Comparing Urban Elements Effects on Objective and Subjective Cycling Safety

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SHORT SUMMARY

Understanding factors influencing cycling safety is critical for promoting sustainable mobility. Cyclists require both objective safety (protection from crashes) and subjective safety (feeling safe). Previous research has examined these two safety components separately, i.e., they typically focus on one safety type at a time, or it has analyzed the effects of a limited number of urban elements on either type of safety. This study integrates street-level imagery and spatial data to characterize and compare how urban cycling contexts influence both objective and subjective safety. Using machine learning (XGBoost + SHAP), we analyze 120 urban elements' impacts on 3,850 cycling crash locations in Berlin, Germany. Results show that some elements have similar effects on both safety types (e.g.: buildings and amenities), while others affect only one type (e.g.: crosswalks and truck presence), and some have opposing effects (e.g.: roadside features). These findings highlight the importance of aligning urban planning with both actual and perceived safety needs, as interventions targeting one type may inadvertently harm the other.

Keywords: Cycling Safety, Objective Safety, Subjective Safety, Machine Learning, Berlin (Germany).

1. INTRODUCTION

Cycling is promoted as key to sustainable urban mobility, yet safety concerns remain a main barrier to broader uptake (Sanders, 2015; Aldred, 2016; Félix et al., 2019). Providing cyclists with environments where they are both objectively safe from crashes and subjectively feel safe is vital for creating overall safer cycling networks and increase cycling numbers.

Cycling safety is often divided in two distinct components: objective safety (i.e., actual or observed safety) and subjective safety (i.e., perception of safety). On the one hand, objective safety is related with measures of injury-related risk and is typically quantified through crash, injury, or fall statistics (Sørensen & Mosslemi, 2009). On the other hand, subjective safety often relates to a person's individual risk level assessment, i.e., the perception of risk of being involved in a cycling crash (Deery, 1999).

Objective safety is often studied using multiple analytical approaches (Salmon et al., 2022; Scarano et al., 2023) to understand what, how, and why different factors impact the frequency or severity of cycling crashes. Uncovering how factors, such as built environment, road network, weather, or personal characteristics (Chen and Shen, 2016; Marshall and Ferenchak, 2019; Samerei et al., 2021) impact crashes, allow authorities and researchers to create and implement interventions to decrease either the number of crashes or the impacts to cyclists.

Subjective safety research explores how different factors influence individuals' perceptions of safety when cycling. These perceptions are usually measured through surveys and interviews and have been found to be influenced by factors such as travel behavior, traffic speed and volume, infrastructure design, and personal cycling experience (Sørensen and Mosslemi, 2009; Sanders, 2015; von Stülpnagel and Binnig, 2022).

Yet these two safety dimensions do not necessarily align. Environments that are objectively safe may feel unsafe, and vice versa. Some studies that have explored such relations have found both agreements and disagreements in their relationship (Costa et al., 2025a). Thus, it is vital to understand how factors simultaneously impact objective and subjective cycling safety or why interventions that seek to improve one safety type can have opposing effects on the other. Furthermore, previous comparative analyses typically examined environment typologies or limited numbers (<20) of characteristics, constrained by traditional statistical methods unable to handle high-dimensional datasets.

In this work, we present a novel approach to assess and compare urban elements' impacts on both safety types using a machine learning (ML) approach. Our contributions are two-fold:

1) Present and deploy a data-driven approach using open data and machine learning to enable a large-scale, fine-grained analysis or urban elements effects on objective and subjective safety.
2) Reveal systematic alignments and mismatches between elements' effects on perceived and actual safety, effectively showcasing the value of using ML to capture complex, non-linear relationships between the two safety dimensions.

2. METHODOLOGY

This section describes the approach used in our work. We start by describing the data used, including both objective safety, subjective safety, and available cycling environment context data. Next, we explain our modeling approach using an explainable boosting machine method to the effects of urban elements on each type of safety. Figure 1 depicts a summary diagram of our approach.

Data

Objective Safety: We used cycling crash records from Berlin, Germany, for 2018-2019 (Statistische Ämter des Bundes und der Länder, 2021), filtered to include crashes with at least one bicycle and geographic coordinates (n=7,516). Observations were grouped into two classes as often done in cycling safety literature: (1) fatalities and serious injuries (KSI), and (2) light injuries (LI).

