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Perceived streetscape quality and bike lane effectiveness: a computer vision approach ☆

Uijeong Hwang [a,*], Patricia L. Mokhtarian [b], Bon Woo Koo [c], Subhrajit Guhathakurta [d]

[a] *Transportation Planning Department, Atlanta Regional Commission, 229 Peachtree St #100, Atlanta, GA 30303, USA*
[b] *School of Civil and Environmental Engineering, Georgia Institute of Technology, 790 Atlantic Dr NW, Atlanta, GA 30332, USA*
[c] *Department of Urban Planning and Engineering, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea*
[d] *School of City and Regional Planning, Georgia Institute of Technology, 245 4th St NW, Atlanta, GA 30332, USA*

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ABSTRACT

This study explores how perceived streetscape quality and bike lane types—striped and protected—are associated with urban cycling behavior. Using computer vision technology to analyze street view images from Berlin, Germany, we assessed visual safety scores and their association with cycling trips. Our findings reveal that both perceived safety and bike lanes significantly enhance cycling activity; however, the interplay between the two varies by the type of bike lanes. Striped bike lanes are more effective than protected bike lanes on streets perceived as safe, while protected bike lanes provide greater benefits in visually unsafe areas compared to striped bike lanes. These results imply that by enhancing the visual appeal and safety of streetscapes alongside bike lane installations, cities can promote active transportation, fostering more sustainable, healthy, and vibrant urban environments.

1. Introduction

Urban streetscapes play a vital role in fostering active mobility. The visual and aesthetic qualities of the street environment – its architecture, sidewalks, amenities, greenery, and the interplay between these elements – have a significant influence on movement choices (Ewing & Handy, 2009; Ewing et al., 2013). As cities prioritize sustainable transportation, it is crucial to understand how streetscapes shape active mobility decisions, particularly cycling.

Perception lies at the core of this dynamic. Studies repeatedly demonstrate that how individuals perceive the streetscape – its aesthetic appeal, sense of safety, and overall atmosphere – impacts their inclination toward active travel (Sugiyama et al., 2012; Reynolds et al., 2009). Perceptions can even outweigh the impact of objective environmental characteristics (Guo & He, 2021; Ma & Cao, 2019; Ma & Dill, 2017).

However, a research gap exists regarding the interaction between perceived streetscape quality and bike lanes – a key component of cycling infrastructure. While bike lanes receive attention for their direct impact on cycling usage and safety, their effectiveness may be closely tied to streetscape perceptions. This study aims to unravel this complex interplay: *Does a positively perceived streetscape boost the*

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* Corresponding author.
E-mail address: uhwang@atlantaregional.org (U. Hwang).

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appeal of bike lanes, or could it overshadow the need for these lanes?

This study bridges this gap with a novel methodology. Instead of relying solely on surveys prone to geographical and resource constraints, we utilize cutting-edge computer vision technology. A deep learning model trained on the vast Place Pulse 2.0 dataset (which collects perceptual impressions of street view images worldwide) is used to predict the perceived quality of a given streetscape image. This scalable approach offers a quick and efficient method to obtain streetscape perception data.

In this study, we focus specifically on visual safety – that is, the perceived safety of a streetscape based on its visual characteristics. While streetscape quality includes multiple dimensions such as aesthetics, liveliness, and cleanliness, visual safety reflects a subjective judgment of how secure or threatening an environment appears to the general public. This perceptual quality is particularly relevant for understanding how people experience public space and make decisions about active transportation, such as cycling.

This study seeks to inform the design and implementation of bike lanes within the broader urban context. By understanding how streetscape perceptions are associated with the use and effectiveness of cycling infrastructure, we can create spaces that are not only functional but also resonate aesthetically and psychologically with the community. The research could contribute to a paradigm shift in active mobility planning, prioritizing appropriate infrastructure based on streetscape perception to promote active, healthy, and sustainable cities.

2. Literature review

2.1. The built environment and active mobility

The built environment – defined as human-made surroundings that provide the settings for human activities – plays a crucial role in facilitating active mobility such as walking and cycling. This well-established relationship has garnered substantial attention across various disciplines, from urban planning to public health. A wealth of research has consistently revealed built environment characteristics that significantly impact active mobility (Cervero & Kockelman, 1997; Frank et al., 2006; Ewing & Cervero, 2010; McCormack & Shiell, 2011; Saelens, Sallis, & Frank, 2003; Sallis, Owen, & Fisher, 2015).

For instance, increased street connectivity can foster active mobility by creating a network of pedestrian- and cycling-friendly routes (Ewing & Cervero, 2010). Additionally, mixed land use, where residential, commercial, and recreational areas coexist, has been linked to higher rates of walking and cycling (Saelens, Sallis, & Frank, 2003). High population and employment density contribute to urban vibrancy, encouraging active modes of transportation (Cervero & Kockelman, 1997). Furthermore, research highlights the significance of public transit access, as it complements active mobility by offering multimodal options (McCormack & Shiell, 2011; Owen et al., 2007). The availability of public open spaces, such as parks and green areas, enhances the attractiveness of walking and cycling while contributing to overall community well-being (Bedimo-Rung, Mowen, & Cohen, 2005). Finally, proximity to essential destinations like schools, workplaces, and shopping centers is consistently associated with increased engagement in active transportation (Boarnet & Sarmiento, 1998; Pucher & Dijkstra, 2003), encouraging individuals to incorporate it into their daily routines.

2.2. Streetscapes and active mobility

Unlike motorized transportation, the decision to walk or cycle is heavily impacted by the visual and experiential qualities of the street environment, or streetscapes (Ewing & Handy, 2009; Ewing et al., 2013; Harvey et al., 2015). The term "streetscape" refers to the combination of visual components along a street: buildings, sidewalks, bike paths, furnishings, greenery, and open areas. These features create the street's unique identity and influence perceptions.

Studies indicate that the appearance and feeling of a streetscape fundamentally affect how people view their surroundings, which in turn impacts their willingness to walk or bike. Streets that offer positive visual experiences – through public art, landscaping, and inviting walkways – make walking and cycling more pleasurable and thus more likely (Sugiyama et al., 2012). More recent work on cyclists' preferred streets also confirms the strong influence of the street environment on cycling behaviors, which emphasizes the need to assess these visual elements (Zhao et al., 2025).

Crucially, streetscapes must also promote feelings of safety. People are more likely to cycle when they believe the route poses minimal risk (Reynolds et al., 2009). Safety concerns encompass both protection from traffic accidents as well as the perception of safety from potential crime. Bright lighting, upkeep, and a sense of community presence within a streetscape all promote a feeling of security, which encourages active mobility options. A current focus in transportation research is on how cyclists perceive infrastructure in terms of comfort, safety, and comprehensibility, which demonstrates that these subjective factors are critical to adoption (Berghoefer & Vollrath, 2022; Friel & Wachholz, 2025).

2.3. Perception of streetscapes as a key factor in cycling

Understanding how people perceive their surroundings is crucial for explaining the complex relationship between streetscapes and active travel behaviors. A significant amount of research examines how both objective and subjective (or perceived) elements of the street environment shape active travel choices (Ewing et al., 2003; Handy & Clifton, 2001; Handy, Cao, & Mokhtarian, 2005; Harvey et al., 2015; Hoehner et al., 2005; Lin & Moudon, 2010; Moudon et al., 2007). This highlights the importance of considering perceptions alongside objective measurements.

