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Unpacking the perceived cycling safety of road environment using street view imagery and cycle accident data

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ABSTRACT

Cycling, as a routine mode of travel, offers significant benefits in promoting health, eliminating emissions, and alleviating traffic congestion. Many cities, including London, have introduced various policies and measures to promote 'active travel' in view of its manifold advantages. Nevertheless, the reality is not as desirable as expected. Existing studies suggest that cyclists' perceptions of cycling safety significantly hinder the broader adoption of cycling. Our study investigates the perceived cycling safety and unpacks the association between the cycling safety level and the road environment, taking London as a case study. First, we proposed novel cycling safety level indicators that incorporate both collision and injury risks, based on which a tri-tiered cycling safety level prediction spanning the entirety of London's road network has been generated with good accuracy. Second, we assessed the road environment by harnessing imagery features of street view reflecting the cyclist's perception of space and combined it with road features of cycle accident sites. Finally, associations between road environment features and cycling safety levels have been explained using SHAP values, leading to tailored policy recommendations. Our research has identified several key factors that contribute to a risky environment for cycling. Among these, the "second road effects," which refers to roads intersecting with the road where the accident occurred, is the most critical to cycling safety levels. This would also support and further contribute to the literature on road safety. Other results related to road greenery, speed limits, etc, are also discussed in detail. In summary, our study offers insights into urban design and transport planning, emphasising the perceived cycling safety of road environment.

1. Introduction

Cycling is commonly regarded as an environmentally friendly mode of daily transportation. Its benefits encompass reducing air pollution and carbon emissions and alleviating traffic congestion (Handy et al., 2014; Elvik, 2009). Moreover, evidence substantiates that cycling mitigates several health risks, including obesity, stroke, and type 2 diabetes (Oja, 2011). The World Health Organisation has thus recognised cycling as one of the primary interventions to counteract non-communicable diseases (Pucher et al., 2010; Beaglehole et al., 2011; Rojas-Rueda et al., 2013). Despite various policies and initiatives that promote cycling and active travel, the reality is far from ideal. In the case of London, according to the report from DfT (Department for Transport, 2019), by 2018, while the average distance travelled by cycling had increased by half compared to 2002, the proportion of trips made by cycling had barely changed.

Extensive research has suggested that a lack of information regarding cycling safety poses a significant impediment to promoting cycling (Winters et al., 2010; Chataway et al., 2014; Fernández-Heredia et al., 2014; Sanders, 2015; UI-Abdin et al., 2019). In contrast to car drivers, cyclists as vulnerable road users (VRU), are more susceptible to injuries in traffic accidents. Behavioural decision-making studies have shown that fear of the unknown often leads individuals to opt for familiar methods or domains (Cao et al., 2011). While many studies have explored how road environments affect cycling safety, they predominantly focus on the inherent features of the road, such as the design improvements of bike lanes and intersections (Leaf and Preusser, 1999; Nosal and Miranda-Moreno, 2012; Loskorn et al., 2013). Some studies have delved deeper into spatial perception but have only established the relationship between perception and cycling behaviours or willingness (Marquart et al., 2020; Van Holle et al., 2014; Lu et al., 2019). There's a lack of studies on the relationship between perception and cycling safety. A good understanding of which can break cyclists' fear of unknown risks and better inform road design guidelines for cycling safety.

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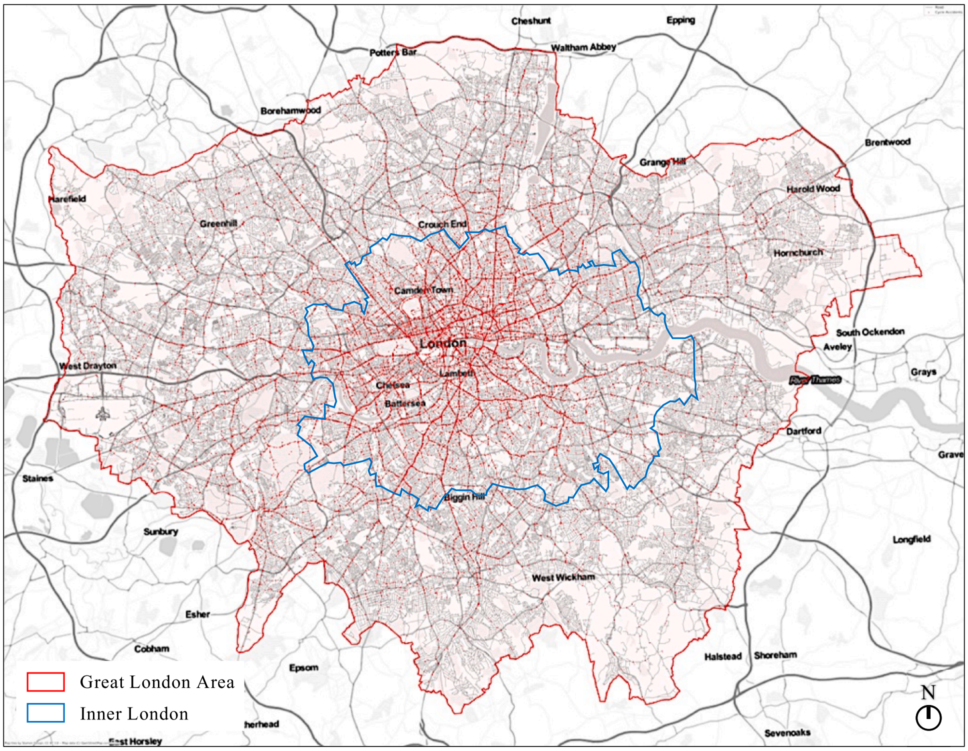


Fig. 1. Distribution of cycling accidents in the Great London Area, 2017–2021.

This research evaluates the cycling safety levels of the road environment using novel indicators that combine a comprehensive assessment of the proportion and severity of cycle accidents. Based on which, we identified key environmental factors affecting cycling safety and links the results with practical design suggestions by the state-of-the-art interpretable machine learning approach, taking the Greater London Area as a case study. The innovation of the research is threefold. Firstly, this study integrates the extensive road visual environment recognised from a cyclist's perspective, captured through street view images where features were extracted using deep learning techniques. Secondly, the notions of collision risk and injury risk, as traditionally used in cycling accident research, were integrated into a new concept termed "Cycling Safety Level of Road Environment". Finally, by employing the SHAP algorithm, this study analyses the relationships and weights of different factors affecting risk levels, contributing insights into urban design and transport planning in practice.

2. Literature review

This section reviews the relevant literature about associations between built environment features and cycling safety and emerging machine learning methods for accident evaluation. From this, we identified the research gap around perceived cycling safety, features of the road environment and interpretable machine learning results for urban design practice, aspects upon which our research innovation is based.

2.1. Perceived cycling safety and built environment impacts

With the recognised health and environmental benefits of cycling gaining broader acceptance (Gatersleben and Haddad, 2010; Gotschi et al., 2016; Almannaa et al., 2020), attention and research towards cycling safety have been increasingly emphasised in recent years (Schepers et al., 2017). Extensive past research has explored the influence of road environments on collision and injury risks for cyclists (Santos et al., 2022), informing city authorities and transportation agencies in policy formulation and decision-making for environmental improvements. However, these studies often concentrate on individual factors or the isolated effects of multiple factors (Schepers et al., 2014). The actual road environment is intricate and dynamic, with distinct features across different roads. Consequently, comprehensive evaluations of cycling safety from an interconnected perspective are sorely lacking. Also, collision and injury risks are typically examined separately, even though they represent different facets of the cycling safety issue (Rumar, 1999). Few studies have integrated these two aspects (Schepers et al., 2014), such an integrated perspective has not been adequately emphasised in existing research.