Subjective Safety: Street-level images corresponding to the above crash locations were extracted from Mapillary (https://www.mapillary.com/) and processed through PCS-Net (Costa et al., 2025b), a deep learning model that estimates perception of cycling safety scores based on Berlin data. Of all crash locations, 3,850 locations had available images. Each one of these images is assigned a perception of safety score ϕ, which we later normalize so $\phi \in [0,1]$. Finally, similar to the objective safety data, we split our observations (image scores) into two classes: i) those where images depict environments perceived as less safe ($\phi < \bar{\phi}$) and ii) environments perceived as safer ($\phi \geq \bar{\phi}$) with $\bar{\phi}$ being the mean of all predicted scores.

Urban Elements: To analyze the impact of urban elements on both cycling safety types, we used openly available data about urban environments to contextualize locations where bicycle crashes have occurred and their perceived cycling safety scores could be estimated. For this, we used two data types: (1) street-level imagery and (2) spatial data. First, the previously retrieved images were processed to extract information about which urban elements are present in each cycling environment. We used Mask2Former model (Cheng et al., 2022), trained using street-view images, to detect areas in the image corresponding to 65 different urban elements. Second, built environment spatial data from OpenStreetMap (OSM, https://www.openstreetmap.org) was retrieved. Again, using each crash location we extracted all available information from OSM within a 25-meter radius of crashes' locations, including the existence of, for example, road typologies, street furniture, shops, trees, or bollards. Figure 2 shows examples of different urban elements being extract from images and spatial data. In total, 3,850 observations with 120 different urban elements (variables) are created to form our final dataset.

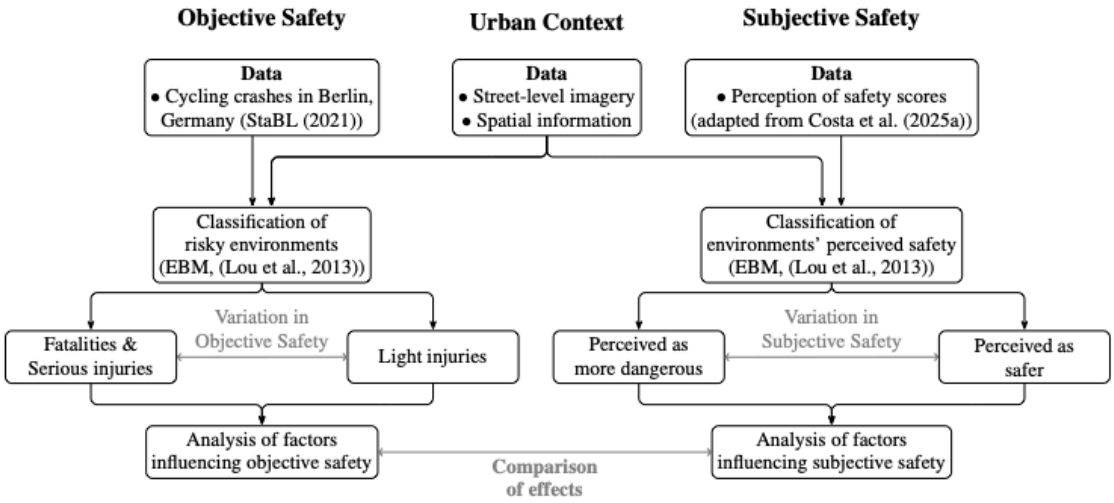


Figure 1: Methodological framework. We use urban context data together with cycling crashes to understand how elements increase crash outcome severity. The same context data is used with perception of safety scores to understand how elements increase or decrease the sense of safety felt by individuals. Finally, elements' effects are compared between objective and subjective safety.



(a) (b)

Figure 2: Example of a street-level image and its semantic segmentation map (a), where different classes are shown in various colors; and an example of how data is extracted from OSM around a 25m radius.

Analysis

We frame our approach as two distinct classification problems that aim to quantify the impacts of urban elements on i) cycling crash outcomes (objective safety) and on ii) whether environments are perceived as unsafer or safer (subjective safety). To achieve this, we use XGBoost (Chen & Guestrin, 2016) in two binary classification tasks.

XGBoost is an ensemble learning technique using gradient boosted decision trees that can capture non-linear relationships and interactions between features. It is a tree ensemble model that seeks to predict an output $\hat{y}$ using i independent variables x_i using K additive functions and has the form:

$$\hat{y} = \sum_{k}^{K} f_k(x_i) \quad (1)$$

where $f_k \in F$ are independent tree structures in a F space of trees. For further details on XGBoost, we refer the readers to Chen and Guestrin (2016).