The influence of perception is particularly pronounced for bicycling decisions, with several studies finding that perceptions hold more sway over cycling choices than objectively measured features. For example, Ma and Dill (2017) discovered that perceived bikeability significantly influences recreational cycling, while objective bikeability does not. This aligns with Ma and Cao's (2019) assertion that perceptions act as mediators between the objectively measured environment and cycling/walking behaviors. These studies suggest that our perceptions have a more direct influence on active mobility than purely objective factors. Similarly, Guo and He (2021) showed that the perceived built environment directly promotes frequent shared bike use while also mediating the impact of public transit access on bike usage.

In this context, it is important to consider that the effectiveness of bike lanes themselves may depend on overall streetscape perception. While many studies examine bike lanes and perceived streetscapes individually, less research investigates how these elements interact. Some studies indicate that bike lanes can enhance perceptions of safety and convenience, thus encouraging cycling (Broach, Dill, & Gliebe, 2012). However, they often do not examine how perceptions of the broader streetscape (beyond just the bike lane) influence this dynamic. This study addresses a critical gap by exploring how different dimensions of perceived streetscape quality—specifically visual safety—moderate the association between the installation and type of bike lanes and actual cycling behavior.

2.4. *Measuring streetscape perception with computer vision*

Traditionally, measuring the subjective perception of streetscapes has relied on resource-intensive methods, such as on-site audits or surveys. While valuable, these approaches are limited in their spatial coverage, prone to subjective rater bias, and difficult to scale across large urban areas. In recent years, the convergence of deep learning, computer vision, and ubiquitous street-view imagery has revolutionized the field of urban perception research.

Deep learning models, trained on extensive human-labeled datasets of street view images, are now capable of reliably predicting human perceptions—including safety, aesthetics, and walkability—directly from images. Studies now successfully employ this methodology to map and evaluate human perception across entire cities, which demonstrates the technique's utility for large-scale comparative analysis and for understanding spatial patterns in subjective experience (Wei et al., 2022; Liang et al., 2024; Lei et al., 2024). This technological shift has also been applied directly to active mobility research, with methods developed to measure walkability perception using deep learning and street view images (Li et al., 2022; Kang et al., 2023). Adopting this cutting-edge computer vision approach allows our study to conduct a robust, spatially comprehensive analysis of the interaction between perceived streetscape quality and the effectiveness of different bike lane types.

3. Conceptual framework

The visual and functional characteristics of streets significantly impact how people perceive them and, consequently, how they use them. Our surroundings influence our behavior, particularly when it comes to transportation choices. This research investigates the complex interplay between streetscapes and bike lanes in motivating cycling behavior.

Consider two hypothetical streets: Street A, which has a neglected and unappealing streetscape, and Street B, which is aesthetically

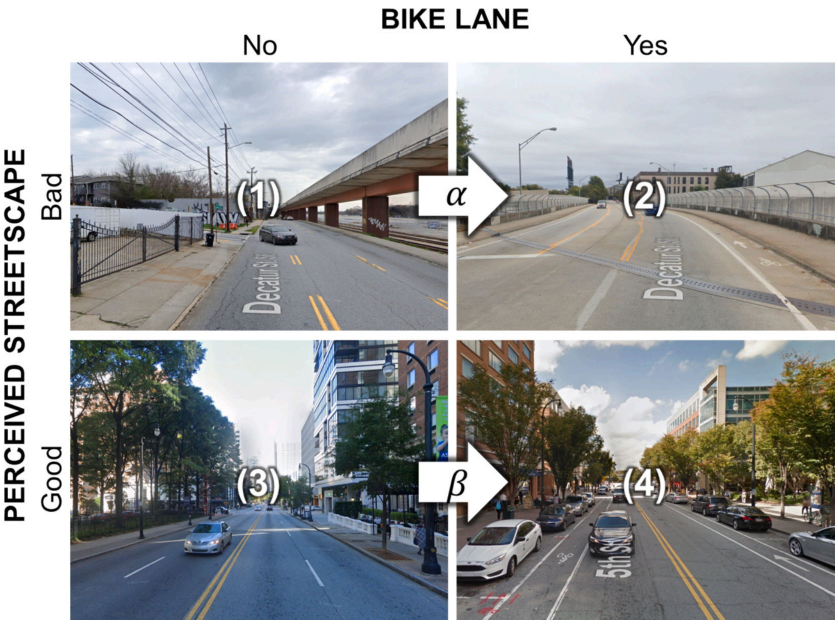

Fig. 1. Four street view images: (1) bad perceived streetscape without bike lane, (2) bad perceived streetscape with bike lane, (3) good perceived streetscape without bike lane, (4) good perceived streetscape with bike lane.

pleasing and feels safe. Both currently lack bike lanes, and we assume similar baseline propensity to bike among their users. If dedicated bike lanes were added to both streets, would the resulting increase in cycling behavior be the same? We define α as the change in cycling behavior on Street A after bike lanes are added, and β as the corresponding change on Street B.

Fig. 1 visually represents this conceptual scenario using real-world street view images. Images (1) and (3) correspond to the baseline conditions of Streets A and B, respectively, while Images (2) and (4) represent the condition after bike lane installation. The variables α and β quantify the change in cycling activity transitioning from (1) to (2) and from (3) to (4).

If α and β differ significantly (regardless of which is greater), this suggests that streetscapes may moderate the relationship between bike lanes and cycling. If β exceeds α, this indicates a positive moderation effect, where bike lanes have a greater impact in already inviting and safe streetscapes. Conversely, if α is greater than β, bike lanes may be more effective in less appealing or less safe-feeling environments.

This study hypothesizes that streetscape perception significantly moderates this relationship, expecting a negative moderation effect ($\alpha > \beta$). This implies that bike lanes hold greater potential to increase cycling in neighborhoods with less inviting streetscapes. Beyond aesthetics, this study explores how urban design choices can address disparities by promoting cycling infrastructure equitably across diverse communities.

By understanding the interplay between streetscape perception and the bike lane effectiveness, this study aims to provide insights that guide urban planning initiatives to promote cycling inclusively and equitably.

4. Methodology

4.1. Perceptions of streetscapes

Traditional studies on streetscape perception rely heavily on surveys administered to individuals. While valuable, these surveys face challenges with cost, time, and geographic scalability, which can limit the generalizability of findings. This study addresses these limitations by leveraging the power of computer vision technology.

The underlying concept is to "show" street images to a computer and train it to understand human perceptions. This approach has become increasingly feasible due to advances in deep learning, a subfield of machine learning. Deep learning models, with their multi-layered "neuron" structures inspired by the human brain, can learn abstract concepts like perception when provided with sufficient data. A detailed explanation of computer vision can be found in Section 4.2.

To train our model, we require a ground truth dataset containing both street view images and labels reflecting how humans perceive those images. Place Pulse 2.0, an online crowdsourced dataset created by researchers at the Massachusetts Institute of Technology Media Lab (Dubey et al., 2016), serves this purpose well. Place Pulse 2.0 collected approximately 1.6 million votes on 110,988 images from 56 cities worldwide. In the survey, participants were simply given two randomly selected images and asked to choose the one that looks better in terms of perceptual attributes like 'safe', 'lively', 'beautiful', 'wealthy', 'depressing', and 'boring'. The dataset includes a calculated perception score for each image, determined by applying the TrueSkill algorithm (Herbrich, Minka, & Graepel, 2006) to the collected voting results.

