatory constraints (Lawrence and Oxley, 2019).

5. Limitation

This study has certain limitations. The first limitation is the homogeneity of the participants in terms of their cycling experience. Previous studies have found significant discrepancies in subjective perception between cyclists who are familiar with cycling and those who are not (Lawrence and Oxley, 2019). In this experiment, all participants had some experience with bicycles and were familiar with cycling. Although this study mitigated evaluator bias related to age and gender through multiple votes and iterative comparisons using the pairwise voting and TrueSkill

1 algorithms, the overarching evaluator tendencies, particularly among different groups of cyclists,
2 necessitate additional scrutiny. Furthermore, the study did not explicitly account for trip purpose
3 (e.g., commuting, recreation, or exercise), which may also shape cyclists' subjective perceptions and
4 evaluative priorities (Habib et al., 2014). Future research could incorporate trip purpose as a
5 contextual variable to examine its moderating role in subjective appraisal.

6 The second limitation stems from the static nature of SVIs. First, SVIs collected from the
7 driver's perspective may inadequately represent cyclists' viewpoints, particularly their perception of
8 separated cycling lanes on wide streets. Although the study provided a rigorous introduction to
9 standardized street settings and accounted for participants' lived experiences in the study area,
10 certain nuanced aspects of cyclists' perceptions may still not have been fully represented. Second,
11 SVI may not accurately reflect real-time traffic conditions. While it allows for the extraction of
12 counts of vehicles, pedestrians, and cyclists as proxy measures for local traffic volume, the lack of
13 precise timestamp data associated with image capture means that actual traffic density fluctuations
14 may be partially obscured. Moreover, static representations cannot simulate the psychological
15 pressure induced by dynamic traffic flows, such as vehicles moving past cyclists. Therefore, the
16 effects of “crowdedness” should be further investigated in future research. Nevertheless, SVIs
17 provide valuable snapshots of traffic conditions, and large-scale image analysis yields meaningful
18 statistical insights into general traffic patterns (Ito and Biljecki, 2021). Overall, despite these
19 limitations, the use of SVI represents a practical compromise between detailed observation and
20 scalable data collection. Future research could enhance perception analysis by incorporating
21 historical collision data or employing Virtual Reality (VR) for more immersive experiential
22 measurements (Nazemi et al., 2021).

A further limitation concerns the scope of variables considered. The selection in this study was constrained not only by theoretical relevance but also by the feasibility of extraction using current computer vision and deep learning methods. As a result, some factors highlighted in the literature, such as on-street parking (Jashami et al., 2020), were not included. Although these elements may also affect cyclists' perceptions, future advances in computer vision methods could facilitate the integration of a broader spectrum of BE features. Nonetheless, the variables included in this study capture the most critical perceptual determinants, and the proposed framework remains robust in identifying non-linear thresholds and providing actionable insights for cycling-oriented planning.

6. Conclusion

This research evaluates cyclists' perceived safety and comfort, by integrating Street View Images (SVIs), Computer Vision (CV), and Machine Learning (ML). Using the Shapley Additive Explanation (SHAP) model, the study examines the non-linear relationships between built environment (BE) features and subjective perceptions, revealing several key findings. Spatial chaos, greenery, cycle lane category, feature entropy, perceived road width, and crowdedness collectively account for over 80% of the contributions to both safety and comfort perceptions, though their relative importance differs between the two. Notably, the threshold effects of BE features exhibit shared threshold-driven dynamics but a perceptual duality: safety and comfort respond asymmetrically to the same BE features. For instance, comfort tolerates higher spatial chaos (threshold=0.40) than safety (threshold=0.28), while feature entropy's inflection point at which shifting from negative to positive impacts occurs later for comfort (0.50) than safety (0.42). Similarly, greenery's saturation point for safety (0.36) is lower than for comfort (0.50), reflecting

1 divergent cognitive demands that safety prioritizes legibility, whereas comfort embraces higher
2 complexity to enhance experiential richness.

3 The policy implications suggest context-sensitive strategies that prioritize either safety or
4 comfort depending on local spatial constraints and objectives. Comfort-oriented interventions are
5 most effective in settings like transportation hubs & commercial centers, where measures such as
6 expanding greenery and incorporating well-designed street furniture can balance visual uniformity
7 and variety. Safety-oriented interventions, by contrast, are crucial in old town leisure zones, where
8 measures like adding painted bike lanes, implementing traffic-calming strategies (e.g., lower speed
9 limits or speed bumps), and removing obstructive signage or visual clutter can substantially improve
10 perceived safety. In heritage-sensitive areas, where both perceived safety and comfort are currently
11 low due to high spatial disorder and imbalanced visual composition, non-invasive comfort-oriented
12 interventions are recommended. Efforts should focus on aesthetic and managerial improvements:
13 for example, refurbishing deteriorated building façades, reactivating vacant storefronts, regulating
14 and decluttering signage, repairing damaged pavements, and clearing barriers from the right-of-way.
15 Incremental improvements to greenery, maintained in a neat and coherent manner, can further enrich
16 visual diversity while mitigating disorder. Collectively, these insights provide a scalable model for
17 cities navigating heritage-modernization tensions, balancing infrastructural pragmatism with
18 cultural vitality to foster inclusive cycling environments.

19 This study makes several key contributions. It identifies the divergent threshold effects of BE
20 on perceived safety and comfort through a scalable data fusion framework that integrates SVIs,
21 crowdsourced data, and explainable ML. By moving beyond traditional reliance on either labor-

1 intensive survey with limited spatial granularity or indices that rely solely on physical proxy
2 indicators and neglect subjective perceptions, this study highlights the necessity of distinct safety-
3 and comfort-specific optimization strategies. Furthermore, it offers a policy-relevant framework for
4 balancing heritage preservation with modernization and supports evidence-based policymaking in
5 different urban contexts.

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