In our setting, since we want to analyze the impact of urban elements on either bicycle crash outcomes (for objective safety) or whether urban environments are perceived as more dangerous or safer (for subjective safety), we employed a logit link function, and y corresponds to a binary class label (in objective safety: 0 for KSI and 1 for LI; in subjective safety: 0 for environments perceived as less safe and 1 for perceived as safer), x_i a variable for urban element i, and $f_k(\cdot)$ a learnable feature function. In the end, by using XGBoost we can find non-linear effects of urban contextual elements (drawn from both street-level images and spatial data) on severity outcomes of bicycle crashes and on how these influence perceptions of cycling safety.

XGBoost's results, however, cannot be directly interpreted. To overcome this, we used SHAP (Lundberg and Lee, 2017; Lundberg et al., 2020) to interpret its outputs. SHAP (SHapley Additive exPlanations) provides consistent feature attribution by quantifying each feature's marginal contribution to predictions, enabling us to analyze how urban elements influence each safety type and systematically compare effects between them.

3. RESULTS AND DISCUSSION

Modelling Results

All models were implemented in Python using the `xgboost` and `shap` packages. We used 80/20 train-test split with 5-fold cross-validation and hyperparameter optimization via random search (hyperparameters can be found in Appendix A). Following the hyperparameter optimization on the training data, we evaluated the final model's performance on the held-out test set. The objective safety model achieved moderate performance (Acc=68%, AUC=0.60), reflecting the inherent complexity and stochasticity of crash severity outcomes. The subjective safety model achieved strong performance (Acc=79%, AUC=0.85), demonstrating its capacity to differentiate between perceived safe and unsafe environments.

As shown in Figure 3, for objective safety, the most influential elements were roadside objects (poles, traffic lights, vegetation), roadside elements (buildings, curbs, sidewalks), and road elements (roads, lane markings, vehicles). For subjective safety, the most influential elements related to road infrastructure (bike lanes, lane markings, roads), roadside elements (sidewalks, fences, vegetation, terrain), and vehicles/road users (cars, bicyclists). Among the 15 most influential elements, 10 appeared in both safety types.



Figure 3: Urban elements mean absolute log-odd values (i.e., average feature importance) on objective safety (left) and subjective safety (right). Shared elements between the two safety types are shown in the same color while elements appearing in only one type are shown in gray. Note the different scales between the two types of safety.

Figure 4 shows the effects of a few selected urban elements effects on both types of safety (the full list of effects is available in Appendix B). For objective safety, built environment features like poles showed positive safety associations (greater presence associated with reduced crash severity), while curbs and sidewalks exhibited opposite patterns. Non-linear effects were observed for pedestrians and bicycles. Various amenities (bars, restaurants, cafes) were associated with decreased actual safety, potentially due to increased distractions. Poles, buildings, amenities, and barriers decreased perceived safety, while curbs, bike lanes, sidewalks, and greenery increased it.

Critically, several elements showed opposing effects: increased pole presence improved objective safety but decreased subjective safety. Conversely, curbs, sidewalks, green spaces, and bike lanes showed increased presence associated with decreased objective safety but increased subjective

safety. Other elements (residential buildings, amenities, barriers) demonstrated consistent effects across both types. Some elements exhibited non-linear effects where increased presence was associated with both increases and decreases in safety, suggesting highly context-dependent impacts.