Additionally, perceived safety has been identified as a major barrier to people travelling by bicycle (Dill and Voros, 2007; Winters, 2011; Fernández-Heredia et al., 2014; Sanders, 2015). In recent years, subjective safety perceptions have transitioned from an overlooked element to a major research focus. Decision-making studies suggest that fear of the unknown can lead individuals to gravitate towards familiar options (Cao et al., 2011). A lack of assessments on the safety levels of cycling routes means cyclists lack benchmarks for evaluating risks, which might make them overly reliant on subjective perceptions. As such, an urgent need arises for actual evaluations integrating both collision and injury risks in cycling environments. Demystifying the actual safety levels of these environments would be a proactive attempt to alleviate cyclists' fears and reduce barriers to promoting cycling as a preferred mode of travel. Simultaneously, this information would form the foundation for city authorities and transport agencies to make informed decisions and implement measures to enhance cycling environments.

While there are established studies that have explored the relationship between the built environment and road safety (Megnidio-Tchoukouegno and Adedeji, 2023; Asadi et al., 2022), most of the relevant quantitative studies using geographical analysis assess the built environment directly rather than perceived urban space, due to the limitations in acquiring real-world data from travelers' point of view (Harvey et al., 2015). Recently, the rise of computer vision recognition methodologies underpinned by deep learning and reliant on Street View Image (SVI) has proffered an excellent low-cost and scalable opportunity for the capture and analysis of perceived road environments (Li et al.,

Table 1
The road features of cycle accident dataset chosen for the research.

Element	Item		Element	Item	
First Road Class (The road where the accident occurred)	1	Motorway – the highest class of road in the UK, designed for high-speed long-distance vehicular traffic	Road Surface Conditions	1	Dry
				2	Wet or damp
				3	Snow
				4	Frost or ice
	2	A(M) roads – special A roads that have regulations and design characteristics similar to motorways, serving as short sections or connectors of motorways		5	Flood over 3 cm. deep
				6	Oil or diesel
				7	Mud
				−1	Missing
				9	Unknown
	3	A roads – major roads intended to provide large-scale transport links within or between areas	Speed Limit	20	Speed limit 20mph
				30	Speed limit 30mph
				40	Speed limit 40mph
	4	B roads – roads intended to connect different areas, and to feed traffic between A roads and smaller roads on the network		50	Speed limit 50mph
				60	Speed limit 60mph
				70	Speed limit 70mph
				−1	Missing
	5	C roads – smaller roads intended to connect together unclassified roads with A and B roads	Day of Week	1	Sunday
				2	Monday
				3	Tuesday
	6	Unclassified – local roads intended for local traffic. The vast majority (60 %) of roads in the UK fall within this category		4	Wednesday
				5	Thursday
				6	Friday
				7	Saturday
Second Road Class (The road that intersects with the road where the accident occurred)	0	Not at junction or within 20 m	Junction Control	0	Not at junction or within 20 m
	1	Motorway – as above		1	Authorised person
	2	A(M) roads – as above		2	Auto traffic signal
	3	A roads – as above		3	Stop sign
	4	B roads – as above		4	Give way or uncontrolled
	5	C roads – as above		−1	Missing
	6	Unclassified – as above		9	Unknown
Weather Conditions	2	Raining no high winds	Junction Detail	0	Not at junction or within 20 m
	3	Snowing no high winds		1	Roundabout
	4	Fine + high winds		2	Mini-roundabout
	5	Raining + high winds		3	T or staggered junction
	6	Snowing + high winds		5	Slip road
	7	Fog or mist		6	Crossroads
	8	Other		7	More than 4 arms not roundabout
	9	Unknown			
	−1	Missing		8	Private drive or entrance
Light Conditions	1	Daylight		9	Other junction
	4	Darkness – lights lit		99	Unknown
	5	Darkness – lights unlit		−1	Data missing or out of range
	6	Darkness – no lighting	Special Conditions at Site	0	None
	7	Darkness – lighting unknown		1	Auto traffic signal – out
	−1	Missing		2	Auto signal part defective
Road Type	1	Roundabout		3	Road sign or marking defective or obscured
	2	One way street			
	3	Dual carriageway		4	Roadworks
	6	Single carriageway		5	Road surface defective
	7	Slip road		6	Oil or diesel
	9	Unknown		7	Mud
	12	One way street / Slip road		−1	Missing
	−1	Missing		9	Unknown

2017; Larkin et al., 2021, Hu et al., 2023). The research on perceived road environments is typically associated with cycling behaviour and willingness (Marquart et al., 2020; Van Holle et al., 2014; Lu et al., 2019), without addressing the link between perceived road environments and cycling safety.

We fill in the research gap of perceived road safety by leveraging recent advances in deep learning. Models designed for image processing, such as FCN and SefNet, allow for further quantification of these captured environments (Yuan et al., 2021). The development of convolutional neural network-based algorithms has significatnly enhanced semantic segmentation capabilities. They establish direct relationships from image pixels to semantic information, facilitating a higher-level understanding of cycling scenarios (Wang et al., 2020). Thus, innovatively combining imagery features of street view with road features of cycle accident, this research enables a more comprehensive understanding and assessment of road environment features from cyclists' viewpoints, becoming an essential foundation for improving cycling safety level of road environment.

2.2. Machine learning methods for accident evaluation

Analysing the intricate relationships among various attributes of traffic accidents is a prerequisite for enhancing road safety (Megnidio-Tchoukouegno and Adedeji, 2023). In recent years, machine learning (ML) has become a vital method in road safety. Compared to conventional statistical models, ML models can effectively deal with multidimensional data (e.g., the traffic accident database used in this study) and