Among the six perceptual attributes, this study focuses on safety as the representative perception of streetscapes for two key reasons. Firstly, the walkability literature highlights five environmental factors influencing walking: feasibility, accessibility, safety, comfort, and pleasurability. These elements form a hierarchy (Fig. 2), where safety plays a more fundamental role in decision-making than comfort or pleasurability (which encompass other attributes in Place Pulse 2.0). Given that safety is also a paramount concern for cyclists (Sanders, 2013), it is reasonable to assume this hierarchy extends to cycling behavior.

Secondly, as shown in Table 1, safety was the most frequently assessed attribute in Place Pulse 2.0. This suggests its score is more

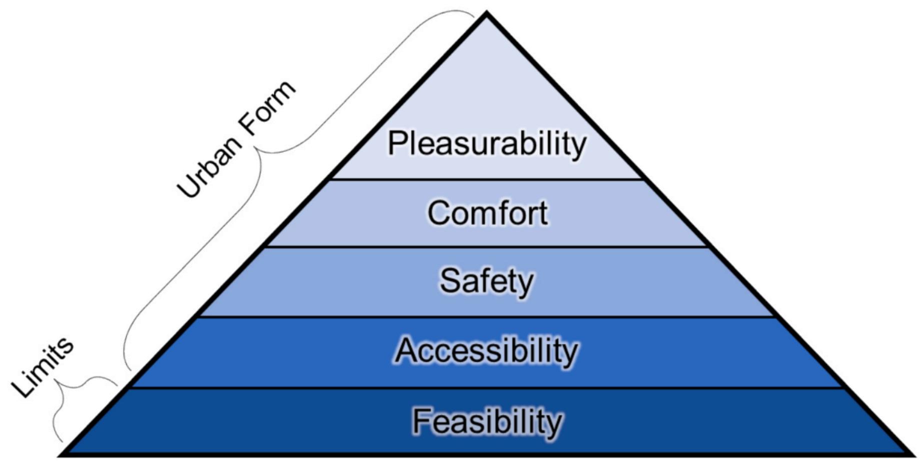

Fig. 2. Hierarchy of walking needs (Alfonzo, 2005).

reliable than those of the other attributes. According to TrueSkill documentation, at least 12 matches per player (in this case, images assessed) are required for reliable scores (Microsoft, n.d.). Compared to the other five attributes, safety has a significantly larger number of images (36,783) meeting this criterion, which is critical to the training performance of a computer vision model.

Using 36,783 images and their scores from Place Pulse 2.0, this study trains a computer vision model that predicts visual safety score for a given image. Visual safety is defined as how safe a street appears based on visual cues in imagery, as perceived by the public. It is important to clarify that the safety measure used in this study is based on visual perception, not objective indicators of crime or traffic incidents. The Place Pulse 2.0 dataset provides a crowdsourced measure of how safe an image appears to respondents, based purely on visual cues. As such, our measure of visual safety should be interpreted as a proxy for perceived environmental security rather than an empirical indicator of actual safety.

4.2. Computer vision and transfer learning

Computer vision, a key field within Artificial Intelligence (AI), enables machines to process and understand visual information, mimicking the way humans use sight and cognition to interpret their surroundings (Szeliski, 2022). Computer vision automates tasks like object detection, image recognition, and scene understanding – interpreting the context and meaning within images (Goodfellow, Bengio, & Courville, 2016).

Street view images offer a rich source of information about urban environments for analysis through computer vision. The challenge lies in teaching machines to recognize patterns that relate to abstract human concepts like perceived safety. This requires not only large datasets but also complex models with many parameters, as they must interpret nuanced elements rather than just tangible visual features (Krizhevsky, Sutskever, & Hinton, 2012).

Traditional training approaches can be demanding in terms of data and computational power. This is where transfer learning offers a powerful solution. Deep learning models, especially those used in computer vision, can have millions or billions of parameters. Training such models from scratch is incredibly resource-intensive (Yosinski et al., 2014). Transfer learning addresses this by starting with a pre-trained model (usually trained on a large dataset for a related task) and adapting it for the new task (Pan & Yang, 2010). This leverages insights the model has already learned, significantly reducing the need for new training data and computations.

Fig. 3 illustrates the transfer learning model framework based on the MaxVit: Multi-Axis Vision Transformer architecture (Tu et al., 2022). This model was initially pretrained on the massive ImageNet 12 k dataset and then fine-tuned on ImageNet 1 k for the task of classifying 1,000 distinct object categories.

During this pretraining process, the model develops an understanding of visual features, starting with low-level elements and progressing to more complex ones. A crucial component is the fully connected layer at the end of the network. This layer synthesizes learned features to recognize patterns that allow the model to accurately classify images. For transfer learning, we leverage the knowledge embedded within this fully connected layer, repurposing it to train a new model for a related task – in this case, predicting perceived street safety. We added five new layers specifically designed to address the question, “How safe does the street look?”. These layers were trained using the 36,783 street view images and their corresponding labels from the Place Pulse 2.0 dataset.

The PyTorch deep learning framework (Paszke et al., 2019) was used for both model architecture and training. The 'timm' (Pytorch Image Models) library provided the pretrained weights. For specific details on the training process, including hyperparameters, please refer to Table A1 in the Appendix.

4.3. Selection of the study area

This research focuses on Berlin, Germany for two primary reasons. Firstly, Berlin offers an exceptional amount of accurate crowdsourced data. Berlin's OpenStreetMap data, for instance, is particularly reliable due to the city's vast contributor network – the largest in the world. This ensures precise and comprehensive analysis of streetscape elements. Additionally, Mapillary, a platform for sharing geotagged street-level images, provides extensive street view coverage throughout Berlin. Crucially, many of these images are contributed by cyclists themselves, offering valuable insights directly from the cyclists' perspective.

Secondly, Berlin boasts a large and active cycling population. In 2018, the cycling modal share was 18% (Gerike et al., 2020), indicating a strong cycling culture. This high prevalence of cycling allows for robust statistical analysis. Studying Berlin, a city with a mature cycling culture, can offer valuable insights and lessons that can inform cycling infrastructure and policy improvements in U.S. cities.

4.4. Data

This study models the number of bike trips at the street segment level. Our model considers variables related to both streetscape

Table 1
Number of survey responses by perceptual attribute in Place Pulse 2.0.