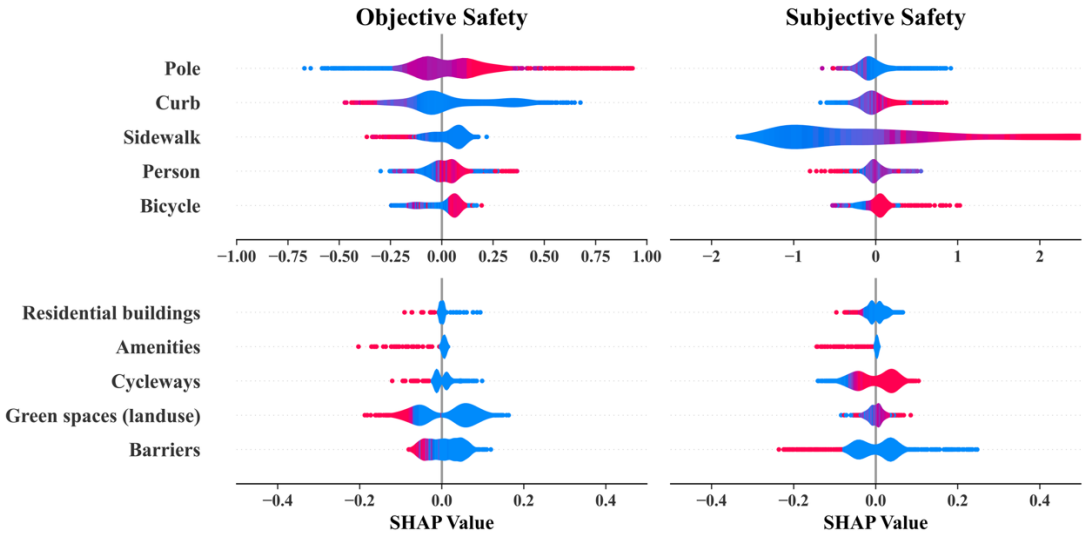


Figure 4: Selected urban elements and their effects on objective and subjective cycling safety. Colors represent a feature's values ranging from low (blue) to high (red). Note the different scales across all features and types of safety.

Implications

Results reveal context-dependent effects of urban elements on both safety types. While some elements align across safety types, others suggest opposing influences. Two critical implications arise: (1) overestimation of subjective unsafety discourages cycling, and (2) underestimation of crash risk leads to dangerous cycling behavior. Our fine-grained approach enables understanding of individual urban characteristics' effects, complementing previous environment typology studies.

Overall, the analysis performed also reveals design challenges. For example, larger sidewalks increase perceived safety but decrease actual safety (potentially from increased pedestrian interactions), while poles increase objective safety but decrease perceived safety. Increased bicycle presence generally associates with improved safety in both domains, potentially reflecting safety-in-numbers phenomena (Elvik & Bjørnskau, 2017). Moreover, while individual element effects provide valuable insights, cyclable locations are complex environments with many interconnected elements, including factors outside of the built environment, such as weather characteristics, vehicle features, or individuals' behaviors.

Understanding where risk is underestimated or overestimated is vital for providing safe environments where cyclists feel safe. Failing to address both may result in increased accidents or reduced cycling uptake. This means that raising cyclists' awareness through traffic signals/signs, education programs, and community initiatives or addressing distracted/aggressive cycling behaviors through targeted signage and urban elements that increase attention to specific situations could prove beneficial in aligning both safety types. Travel diaries may also help users understand how perceptions misalign with actual experiences.

Limitations

The approach used here analyses correlations between urban characteristics and the respective safety type. This means that causality cannot be drawn from these results alone. As such, care should always be exercised when devising policies based on correlations and the safety of cycling (Götschi et al., 2016). Further experiments are needed to understand the causal effects between the two safety types and cycling environment elements, especially considering the full route characterization and heterogenous travel and individual contexts.

More, the data used here primarily relied on volunteered geographic information and constrained to known accident locations. Though its value for cycling safety analysis was established, future analysis should incorporate non-accident areas to fully understand the objective-subjective safety relationship, as sometimes done in road safety research comparing accident versus non-accident locations. Similarly, risk exposure was not considered, while it has been shown to have a relevant role in both objective and subjective safety (von Stülpnagel et al., 2022).

4. CONCLUSIONS

This work explored how urban elements associate with objective and subjective cycling safety using machine learning (XGBoost + SHAP). Analyzing 3,850 crash locations with 120 urban elements in Berlin, Germany, we found that different elements are sometimes perceived differently from their actual risk, while others are congruent between perceived and actual safety. This data-driven approach demonstrates how new strategies and interventions can be devised to ensure alignment between objective and subjective cycling safety.

Future work should explore how risk exposure, cycling behavior, and experience modulate effects on both safety types simultaneously. More detailed knowledge is needed on how these different factors relate to each other in a cycling route setting and to both safety types. This means that interventions should also be combined with observational studies to guarantee that changes are well-delivered to cyclists.