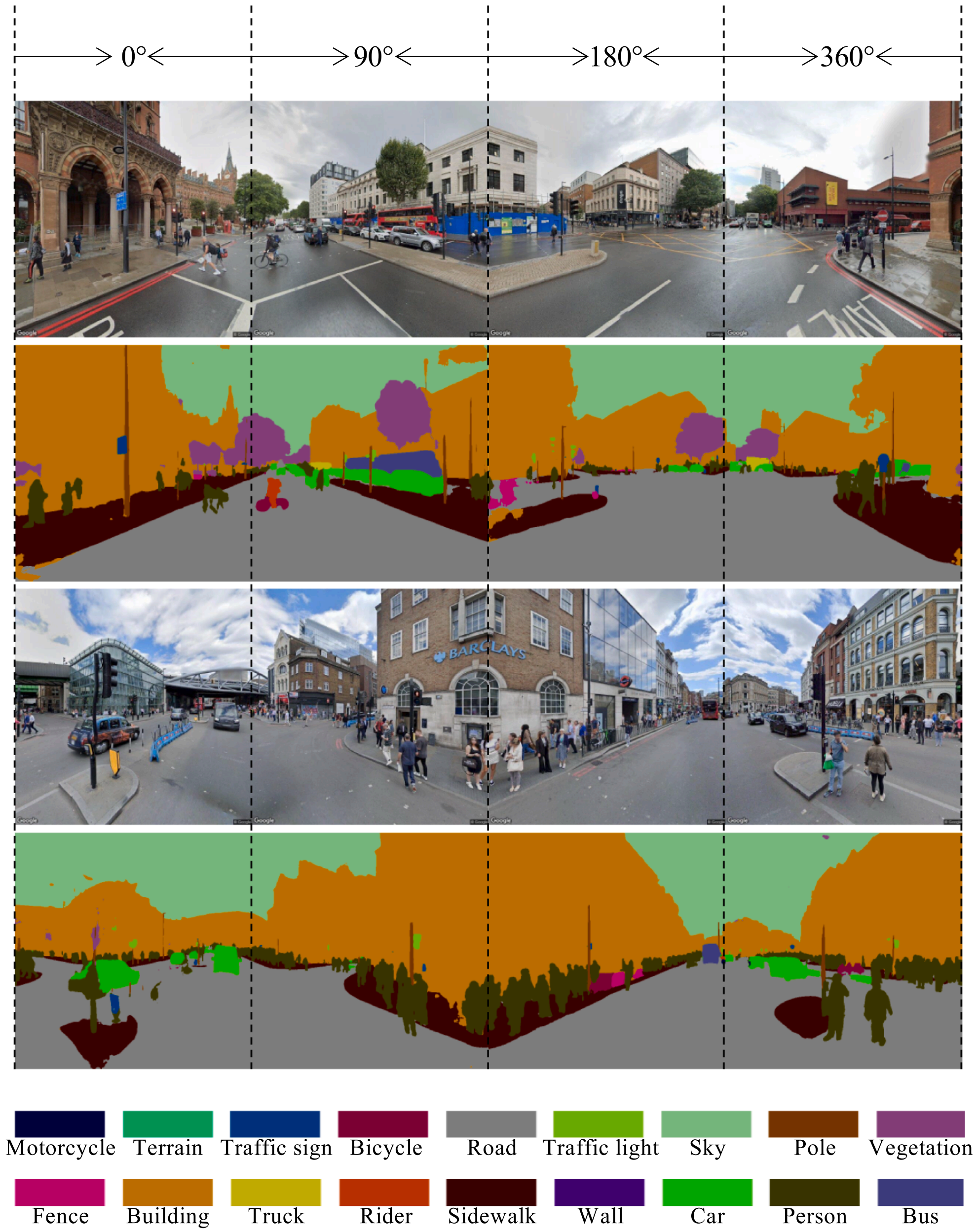


Fig. 2. Semantic segmentation results were obtained by applying HRNet pre-trained on the CityScapes dataset to the collected street images.

sometimes in large volumes, as well as explain complex relationships between variables. Existing quantitative studies on cycling safety primarily employ discrete outcome models, including ordered and unordered discrete models (Scarano et al., 2023). These methods often face strong constraints from the experimental design process, heavily depending on fundamental assumptions about the data, such as probability distributions and relationships among variables (Santos et al., 2022). In contrast, machine learning does not require pre-set assumptions about variable relationships; it allows direct predictions based on data and possesses the robust capability to handle large datasets (Japkowicz and Stephen, 2002; Mokoatle et al., 2019). Especially when confronting new environments without prior training, machine learning can handle tasks adeptly.

Existing research using machine learning to predict traffic accidents has a unified definition of injury risk, which is the severity of the accident (Santos et al., 2022). Such research has employed over a dozen algorithms, including Decision Trees, Random Forests, Support Vector Machines, K-Nearest Neighbors, and Bayesian networks, with the Random Forests, Support Vector Machines and Decision Trees algorithm generally showing superior performance (Santos et al., 2022). These methods typically encompass various types of data related to accidents, including human factors, vehicle factors, weather conditions, and road conditions, with the analyzable factors depending on the scope covered by accident statistics (Santos et al., 2022). Current machine learning research on cycling includes studies on cycling behaviour, willingness, and accident severity (Marquart et al., 2020; Van Holle et al., 2014; Lu et al., 2019; Birfir et al., 2023). However, research on traffic accidents, including cycle accidents, has limited focus on the probability of collision risk or accidents. Part of the reason is that the calculation of collision rates in different studies was based on different exposure measures (denominators), and some metrics are not suitable for widespread application in research (Gotschi et al., 2016). Such a gap might result from the challenges in obtaining collision risk-related data and its relevance (Gotschi et al., 2016), hindering further evaluation and prediction.

Many machine learning models are considered black boxes due to the

Table 2
Imagery features of street view.

Imagery Features	Indicator	Elements (calculated by pixels)
Complex Imagery Features	Enclosure Ratio	building + vegetation
	Openness Ratio	sky
	Greenery Coverage	vegetation
	Cycling Suitability Index	road + sidewalk
	Signage Density Index	traffic light + traffic sign
Proportional Imagery Features	Proportion of road	road
	Proportion of building	building
	Proportion of sidewalk	sidewalk
	Proportion of terrain	terrain
	Proportion of fence	fence
	Proportion of wall	wall
	Proportion of traffic sign	traffic sign
	Proportion of traffic light	traffic light
	Proportion of pole	pole
	Proportion of car	car
	Proportion of bus	bus
	Proportion of truck	truck
	Proportion of motorcycle	motorcycle
	Proportion of bicycle	bicycle
	Proportion of rider	rider
	Proportion of person	person

complexity of their decision-making process (Lee et al., 2022). Explainable Artificial Intelligence (XAI) attempts to open this black box, allowing people to understand the reasons behind the predictions and decisions of AI models (Gunning et al., 2019). One specific implementation of XAI is SHAP, which is based on the Shapley value in cooperative game theory. The Shapley value is a mathematical concept used to equitably distribute the total gain generated in a cooperative game to each participant (Molnar, 2022). In machine learning, SHAP uses this concept to measure the size of each feature's contribution to the model's predictions, providing a way to understand complex model decisions. In the field of road safety research, Mihaita and colleagues (Mihaita et al., 2019) utilised SHAP to examine how various features influence the duration of accidents in 2019. With this approach, machine learning not only analyses the data but also enhances its credibility in real-world applications by using XAI techniques to interpret the results of its models, and the applicability of the approach is expanding further.

3. Data

The research area of this study is the Greater London Area (GLA). The mayor's Transport Strategy has an ambitious goal, which is to make it the world's best big city for cycling and walking. By 2041, 80 % of journeys are expected to be made by walking, cycling and public transport (Mayor of London, 2018). Over the past two decades, cycling has had consistent growth until 2015 and until the outbreak of the pandemic (Transport for London, 2022). "Safer streets for the bike" are one of these major's strategies for unlocking the cycling potential of the next phases (Greater London Authority, 2013). Examining cycling safety in the context of the GLA is timely for London and facilitates the establishment of a universally applicable methodology for evaluating cycling safety in global cities.

3.1. Cycle accident data

The cycle accident dataset used in this research is from the UK Department of Transport, encompassing data from the past years, from 2017 to 2021 (Fig. 1). In total, there were a total of 24,820 traffic accidents (marked as red dots in the figure) involving bicycles. Each accident record contains variables including year, day of the week, the latitude and longitude of the accident locations, and severity of the accident, which is categorised into three levels: slight, serious, and fatal. The Proportion of Cycle Accident (PCA) and the the Severity of Cycle Accident (SCA) are calculated based on this dataset.

3.2. Road features of cycle accident

Along with the accident records, there are variables documenting the road features at each accident location. Each factor is numerically represented according to different classifications. These variables include First Road Class, Second Road Class, Road Surface Conditions, Speed Limit, Special Conditions at Site, Road Type, Light Conditions, Weather Conditions, Junction Control and Junction Detail. Table 1 provides descriptions of these selected feature variables and their corresponding numerical representations.

3.3. Imagery features of street view

Google Street View (GSV) images were obtained using the Street View Static API of Google Maps. Accident locations in the cycle accident data are used as geographic reference points. We calculated the azimuth of the road and downloaded four images at each reference point using the latitude, longitude, and azimuth of the reference point as input parameters. Each street view image covers a 90-degree perspective; the four images form a complete 360-degree street view perspective (Fig. 2) that genuinely reflects the viewpoints of cyclists. In total, out of 24,820 accident sites, 21,410 effective accident sites with valid street view images were selected, with a total of 85,640 street view images collected.

To extract imagery features of street view, we employed the HRNet Semantic Segmentation (High-resolution Representations for Semantic Segmentation) analytical model trained and validated on the Cityscapes Dataset (Cordts et al., 2016). Compared to previously released semantic segmentation models such as FCN, PSPNet, DeepLab, and RefineNet, HRNet Semantic Segmentation maintains high resolution throughout the process, capturing and retaining detailed image information (Wang et al., 2020). In this study, we extracted 18 elements from Google Street View Images, including road, building, sky, vegetation, sidewalk, terrain, fence, wall, traffic sign, traffic light, pole, car, bus, truck, motorcycle, bicycle, rider, and person (listed in Fig. 2), which represent the detailed urban design elements contributing to the road safety. Consequently, the safety recommendations and solutions could be more targeted, increasing the likelihood of actual implementation and effectiveness. Car, bus, truck, motorcycle, bicycle, rider, and person are considered dynamic elements of the street, representing the usage of the street in a snapshot of time, mainly serving as a supplement for detecting the types of vehicles that can travel on the road, and do not represent the traffic volume at the time of an accident.