Perceptual attribute	Safe	Lively	Beautiful	Wealthy	Depressing	Boring
Number of survey responses	511,037	367,476	220,656	174,784	149,361	144,068
Average number of responses per image	9.2	6.6	4.0	3.1	2.7	2.6
Number of images with 12 or more survey responses	36,783	10,149	197	535	311	167

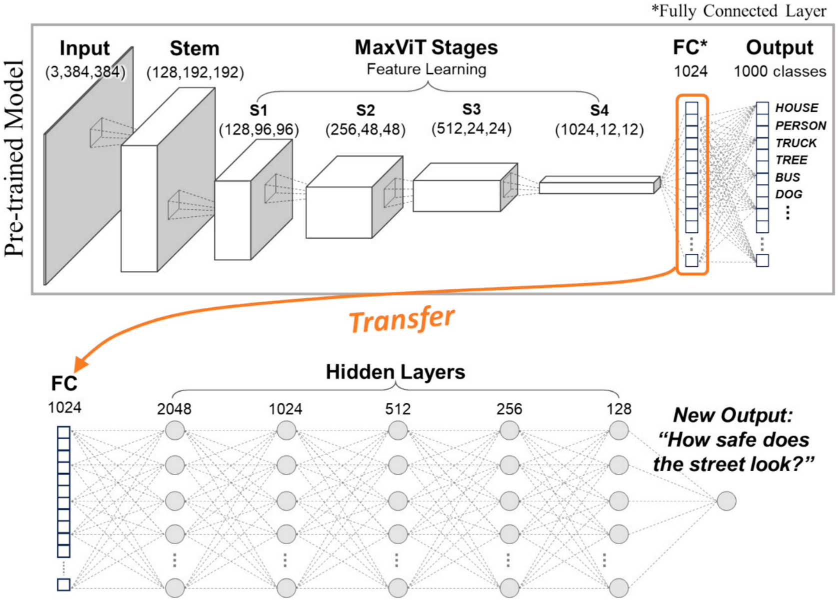

Fig. 3. The framework of the transfer learning model used in this study.

characteristics and perceptions of those streetscapes. Table 2 provides a full list of variables and their data sources. The dependent variable, the number of bike trips, is obtained from SimRa (Karakaya, Hasenburg, & Bermbach, 2020), a large-scale, crowdsourced dataset of GPS traces from cycling smartphone apps. Information on near-miss incidents is also included but excluded from the present analysis. We processed the raw GPS traces using a map-matching algorithm to calculate the number of bike trips on each street segment.

Mapillary street view images are used to determine the visual safety score for each street segment. Our computer vision model (trained on the Place Pulse 2.0 data) analyzes these images. We initially collected metadata on 7.4 million Mapillary images in Berlin, then narrowed this down to 4.6 million by excluding those taken before 2017, outside of 8 am – 6 pm, or during winter months (December-February). We also excluded panoramic images. From the 4.6 million images, we sampled approximately 380,000 images by selecting 12 images within a 15-meter (50-foot) radius of each street segment.

Bike lane classifications are based on OpenStreetMap's system. A 'striped bike lane' is denoted by a solid white line, which includes buffered bike lanes as well in OpenStreetMap. 'Protected bike lanes' are those physically separated from motor traffic by a barrier or designated space.

4.5. Model selection

To predict bike trips at the street segment level, several modeling techniques were considered. Bike trip counts are non-negative integers with many zeros, indicating numerous segments with no bike activity. This excess of zeros and the resulting overdispersion made traditional count models like Poisson regression unsuitable.

Models specifically designed for excess zeros, such as Zero-inflated and Hurdle models, were initially considered. These models assume two zero-generating processes: structural zeros (where events are inherently impossible) and incidental zeros (He et al., 2014; Alemi et al., 2018; Kim & Mokhtarian, 2021). However, since the dataset in this study only included theoretically bikeable streets, structural zeros were not a factor, making these models less applicable.

To handle the overdispersion, Negative Binomial (NB) and quasi-Poisson (QP) models were then explored. However, the NB model's low McFadden's R2 (see Table 3) suggests that standard count models might not be the best fit for this dataset. Consequently, this study employed a semi-log linear model, log-transforming the dependent variable. To ensure a valid comparison across these different model types, we relied primarily on prediction accuracy metrics calculated on the original scale of the dependent variable: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). In both MAE and RMSE, the semi-log linear model outperformed the other two models. While the semi-log model also showed a strong goodness-of-fit (Adjusted R2 of 0.47), the selection was mainly driven by its superior accuracy in predicting observed bike trips.

A semi-log linear (log-lin) model expresses the dependent variable as the natural logarithm of the outcome. This allows us to interpret changes in the independent variables as percentage changes in the outcome. It is represented by the equation:

$$\ln(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + \epsilon \tag{1}$$

where Y is 'number of bike trips + 1' to avoid taking the logarithm of zero. In a semi-log linear model, changes in the independent variables have a multiplicative impact on Y. Specifically, a one-unit change in X_i leads to a $(e^{\beta_i} - 1) \times 100\%$ change in Y. This

Table 2
Variables and data sources.

Variable	Data Source
Number of bike trips (dependent var.)	SimRa
Visual safety score	Place Pulse 2.0 (for training); Mapillary (for inference)
Bike lane type	OpenStreetMap
Road type	OpenStreetMap
Street parking	OpenStreetMap
One-way	OpenStreetMap
Traffic speed	Bing Maps API
Traffic congestion	Bing Maps API
Betweenness centrality	OpenStreetMap; OSMNX (Boeing, 2017)
Length of street segment	OpenStreetMap; OSMNX (Boeing, 2017)
Number of POIs nearby (within 50 m or 164 feet)	Google Places API

Table 3
Comparison of model performance: Negative Binomial, quasi-Poisson, and semi-log linear models.

Performance Measure		Negative Binomial	Quasi-Poisson	Semi-log (log-lin)
Goodness-of-fit[a]	Adj. McFadden's R^2	0.03	–	–
	Adj. Nagelkerke's R^2	0.25	–	–
	Adj. Deviance-based R^2	0.23	0.41	–
	Adj. R^2	–	–	0.47
Prediction	Mean Absolute Error	239.7	214.3	161.8
Accuracy	Root Mean Squared Error	453.5	433.0	369.9

[a] In calculating the three pseudo R^2 measures, the null model was the *intercept-only* model.

interpretation aligns with count models such as Poisson.

5. Results

5.1. Computer vision model training result

This study employed transfer learning to train a computer vision model for predicting street view images' visual safety scores. The Place Pulse 2.0 dataset's ground truth safety scores were normalized to a 0–10 range. The trained model achieved a Mean Absolute

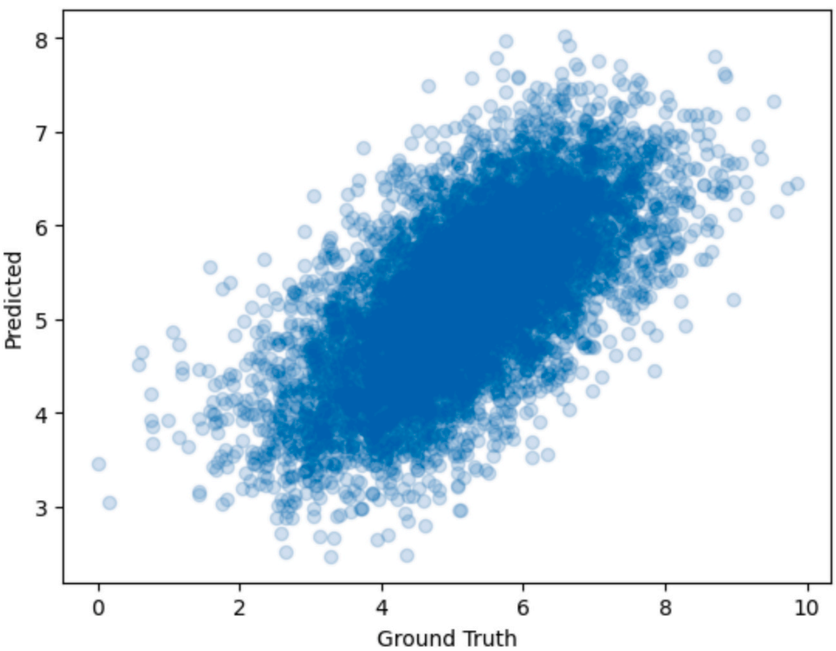

Fig. 4. Ground truth (x-axis) and predicted values (y-axis) of the visual safety score.