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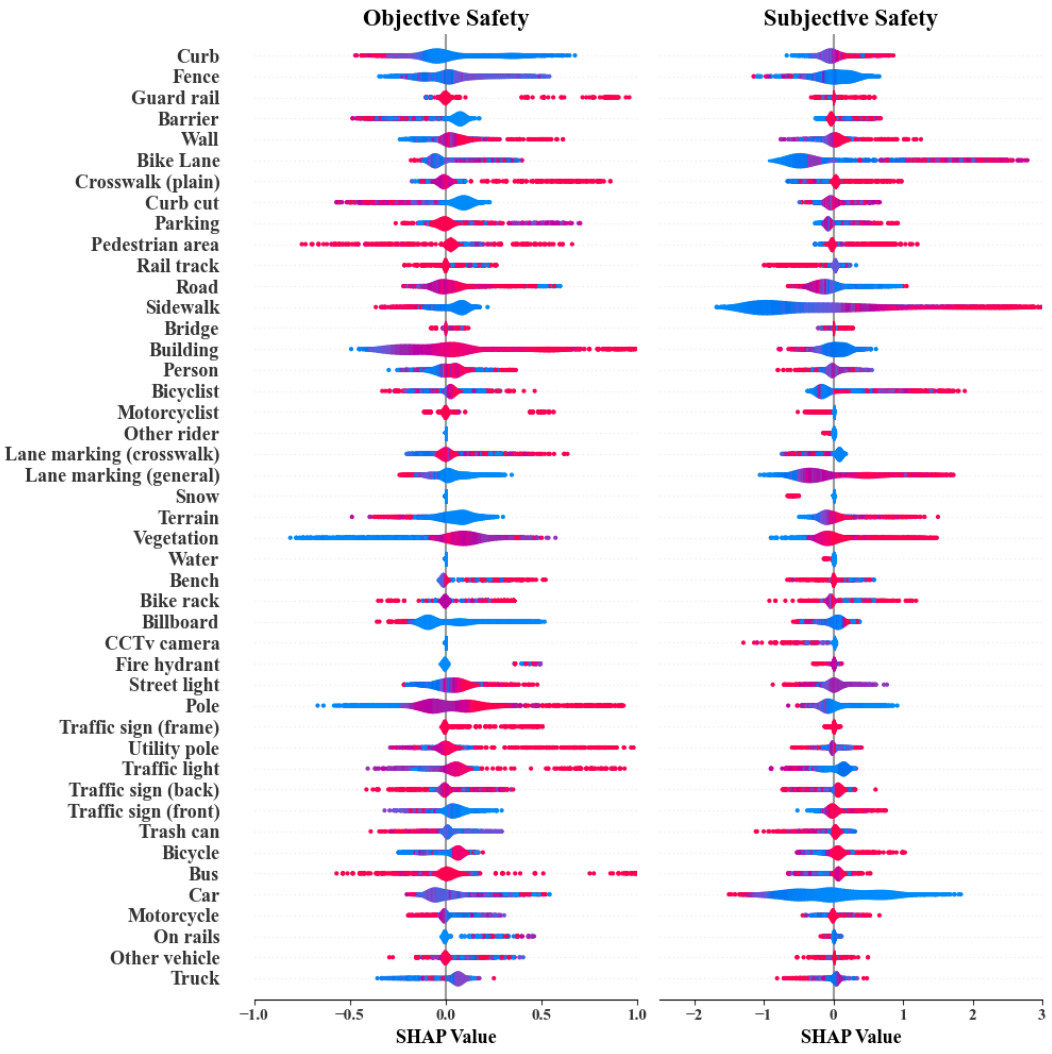
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APPENDIX A. BINARY XGBOOST CLASSIFICATION MODELS' HYPERPARAMETERS GRID SEARCH.

Table A.1: XGBoost hyperparameters used in the grid search. Hyperparameters corresponding to the best model are shown in bold.

Model	Objective Safety	Subjective Safety
Hyperparameters	Max depth = {2, **3**, 4, 5, 6, 7, 8, 9, 10} N Estimators = {100, **150**, 200, ..., 450, 500} Learning Rate = {0.001, 0.01, 0.1, **0.15**, 0.2, 0.3, 0.4, 0.5} Subsample = {.6, .7, **.8**, .9, 1.} Feature sample by tree = {.6, .7, **.8**, .9, 1.}	Max depth = {2, 3, 4, **5**, 6, 7, 8, 9, 10} N Estimators = {100, 150, ..., **300**, ..., 450, 500} Learning Rate = {0.001, 0.01, **0.1**, 0.15, 0.2, 0.3, 0.4, 0.5} Subsample = {.6, .7, **.8**, .9, 1.} Feature sample by tree = {.6, .7, .8, .9, **1.**}