Subsequently, we compute the proportion of elements as the average pixel ratio of these elements. Additionally, we computed five composite variables based on the basic elements, namely, Enclosure, Openness, Greenery Coverage, Cycling Suitability Index and Signage Density Index (summarised in Table 2).

4. Methods

With the pre-processed data sets, the analysis conducted in this study can be decomposed into three steps (shown in Fig. 3). First, we defined new indicators to classify the safety levels, the cycling safety level for road environment (CSL-RE), by combining the proportion of cycle accidents (PCA) and the severity of cycle accidents (SCA). Second, a regression analysis was conducted using the gradient boosting algorithm XGBoost to establish a reliable prediction model for cycling safety level and 32 road environment features. Third, the SHAP algorithm is used to explain the contribution of each feature to the model, thus providing

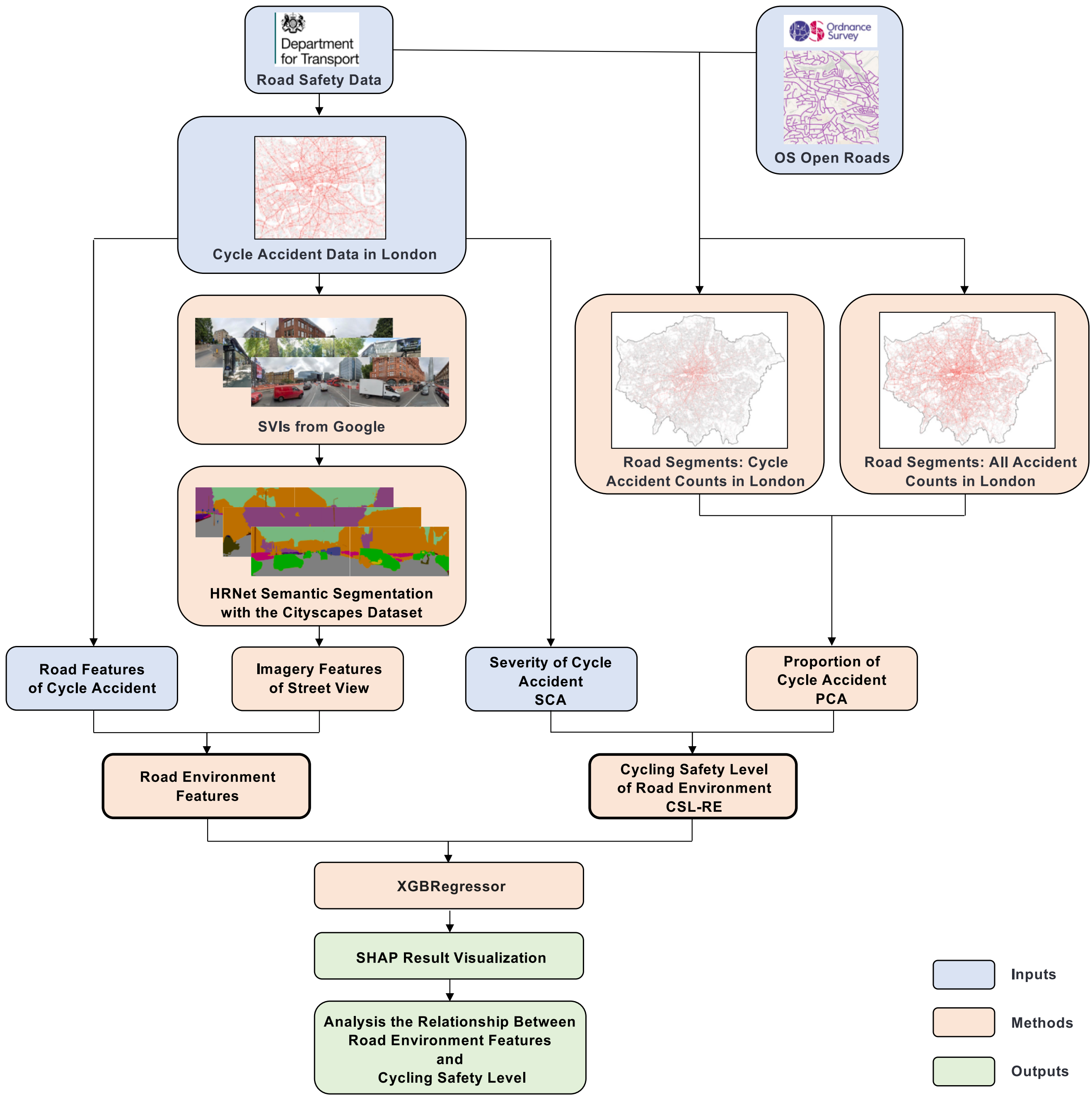


Fig. 3. Research design: overall workflow.

insights into the factors affecting cycling safety.

4.1. *Definition of cycling safety level*

Our proposed metric evaluates the cycling safety level at the road segment level. We transformed the road network into a simple undirected planar graph by merging multiple lanes into a single line. As demonstrated in Fig. 4, each junction of roads is rendered as a "road node"; a road segment is the "road link" between two connected nodes. This is a common approach used for planar network analysis in urban applications (Molinero et al., 2017). The road segments could come with various features. For instance, we utilised Ordnance Survey Open Roads Data (OSORD), which delineates all roads of varying grades, offering additional information on the road's hierarchical structure, which makes our analysis more comprehensive. The cycle accidents records are georeferenced, therefore easily joint to the nearest road segment line.

We consider two components simultaneously contributing to the cycling safety level of the road environment. The first component – PCA is the likelihood of cycle accidents relative to all types of traffic accidents in that segment. The second – SCA is the potential severity of these cycle accidents.

The first is simply quantified as the **proportion of cycle accidents (PCA)** to all types of traffic accidents on each road segment. We consider PCA a generic urban context-independent measure that eliminates the influence of city-specific factors. Absolute values, such as the total number of bicycle accidents on the road, may be heavily influenced by traffic flows (Aldred et al., 2018), which are not always recorded. Employing the relative safety levels of a city's road environment facilitates a focus on intra-city differences, yielding evaluations grounded in localised features. In addition, as many cities lack systematic monitoring

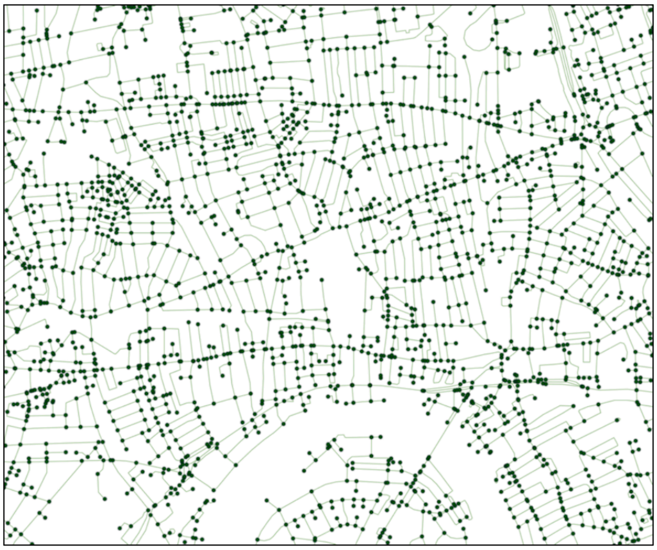


Fig. 4. The visualisation of OSORD – partial region of Inner London.

and recording of cycling flows, this comprehensive approach to on-site evaluation could provide a more widely applicable, easily accessible, data-supported, and city-specific analysis that would be useful for application in cities around the world. The numerical range of the PCA is further categorised into three classed by equal intervals, which are respectively defined as High PCA, Medium PCA, and Low PCA.