Error (MAE) of 0.766 on the test set, indicating an average deviation of 0.766 between predicted and true scores. Fig. 4 visualizes this correlation (coefficient = 0.66) between ground truth and predicted safety scores.

To evaluate performance, it is standard to compare machine learning models against other benchmarks. Several studies have used the Place Pulse 2.0 to predict street perceptions, employing techniques like Support Vector Machines (Naik et al., 2014; Zhang et al., 2018), Random Forests (Yao et al., 2019), and deep learning (Dubey et al., 2016; Moreno-Vera, Lavi, & Poco, 2021). While direct comparisons are difficult due to differing metrics, two studies (Moreno-Vera et al., 2021; Zhang et al., 2018) framed safety prediction similarly as a binary classification problem. They transformed continuous ground truth scores into binary cases using the following formula:

$$y_i = \begin{cases} \textbf{\textit{safe}} \text{ if } gt_i > \mu_{gt} + \delta \bullet \sigma_{gt} \\ \textbf{\textit{unsafe}} \text{ if } gt_i < \mu_{gt} - \delta \bullet \sigma_{gt} \end{cases} \quad (2)$$

Where μ_{gt} and σ_{gt} are the mean and standard deviation of ground truth values, and δ is a threshold determining parameter. For comparison, we converted Fig. 4′s ground truth and predicted values into binary measures using this formula and calculated accuracy (see Fig. A1 in the Appendix for an illustration). Fig. 5 demonstrates that this study's deep learning model significantly outperforms the two previous models, for any plausible value of δ.

5.2. Inference result: visual safety scores in Berlin

This study used the trained computer vision model to predict visual safety scores for about 380,000 Mapillary street view images in Berlin, Germany. Fig. 6 provides examples, demonstrating a connection between image elements and perceived safety. Images with features such as graffiti typically receive lower safety scores. Conversely, those in the third row appear safer and convey a sense of pleasantness.

For analysis, safety scores were compiled at the street segment level. Each segment comprises 12 images. To mitigate the impact of outliers, we excluded the two images with scores furthest from the mean, leaving an average score based on 10 images per segment. Fig. 7 illustrates the distribution of these segment-level safety scores. Berlin's average score of 5.5 (on a 0–10 scale) suggests higher overall perceived safety compared to the 56 cities within the Place Pulse 2.0 dataset (average score of 5.0).

Interestingly, the Berlin scores mostly range between 4 and 6.5, exhibiting a narrower distribution than the original dataset. This is likely due to two factors: 1) Berlin's streetscapes are more homogenous than the globally diverse Place Pulse 2.0 data, and 2) our segment-level scores represent averages of 10 images, naturally resulting in values closer to the overall average.

Fig. 8 visualizes the geographic distribution of scores. Central and southwestern areas of Berlin exhibit higher perceived safety, while eastern sections and major arterial roads tend to score lower. These patterns offer insights for further investigation and potential urban planning interventions.

5.3. Semi-log linear model result

Table 4 presents the outcomes from a semi-log linear model evaluating the frequency of bicycle trips at the level of individual street segments. This model explores how the visual safety score moderates the relationship between the existence of bike lanes and the number of bike trips, by integrating an interaction term. Additionally, it considers a range of street features and traffic conditions. We first briefly discuss these control variables and then provide details on the findings regarding the visual safety score's moderating effect.

In terms of ‘road type’, the analysis reveals a hierarchy of cycling volume, with secondary roads having the highest cycling activity,

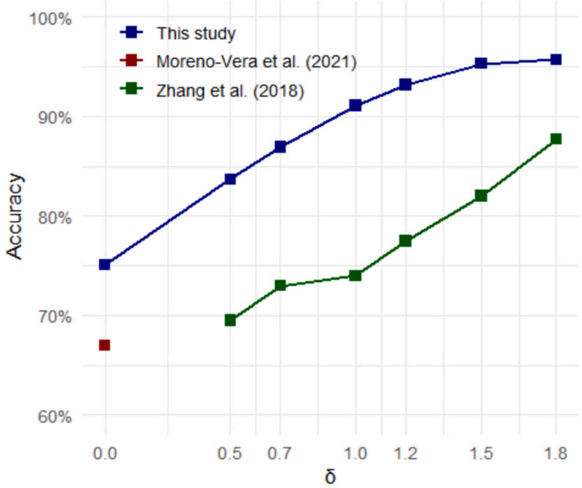

Fig. 5. Computer vision model performance comparison.

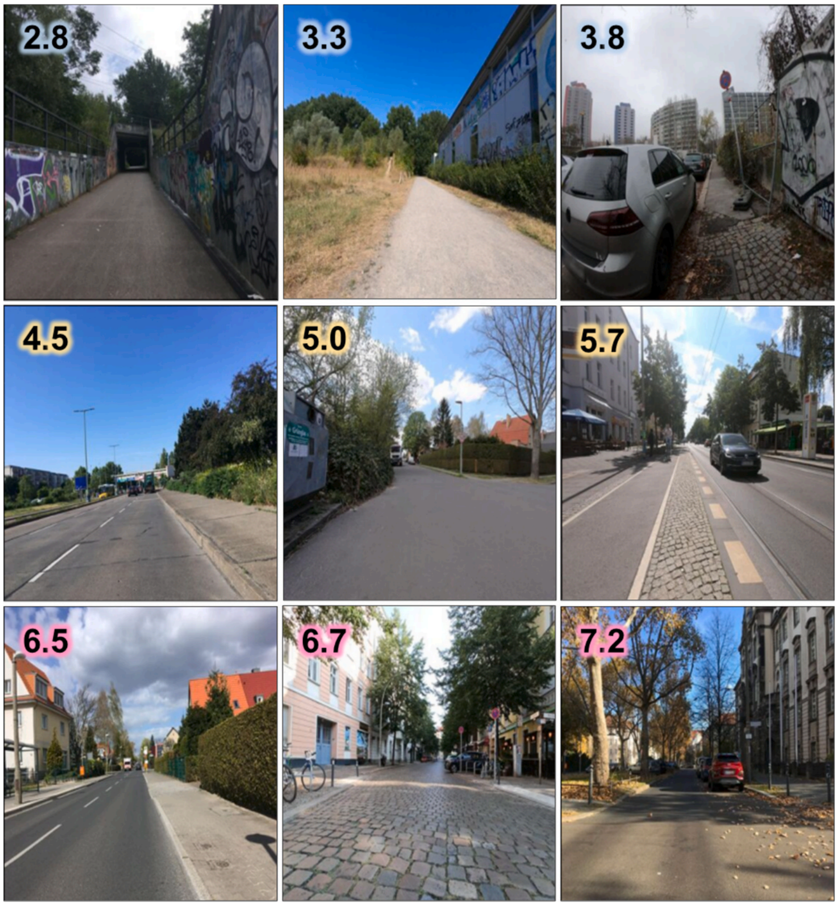

Fig. 6. Examples of Mapillary street view images in Berlin, Germany and their visual safety scores inferred by the computer vision model trained in this study.