APPENDIX B. FULL LIST OF EFFECTS OF URBAN ELEMENTS ON OBJECTIVE AND SUBJECTIVE CYCLING SAFETY



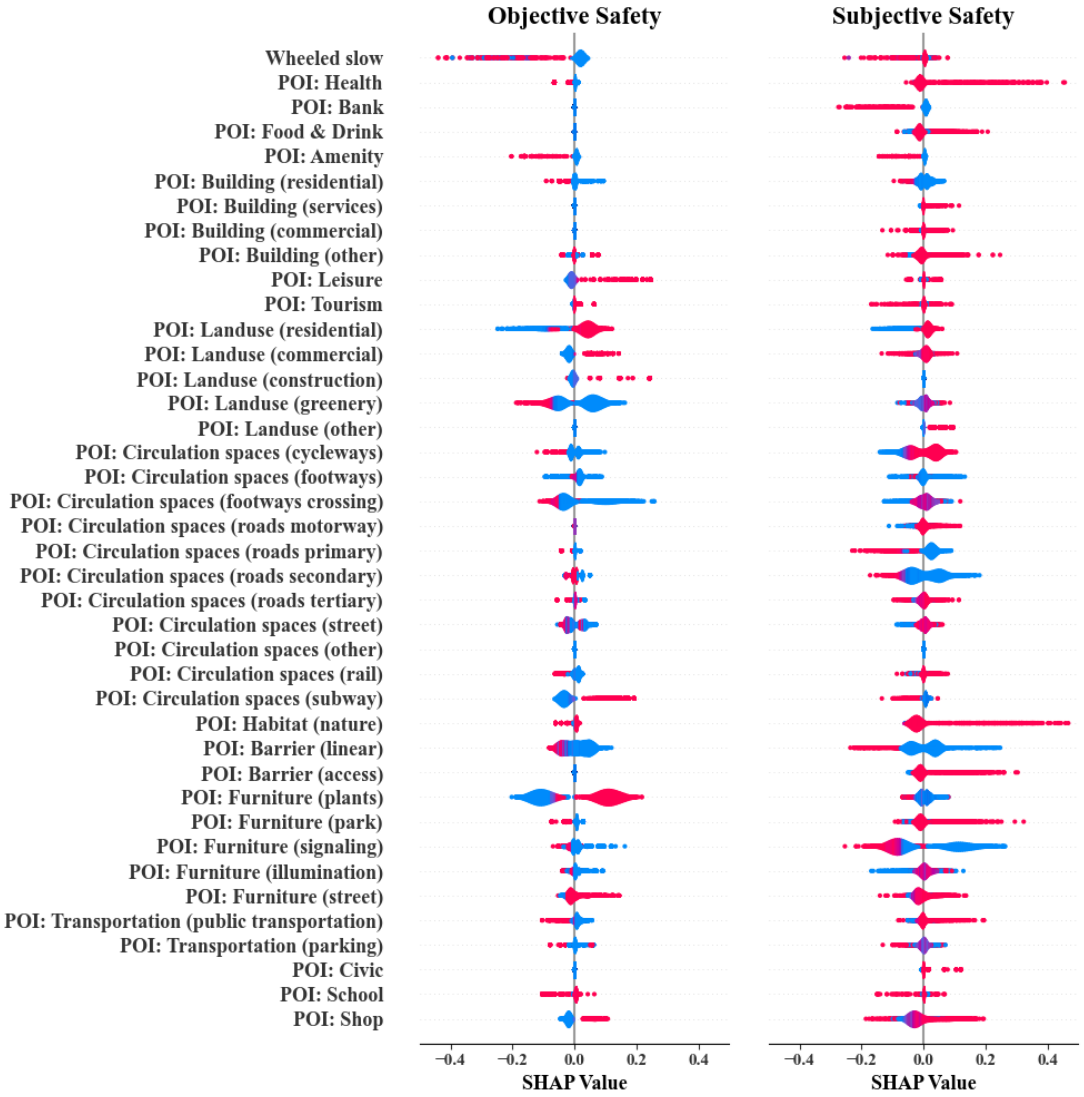


Figure B.1: Full list of urban elements and their effects on objective and subjective cycling safety. Colors represent a feature's values ranging from low (blue) to high (red).