The consequences of traffic accidents are normally documented with an 'accident severity' rating with varied coding systems, which we addressed the potential **Severity of Cycle Accident (SCA)**. For example, in London, SCA is recorded using "slight, serious, fatal" in the original data. The coding system has to be adjusted to reflect the concept of PCA. Cycle accidents are normally less severe than general traffic accidents, suggesting that a universal rating system might not adequately address the nuances of cycle accidents. For instance, of the 24,820 cycle accidents recorded in London over a span of five years, 20,373 were slight, 4,397 were serious, and only 50 were fatal. A relatively very small portion (0.2 %) of accidents labelled as "fatal" may mislead our perception of cycling safety and consequently underestimate the safety issue.

Cycling Environment Safety Level of Road Environment (CSL-RE) is, therefore, proposed as a novel metric by combining the 'Proportion of Cycle Accidents (PCA)' and 'Severity of Cycle Accidents (SCA)', delineated in Fig. 5. Specifically, a combination of high and medium PCAs, and both fatal and serious SCAs have been labelled as a risky environment. Combinations of high, medium and low PCAs with slight SCA and a low PCA with fatal, serious and slight SCAs are categorised as a neutral environment. Road segments where no cycle accidents have occurred are classified as a safe environment.

4.2. Regression analysis with model-agnostic method

Regression analysis is conducted to unveil the association between the cycling safety level and the selected road environment features. The prediction model in this research consists of 32 features that include road features of cycle accident (categorical data) and imagery features of street view (numerical data). Based on a review of machine learning models applied in traffic accident-related predictions (Santos et al., 2022), we applied XGBoost, a gradient boosting algorithm which is particularly apt for vast data sets and complex data structures(Lee et al., 2022) and outperforms other regression models experimented.

To address the persistent data imbalance after redefining cycling safety levels, this research employed the SMOTE (Synthetic Minority Over-sampling Technique) (Chawla et al., 2002) to resample the imbalanced data, thereby equating the lesser-represented category with the more prevalent one. This method of data augmentation prevents models from favouring the more common data, significantly enhancing recognition rates for underrepresented data. To avoid overfitting potentially introduced by SMOTE's data augmentation, this research also implemented ten-fold cross-validation. In each iteration, SMOTE augments the data on a new training set. As such, the synthesised samples might vary with each iteration, ensuring sample quality while avoiding sensitivity to noise or outliers from specific augmentations, resulting in a more comprehensive and stable model evaluation.

It is important to unpack the effects of each individual feature on the modelled results and then to provide a practical guide on safety enhancement measures and policy making. Apart from the commonly used model agnostic metrics, e.g., accuracy, we advanced the start-of-

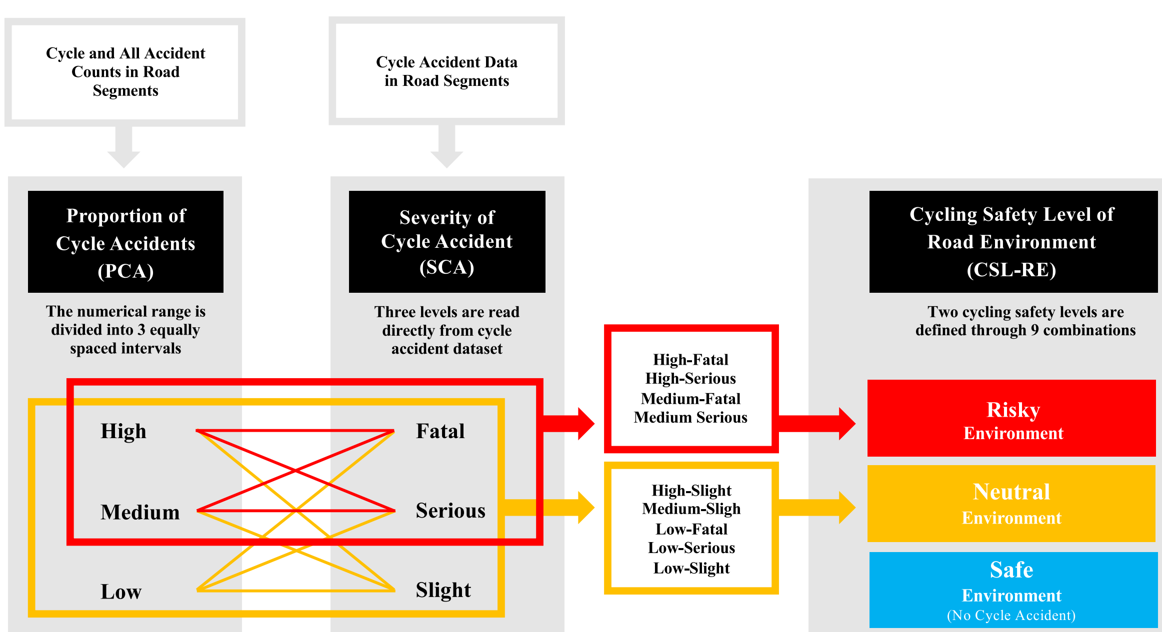


Fig. 5. The combination of PCAs and SCAs.