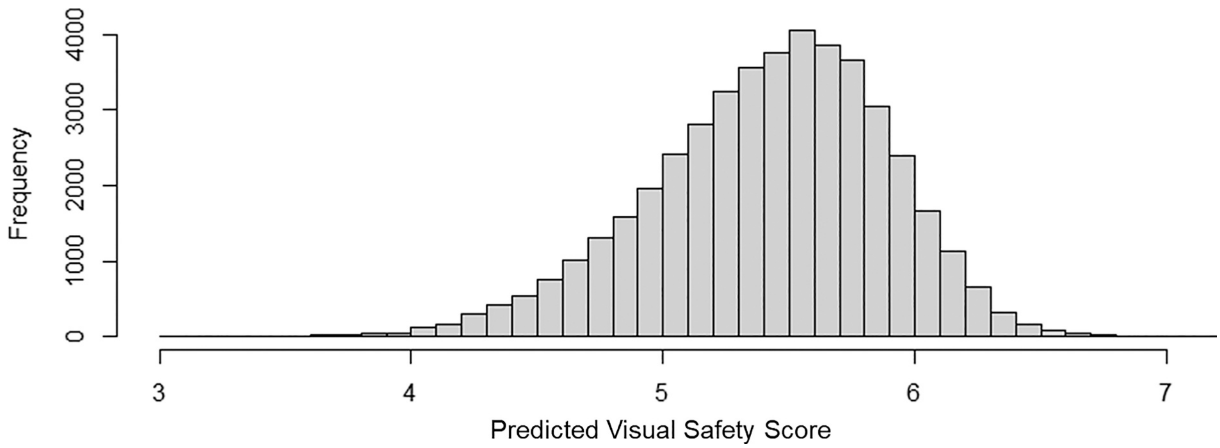

Fig. 7. Distribution of the predicted visual safety scores at the street segment level in Berlin, Germany.

followed by primary, tertiary, and residential roads in descending order. The positive coefficient of 'street parking' shows that streets with on-street parking facilities report a higher frequency of bicycle trips than those lacking such amenities, all else being equal. Furthermore, one-way streets seem to be more appealing to cyclists compared to two-way streets.

To accurately assess the potential non-linear relationships with the number of bike trips, three variables—'vehicle speed', 'traffic congestion', and 'distance from the city center'—were categorized rather than treated as continuous. The analysis of 'vehicle speed'

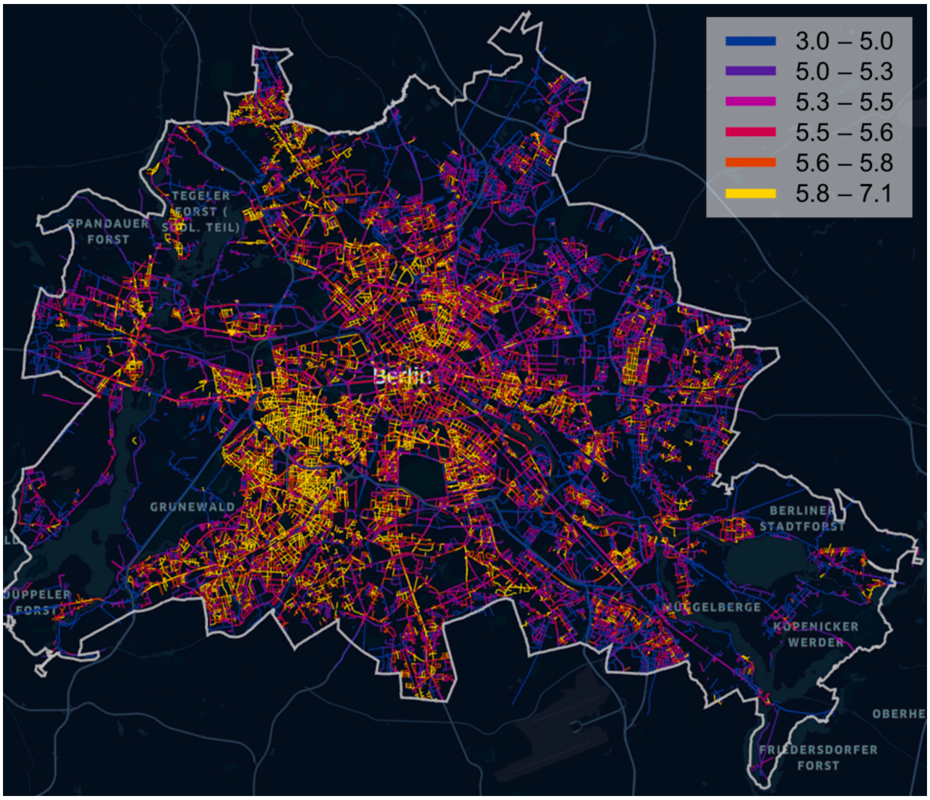

Fig. 8. Geographic distribution of the predicted visual safety scores at the street segment level in Berlin, Germany.

shows higher bicycle volumes on roads where vehicle speeds range between 20–30 mph, with roads at the extremes of very low or high speeds being relatively less often traveled by cyclists. The 'traffic congestion' coefficients indicate a positive relationship with bicycle trips, suggesting that areas with higher congestion might also witness more bicycle traffic. Regarding 'distance from the city center', a fairly linear relationship is observed, with roads nearer to the city center experiencing more bicycle traffic.

Positive coefficients for 'betweenness centrality' and the 'number of POIs nearby' suggest that roads with strategic importance in the network and those in close proximity to numerous points of interest are more likely to attract cyclists. Lastly, the coefficient for 'length of street segment' indicates that shorter segments are associated with higher cycling activity.

Let's examine the moderating effect. The interaction between 'visual safety score' and 'bike lane type' indicates a significant relationship, with distinct effects for striped and protected bike lanes. Notably, as the 'visual safety score' increases, its positive correlation with cycling behavior strengthens for striped lanes but lessens for protected lanes.

Fig. 9 displays the interaction effect between the 'visual safety score' and 'bike lane type', deliberately excluding the main effect of the 'visual safety score' to streamline the presentation. This approach enhances our understanding of the distinct impacts attributed to different types of bike lanes by facilitating a direct comparison of their effects under the same visual safety conditions. For instance, Fig. 9 indicates that streets with striped bike lanes and an average visual safety score are likely to see 198%[1] more bike trips compared to streets with the *same* visual safety score, but no bike lanes.

The interaction term's coefficients, alongside Fig. 9, reveal that the moderating effect of the visual safety score diverges between striped and protected bike lanes. For striped bike lanes, the positive moderating effect of visual safety aligns with the concept of synergistic validation. Striped bike lanes are especially beneficial in environments already perceived as safe, as the low-cost infrastructure works synergistically with positive visual cues (e.g., maintenance, aesthetics) to validate the cyclist's route choice and maximize ridership. The effectiveness of striped bike lanes is thus reliant on the existing psychological comfort signaled by the streetscape.

Conversely, the negative moderating effect observed for protected bike lanes is consistent with risk compensation. Protected bike lanes exhibit a stronger correlation with cycling activity in areas perceived as visually unsafe because the physical separation functions as a necessary psychological and physical countermeasure. The enhanced sense of security provided by the protected bike lanes compensates for the perceived hazard or neglect signaled by the low visual safety score, effectively mitigating the barrier to cycling in those environments.