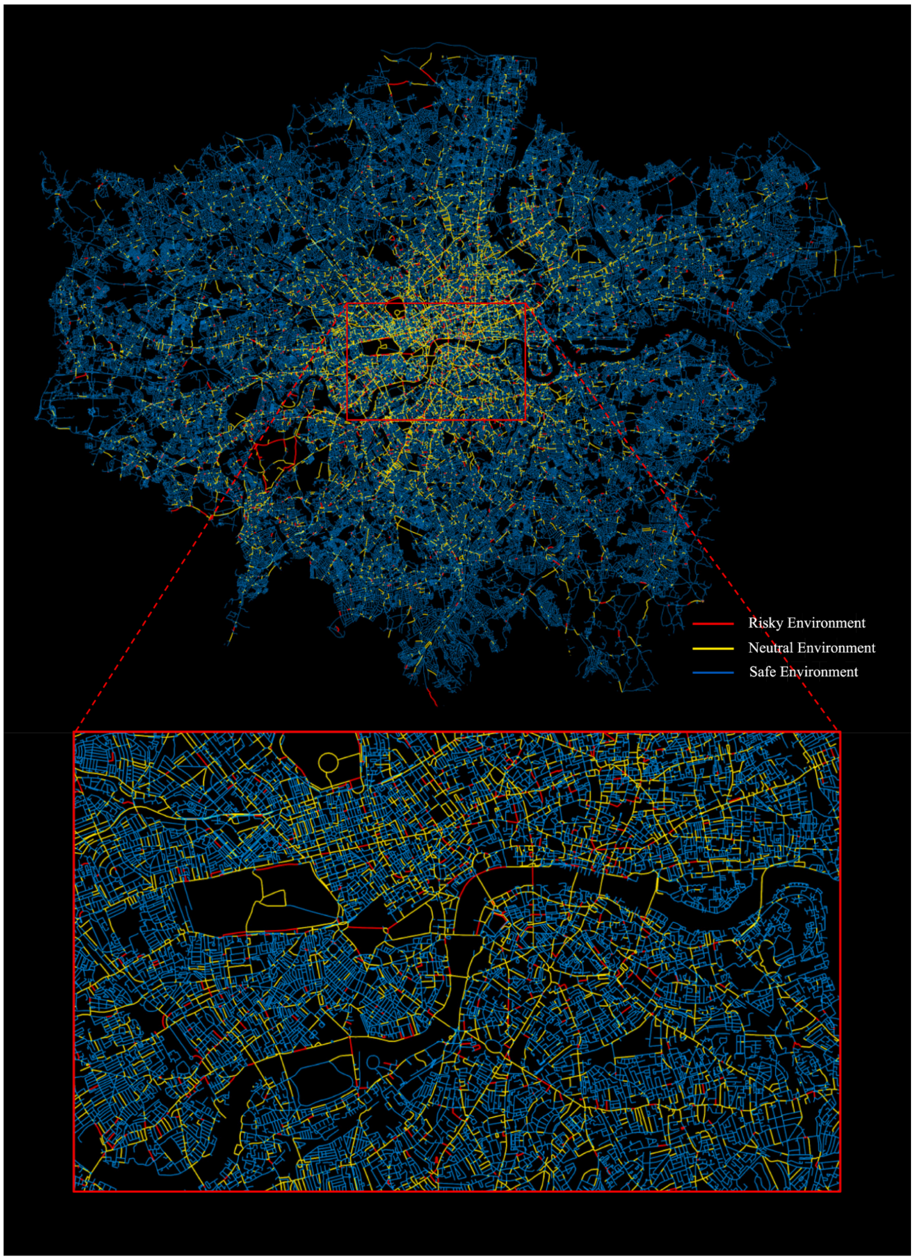


Fig. 6. The cycling safety levels of the Greater London Area's road environment and localised zoomed-in area.

the-art interpretable machine learning methods, in particular, adopted the SHAP (SHapley Additive exPlanations) method. The SHAP framework (Lundberg and Lee, 2017) provides a mathematically rigorous and intuitive way to understand the inner workings of the XGBoost model by calculating how much each feature contributes to the model's prediction results. In particular, SHAP Feature Importance quantifies the negative or positive impact of each road environment feature on CSL-RE; The SHAP Dependence Plot is used to identify any non-linear relationship between various features and CSL-RE. So, a change in road environment should not be simply implemented as an increase or decrease of certain elements; SHAP Interaction Values are used to explore how two road environment features interact, considering that road safety could be a consequential effect of multiple factors, which is not well investigated in previous literature.

5. Results

5.1. Mapping cycling safety of the Greater London Area (GLA)

The present research examined a total of 21,410 cycle accidents spanning from 2017 to 2021, which has been linked to the road segments. Fig. 6 show the cycling safety levels of the Greater London Area's road environment as well as a partial view, respectively. With a total of 210,574 road segments in London using road junctions as the endpoints of road segments, 52,774 road segments have been involved in crashes, and 16,280 road segments have been involved in cycle crashes. Of the 16,280 road segments that have had cycle crashes, 14,049 are in risky environments, and 2,231 are in neutral environments.

5.2. Unpacking the cycling safety of the road environment

The XGBoost regression model performs well, with an overall accuracy of 0.834. The precision, recall, and F1 scores are 0.865, 0.826, and

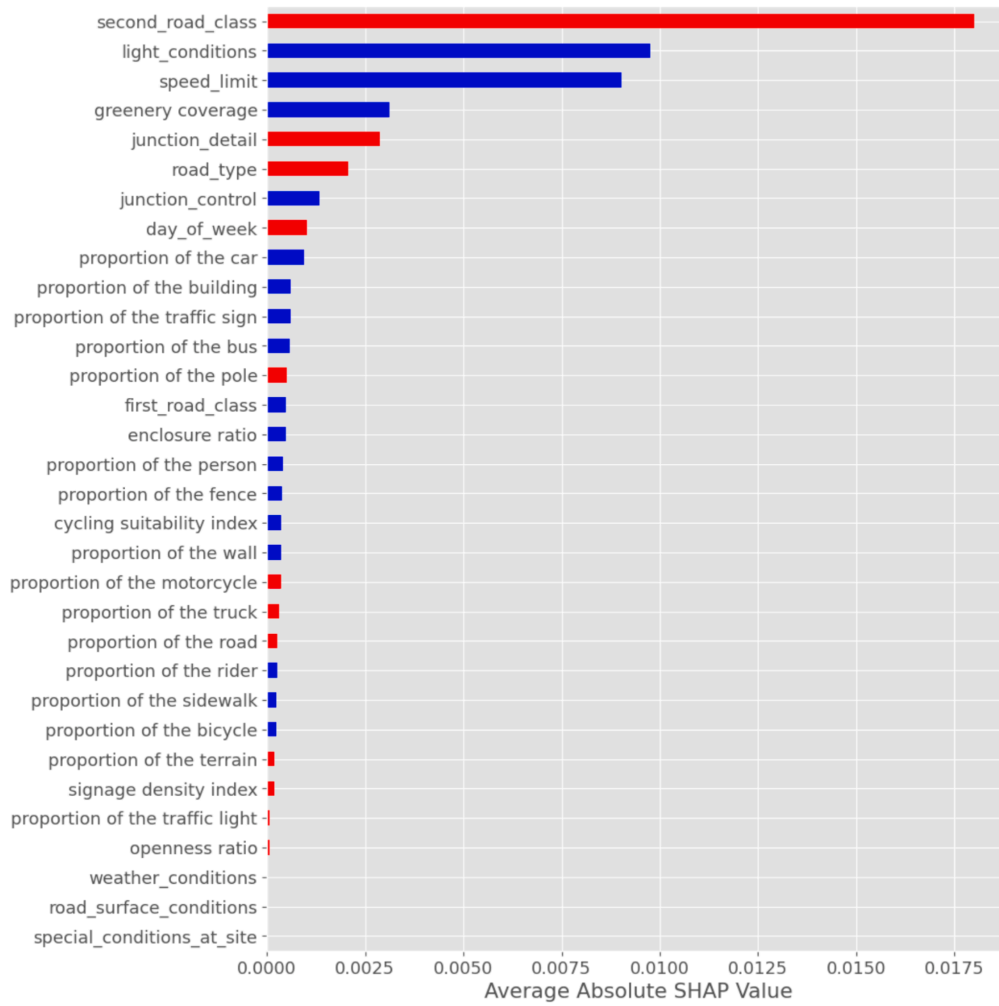


Fig. 7. SHAP feature importance in risky environment (red indicates a positive effect, while blue indicates the opposite and higher values correspond to higher average impacts). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

0.828, respectively. While XGBoost is often regarded as a complex black-box model, this study effectively overcomes this challenge by decoding the model's prediction process through SHAP.

5.2.1. Importance of road environment features

Briefly, the focal point of SHAP bar charts is the significance of the features and their directional influence on the predicted outcomes. As depicted in Fig. 7, the length of the bar indicates the strength of the feature influencing the risk levels in descending order. The colour coding in SHAP indicates the directional impact of increasing feature values on predictions, with red denoting positive association and blue denoting negative association.

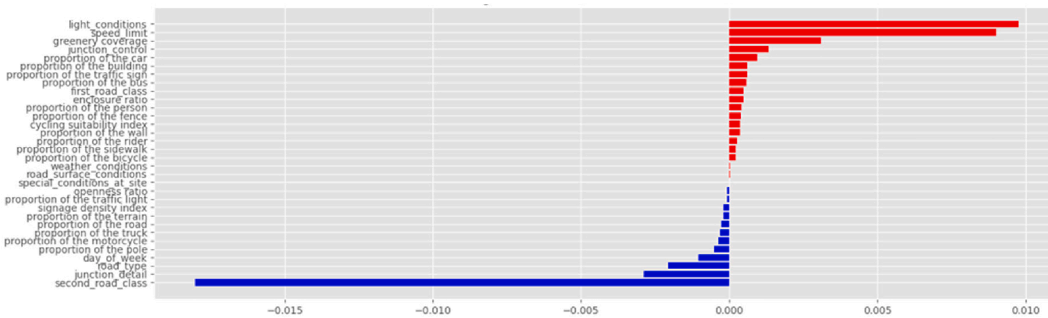
Of the infrastructural features, the 'second road class', 'light conditions', and 'speed limit' emerge as the three most substantial contributors. Following closely is the 'greenery coverage' from the imagery features of street view. In particular, features such as 'second road class', 'junction detail', and 'road type' make a positive contribution to the 'risky environment'. Conversely, 'light condition', 'speed limit', 'greenery coverage', and 'junction control' negatively impact the 'risky environment'. Some of these findings sounds counter-intuitive, which we have further explain in follow up analysis.