[1] $.(e^{Coef.} - 1)*100 = (e^{1.091} - 1)*100 = (2.98 - 1)*100\% = 198\%$

Table 4
Result of the semi-log linear model.

Variable		Coef.		p-value
(Intercept)		0.940	***	0.0000
Visual safety score (mean-centered[a])		0.457	***	0.0000
Bike lane type	None	(base)		
	Striped bike lane (SBL)	1.091	***	0.0000
	Protected bike lane (PBL)	1.050	***	0.0000
Visual safety score × Bike lane type	Safety score – SBL	0.258	**	0.0033
	Safety score – PBL	−0.314	***	0.0000
Road type	Primary	−0.0735	ˆ	0.0828
	Secondary	(base)		
	Tertiary	−0.195	***	0.0000
	Residential	−1.028	***	0.0000
Street parking		0.417	***	0.0000
One-way		0.0918	***	0.0005
Vehicle speed (mph)	Slower than 10	−0.568	***	0.0000
	10–15	−0.455	***	0.0000
	15–20	(base)		
	20–25	0.254	***	0.0000
	25–30	0.151	***	0.0001
	30–35	−0.0434		0.3316
	Faster than 35	−0.248	***	0.0001
Traffic congestion	None	(base)		
	Mild	0.183	***	0.0000
	Medium	0.330	***	0.0000
	Heavy	0.423	***	0.0000
Distance from the city center (miles)	Less than 1.5	2.676	***	0.0000
	1.5–3	1.720	***	0.0000
	3–5	0.822	***	0.0000
	5–7	(base)		
	7–10	−0.520	***	0.0000
	10–15	−0.579	***	0.0000
	Greater than 15	−0.793	**	0.0058
Betweenness centrality (log-transformed)		0.151	***	0.0000
Number of POIs nearby (within 50 m or 164 feet)		0.0424	***	0.0000
Length of street segment (meters)		−0.000192	*	0.0130
Observations		35,131		
Adj. R^2		0.47		

[a] The 'visual safety score' is mean-centered for better interpretability of the interaction term.
*** $p < 0.001$.
** $p < 0.01$.
* $p < 0.05$.
ˆ $p < 0.1$.

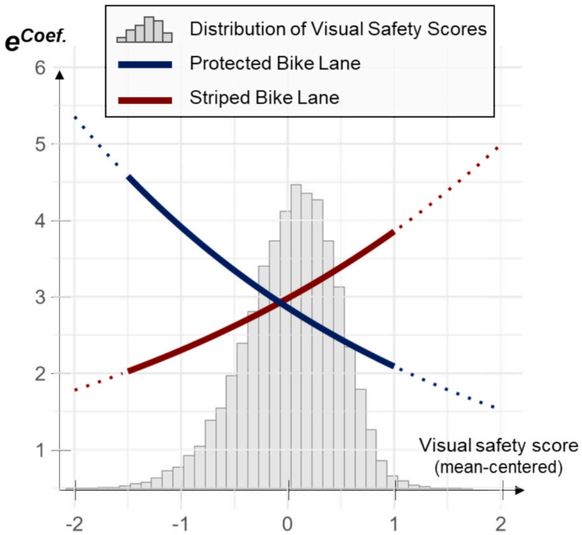

Fig. 9. Interaction effect between the visual safety score and bike lane type (excluding the main effect of the visual safety score).

To avoid misunderstanding, we want to emphasize that the foregoing analysis does not imply that either striped or protected bike lanes lose their efficacy under certain conditions. According to the model's findings, both bike lane types are positively associated with cycling activity across the full range of visual safety scores; nevertheless, the *extent* of their associations is contingent upon the visual context.

Table 5 provides an interpretation of Fig. 9, detailing how different types of bike lanes—striped and protected—affect cycling activity across a range of visual safety conditions.

Regardless of the visual safety score, both striped and protected bike lanes are positively associated with higher levels of cycling. At an average visual safety score, the associations of striped and protected bike lanes with cycling are nearly identical, with roads featuring striped lanes showing 198% more trips than roads without bike lanes, and protected lanes showing 186% more. However, these associations differ when visual safety diverges from the mean. For example, on streets where the visual safety score is one point below average, protected bike lanes are associated with a 291% increase in cycling activity, compared to 130% for striped lanes. Conversely, for streets with a visual safety score one point above average, striped lanes are associated with a 285% increase, while protected lanes show a 109% increase.

To summarize, striped bike lanes are more strongly correlated with increased cycling on streets perceived as safe, whereas protected bike lanes show stronger correlations on streets viewed as less safe.

6. Discussion

The objective of this study was to investigate the interplay between the perceived quality of streetscapes and different types of bike lanes—striped and protected—in shaping the frequency of cycling trips on urban streets. Using a semi-log linear model, this research analyzed the moderating effects of visual safety scores on the relationship between the presence and type of bike lanes and cycling trip frequency. Visual safety scores were generated through computer vision analysis of crowdsourced street view imagery across Berlin, Germany. The findings reveal several key insights that contribute to ongoing urban mobility and planning research.

- Streets perceived as safe tend to be associated with higher cycling activity.
- Both striped and protected bike lanes are positively associated with cycling participation.
- Visual safety perceptions significantly moderate the strength of these associations.
- The direction of this moderating effect differs by bike lane type: positive for striped lanes and negative for protected lanes.

These findings are consistent with research suggesting that perceptions of safety are critical to cyclists' route choices and willingness to ride (Dill & McNeil, 2016; Juarez et al., 2023; Sanders, 2015; Ye et al., 2024). The stronger association between striped bike lanes and cycling on streets perceived as safer supports the idea that visual cues such as cleanliness, greenery, or maintenance may enhance the usability of existing cycling infrastructure (Juarez et al., 2023). This finding is important for urban planners, suggesting that investments in aesthetics and perceived safety of streets can work synergistically with striped bike lanes to encourage cycling. Conversely, these lanes may not be the best option in areas perceived as less safe.

In contrast, protected bike lanes exhibit a different pattern. Their stronger correlation with cycling activity on streets perceived unsafe suggests they may serve as an important resource where perceptions of safety are lower. This finding echoes prior studies that emphasize the importance of physical separation for cyclist comfort and perceived security in more hostile or traffic-heavy contexts (Friel et al., 2023; Furth et al., 2016; Winters et al., 2011). Although our study is observational and cannot establish causality, the correlation suggests that protected infrastructure may mitigate the deterrent effects of visually uninviting environments by enhancing perceived safety and separation. Their presence could contribute to greater rider confidence and participation, potentially supporting broader goals of inclusive urban design.

These patterns support the broader theory that perceptions of urban environments—shaped by visual cues such as graffiti, lighting, and urban design—play a critical role in cycling uptake (Guo & He, 2021; Ma & Cao, 2019; Ma & Dill, 2017). Our findings build on this literature by showing how visual safety may interact differently with types of infrastructure, highlighting the value of tailored infrastructure strategies rather than one-size-fits-all interventions.

The results align with the 'complete streets' planning paradigm, which calls for context-sensitive street designs that address safety, accessibility, and comfort for all users. Our findings suggest that visual safety assessments should be incorporated into cycling infrastructure planning. For instance, enhancing streetscapes with better lighting, maintenance, and landscaping could improve the effectiveness of striped bike lanes in certain neighborhoods. Conversely, in areas lacking visual safety, protected bike lanes may play a more substantial role in encouraging cycling and mitigating the perceived risks of those environments.

These insights can support not only infrastructure development but also broader environmental design and public engagement strategies. Enhancing the visual appeal of neighborhoods—through façade upgrades, cleanliness, and greenery—can reinforce the effectiveness of bike infrastructure and promote sustainable mobility.

While these findings offer practical insights for infrastructure planning, it is also important to reflect on the conceptual basis of the "safety" measure used. In this study, safety is operationalized through visual perception, but safety itself is multi-dimensional—encompassing both crime-related and traffic-related concerns (Naik et al., 2014; Loewen et al., 1993). Prior research shows that perceived crime risk is shaped by cues like graffiti, poor lighting, and environmental neglect (van Rijswijk & Haans, 2018), while perceptions of traffic safety are more strongly linked to infrastructure and vehicle speeds (Ewing & Dumbaugh, 2009). Because the Place Pulse dataset captures general impressions, the visual safety score likely reflects a blend of these concerns rather than isolating one.

Table 5
Interpretation of Fig. 9.

When visual safety score is	Streets with striped bike lanes have___more bike trips than streets without bike lane	Streets with protected bike lanes have___more bike trips than streets without bike lane
1.5 points below average	102%	358%
1 point below average	130%	291%
0.5 points below average	162%	234%
Average	198%	186%
0.5 points above average	239%	144%
1 point above average	285%	109%

These dimensions may also interact with unmeasured factors such as pedestrian activity or land use, which can shape both actual and perceived risk (Willis et al., 2015). Future work could disentangle these domains using data that distinguishes between crime- and traffic-related safety or draws from cyclist-specific perceptions, enabling more targeted insights into how different safety concerns are associated with cycling behavior.

6.1. Limitations

This study, based in Berlin, Germany, has limitations in its generalizability. Berlin's cycling culture, infrastructure, and regulations differ significantly from those of the U.S. To address this, future research could replicate this study in various U.S. cities. This comparative approach would validate findings across varying contexts while revealing how interventions work within specific urban environments. Such studies would be crucial for tailoring successful European cycling models to the unique needs of U.S. cities.

Furthermore, the Place Pulse 2.0 dataset's "visual safety score" represents how safe a street looks, based on visual impressions from general online respondents. This perceptual score does not differentiate between types of safety—such as crime-related risks versus traffic hazards—and may not align with objective safety measures used by traffic or public safety authorities. As such, while visual safety is a meaningful proxy for public perception, its application in transportation planning should be complemented by empirical safety data.

Additionally, the Place Pulse 2.0 dataset relies on input from general online users, rather than cyclists specifically. As cyclists may have unique safety concerns—such as proximity to fast-moving traffic or road surface quality—these scores may not fully capture cyclist-specific perceptions. We suggest that future research build on this work using cyclist-targeted perception data where available.

We also acknowledge potential bias in the Place Pulse 2.0 dataset due to its crowdsourced nature. Since perceptions of safety were collected from online participants who may not represent a demographically or culturally diverse sample, the resulting visual safety scores could reflect subjective or culturally specific views. This may limit the generalizability of the model's predictions, particularly for local populations or cyclists whose perceptions may differ.

Lastly, this study does not include sociodemographic attributes of the cyclists. While such information could provide important insights into how different population groups experience and respond to street environments, individual-level demographic data was not available due to privacy constraints in the SimRa dataset. Future research should incorporate such information where possible to deepen understanding of cycling behavior.

7. Conclusion

This study highlights the complex relationship between streetscape perceptions and the effectiveness of bike lanes. By emphasizing the interaction between visual and tangible elements of street design in shaping cycling behavior, the research provides strong evidence for the importance of integrating visual safety considerations into cycling infrastructure development. The study underscores the vital role of protected bike lanes in offering cyclists a sense of safety, especially in areas where the visual environment is less reassuring. Consequently, implementing urban design strategies with protected bike lanes not only enhances the cycling experience by making it more pleasant and comfortable but also contributes to creating more vibrant, healthy, and sustainable urban environments for the community.

CRediT authorship contribution statement

Uijeong Hwang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patricia L. Mokhtarian:** Writing – review & editing, Validation, Supervision, Methodology. **Bon Woo Koo:** Validation, Supervision, Methodology, Conceptualization. **Subhrajit Guhathakurta:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization.

Appendix

A.1. Computer vision model specification

Table A1
Implementation details of the computer vision model.

Category		Value
	Feature extraction network	MaxVit: Multi-Axis Vision Transformer (Tu et al., 2022)
	Pretraining dataset	ImageNet-12k for pretraining; ImageNet-1k for finetuning
	Input size	384 × 384
	# hidden layers	5
	# nodes in hidden layers	2048 – 1024 – 512 – 256 – 128
Hyper-parameters	Initial learning rate	0.0001
	Learning rate decay	$\gamma = 0.8$ for every 2 epochs
	Batch size	16
	Dropout rate	0.2
	Activation function	ReLU
Training configuration	Optimizer	Adam
	Loss function	Quantile loss ($\alpha = 0.5$)
	Data splitting method	Hold-out validation (training set: 80%; test set: 20%)
	Data sampling method	Simple random sampling
	Data augmentation	Horizontal flip
	Finetuning	None
Training environment	Platform	Google Colab
	GPU	A100
	Framework	PyTorch
# Iterations at the best model		14,713

A.2. Illustration of converting visual safety scores into binary measures

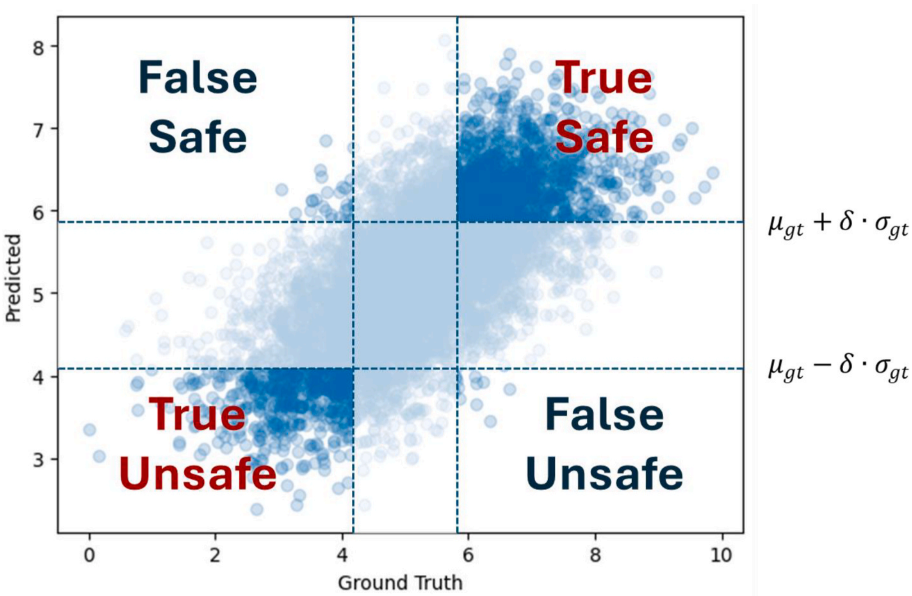

Fig. A1. Illustration of Converting Visual Safety Scores into Binary Measures.

Data availability

Data will be made available on request.

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