The perfectly mirrored SHAP values of various factors on the two target variables (i.e., neutral environment and risky environment) can be observed in Fig. 8. To some aspect, it approved the effectiveness of our defined Cycling Safety Levels. For instance, when the second road class has a positive effect on predicting 'risky environment', it exerts an equivalently negative influence on the prediction of 'neutral environment'.

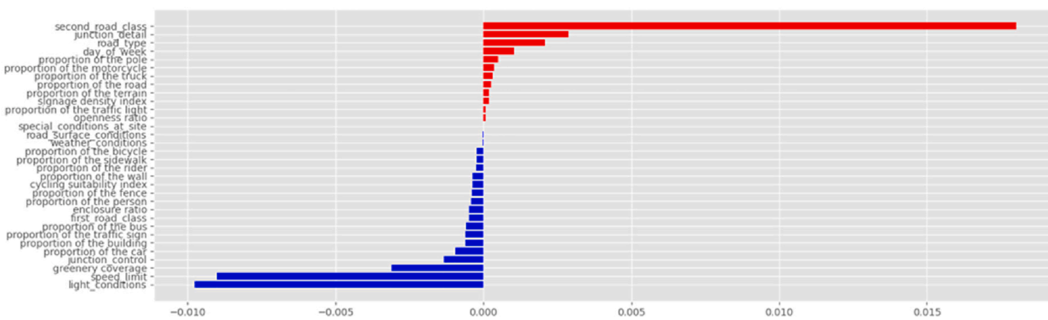
5.2.2. The non-linear relationship of road environment features

The SHAP dependence plot was used to further complement the analyses and reveal the non-linear relationships between the categorical values of the features and the cycling safety levels. In Fig. 9, the plot shows the interplay between the effects of variables. We focused on the four most important features only. The x-axis represents the value of the variable, and the y-axis represents the Shapley value associated with that variable. Shapley values quantify the importance or contribution of each feature to the model's predictions by considering every possible scenario where the feature could be included or excluded, thereby ensuring that the feature's effect is assessed in a comprehensive and fair manner (Molnar, 2022), which contain both positive and negative values. All four graphs are SHAP dependence plots in the risky environment. Positive values indicate a positive effect on the risky environment, while negative values indicate a negative effect on the risky environment. For an overview, we made a summary plot (Figure A1) in the appendix. Each instance that the given explanation is represented by a single dot on each feature row. The plots display an information-dense summary, including ways of impact by colour, strength of importance and non-linear relationships from the distribution.

Taking the "second road class" (Fig. 9a) as an example, when the



Average SHAP value in neutral environment
(a)



Average SHAP value in risky environment
(b)

Fig. 8. SHAP Feature importance mirrored presentation in neutral environment and risky environment: (a) average SHAP value in neutral environment, (b) average SHAP value in risky environment.

second road is a motorway, the SHAP value reaches its highest value, around 0.35–0.6, which has a positive effect on the "risky environment ". As the second road class decreases, the negative absolute value of SHAP increases, indicating that the lower the second road class, the more inclined to predict the neutral environment. Comparatively, the unclassified roads, i.e., lowest class roads, are safer road environments. We refer to this finding as the "second road effect" and investigate it further in Section 5.2.3 through the SHAP interaction values. The distribution of "light conditions" (Fig. 9b) indicates daytime (denoted as "1″ on the y-axis) and night-time scenarios (denoted as "4, 5, 6, 7"). In general, a darker environment tends to generate higher uncertainties towards a safe environment. Some recommendations for road safety level enhancements would be: ensure that all urban roads are adequately lit at night, especially in areas with high pedestrian and cyclist frequency; and when building new or refurbishment of roads, consider lighting as an essential design element to ensure that the layout of lighting equipment provides for the safety of all road users. Fig. 9c shows that the lower the speed limit, especially 20mph, the greater the proportion of predictions tending towards a risky environment, which is against our intuitive thinking. In fact, 20mph Zones have been widely implemented across central London and many residential areas, such as in Camden, Islington, Hackney, as well as within the central London Congestion Charging Zone (Transport for London, 2023). The reason why 20mph Zones are being promoted is because some studies have shown that reducing speed limits on the same road can decrease the severity of injuries to cyclists (Isaksson-Hellman and Töreki, 2019). There are also studies that have investigated different speed limit roads, with lower speed limit roads showing lower bicycle injury odds (Aldred et al., 2018). The speed limits in our study refer to roads with different speed limits, and the road with lower speed limit, the higher the level of cycling risk. This reminds us that for a comprehensive assessment of cycling safety levels, the effect of speed limits on cycling safety is not linear, but a complex issue involving multiple factors and conditions. For 'Greenery coverage' (Fig. 9d), a greater value on the y-axis suggests a higher SHAP value of street greenery. Risky environments tend to be more predictive with higher greenery coverage, which is, again, a counter-intuitive finding. In London, residential areas usually have a higher percentage of greenery than commercial and industrial areas (City of London, 2018), and often, residential roads have less vehicle and pedestrian traffic, which may allow cyclists to ride at excessive speeds or be less vigilant, thus making the risk higher. This requires further targeted research. Furthermore, the non-converged distribution of SHAP value suggests planning of green areas needs comprehensive thinking, taking local characteristics into account, rather than simple and universal measures, such as increasing or decreasing the number of trees.

5.2.3. *The interaction between features: The "second road effects"*

Previous research mostly focuses on individual features, e.g., junctions, and assumes they independently impact road safety. In reality, an accident may be caused by complicated reasons with joint effects by multiple features. It is, therefore, important to investigate the interactions between features. We first, computed SHAP interaction values, which provide a global view of the interactions. Second, we utilised the dependent plot to interpret the nature of interactions at the local level.

Below, we present the most interesting findings about 'second road', which refers to the road that intersects with the road where the accident occurred. As demonstrated in Fig. 10, the top map shows the cycling safety level in and around Row Road; below are Google street view image of the accident location; the white circle on the map above shows the accident point, which is located in the risky environment; the corresponding second road is this Bow Road which is classed as "A Road".

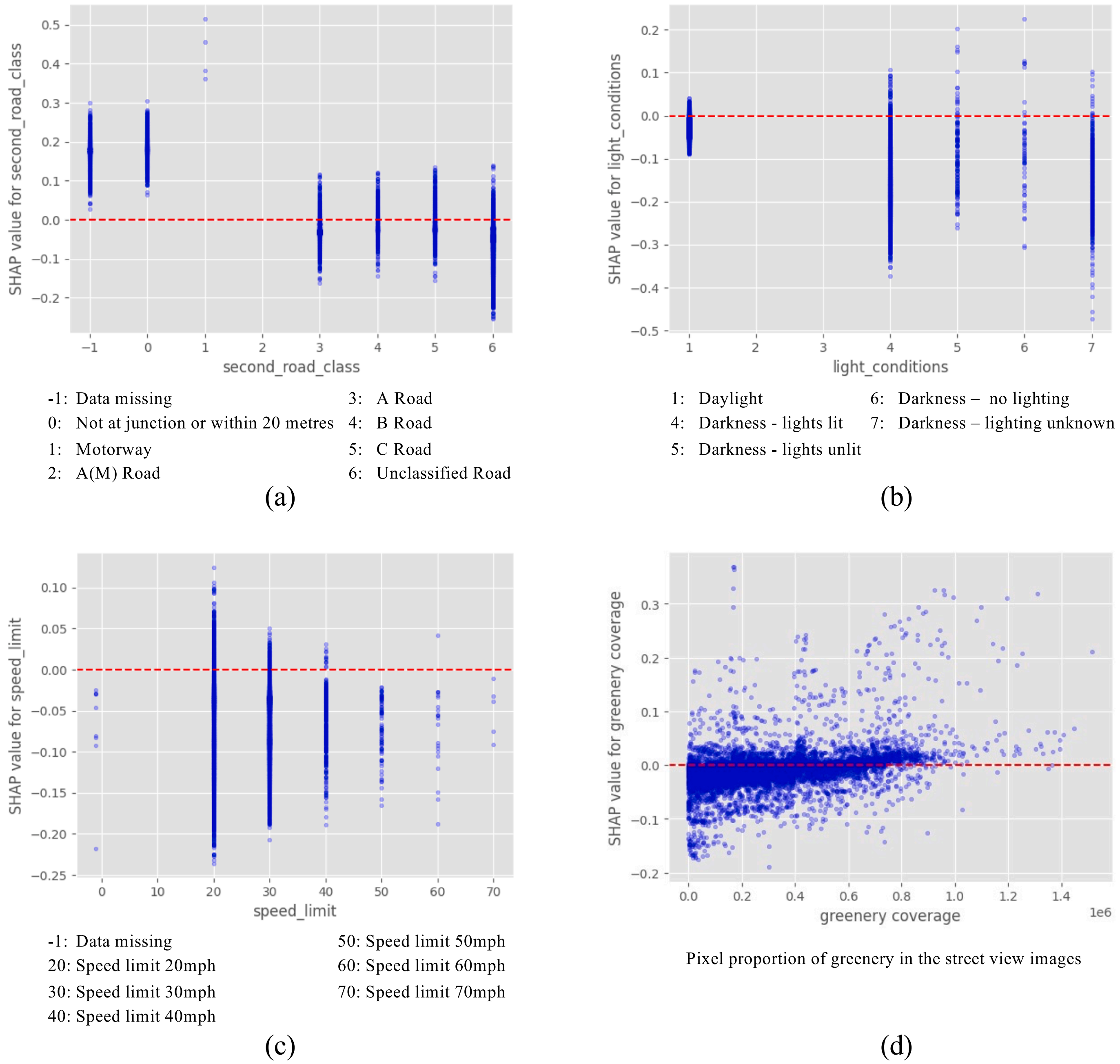


Fig. 9. SHAP dependence plot of the top 4 importance features in risky environment. (a) the category of the road that intersects with the road where the accident occurred, (b) light conditions of cycle accidents, (c) speed limit of the road where the accident occurred, (d) greenery coverage of street view images at accident sites.

Investigating the second road provides a more in-depth understanding of the interactions between complex road elements and provides guidance on the specific type of junction where the accident occurred or where the accident approached.

Fig. 11 shows the junctions between speed limit on the road where the accident occurred and the second road class in the context of cycling safety. The types of roads are represented by the eight numbers on the X-axis. From 1 to 5, there denotes road grading from high to low levels in a hierarchical structure, normally with decreased speed limits. For instance, “Motorways” are the highest class of road in the UK, designed for high-speed long-distance vehicular traffic. “A Roads” are major roads intended to provide large-scale transport links within or between areas. “B Roads” are the roads intended to connect different areas and to feed traffic between A roads and smaller roads on the network. “C Roads” aresmaller roads intended to connect together unclassified roads with A and B roads; “Unclassified Roads” are local roads intended for local traffic (Department for Transport, 2012).

The first three categories (i.e., data missing, not at a junction or with 20 m a motorway) have a significant impact on the increased likelihood of shaping the risky environment in which the ride takes place. The last four categories (i.e., second road class, 3,4,5,6) have essentially the same distribution of positive SHAP values in the risky environment, with a gradually increasing proportion of negative SHAP values. Overall, “second road effects” indicate that the lower the second road class, the safer the first road is. Fig. 11 shows that in the same second road class, the first road with a high-speed limit is more dangerous. Current road signage and intersection controls are primarily designed based on the overall conditions of the road, which is insufficient for guiding road design focused on cycling safety. To establish a bicycle-friendly city, our analysis results from the “second road effect” can be used to develop

Fig. 10. Diagrammatic description of the second road for the accident point.

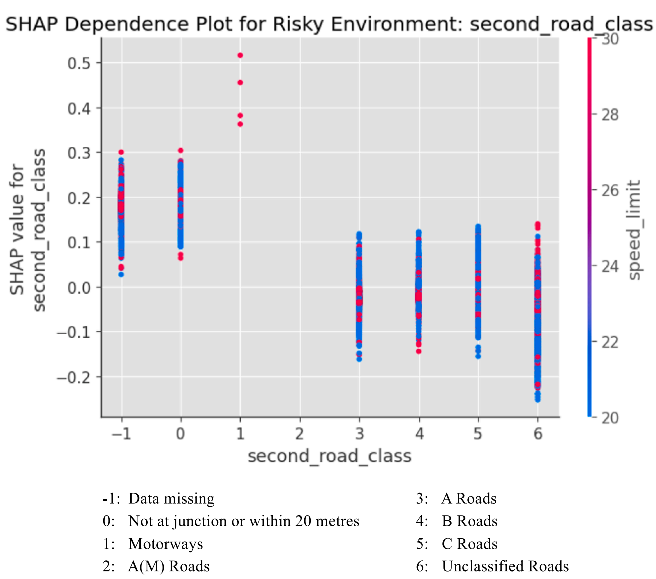


Fig. 11. The interaction effect between second road class and speed limit.

more targeted adjustments and recommendations for cycling safety: Implementing stricter speed limits for both motorised and non-motorised vehicles at junctions with high second road class to reduce the risk of accidents by lowering the speed limit; Continuously collecting and further analysing traffic accident data, with special attention to those junctions with high second road class to identify and address potential high-risk factors; Increasing enforcement of traffic violations at risky junction areas with high accident rates to ensure that cyclists and drivers comply with traffic rules; Developing safe cycling routes for cyclists to avoid high second road class junctions based on cycling safety maps and through education. traffic rules based on the cycling safety map, develop safe cycling routes for cyclists that avoid intersections with high second road classes and promote these routes through education and publicity campaigns to raise cyclists' awareness of cycling safety.

6. Conclusions

In this study, we established an analytical framework for perceived cycling safety of road environment utilising conventional GIS data alongside imagery features of street view, demonstrated through a case study of GLA. Within this framework, first, the study extracts a wide range of imagery features of street view recognised from the cyclist's perspective by using deep learning techniques and integrates them with road features of cycle accident. Second, the notions of collision risk and injury risk, as traditionally used in cycling accident research, are integrated into a new concept termed "Cycling Safety Level of Road Environments". This concept provides a more accurate reflection of the actual cycling risks presented in the road environment. Drawing upon data from all cycle accident locations in London over the past five years, this method has evaluated the cycling safety level of the road environment across the entire London with an overall accuracy of 83.4 % and an F1 score of 82.8 %. Finally, by employing the SHAP algorithm, the study analyses the relationships and weights of different factors affecting risk levels, contributing insights into urban design and transport planning.

We have drawn a number of interesting findings. It was found that the second road class, light condition, and speed limit had the greatest influence on the safety level of riding. This was followed by greenery coverage among the imagery feature of street view, where the proportion of most street scenes played a positive role in determining the risky environment of cycling, and these factors that shape the risky environment of cycling need to be treated with caution. By means of the SHAP dependence plot. The analysis reveals that the second road is the key to the risky environment, and the higher the second road class, the higher the level of risk. The 20mph speed limit is more likely to shape the risky environment compared to higher speed limits. The more trees and vegetation on the road, the more dangerous it is. Because the road environment becomes more complex when an increased number of imagery feature elements are perceived at one time.

There are also limitations in our study that direct our future work. First, the coverage of road features of cycle accident and imagery features of street view considered in this study are not exclusive and subjected to the availability of data sets. Second, a snapshot at a specific location in time doesn't necessarily reflect the dynamic flow of vehicles and pedestrians. Third, the volume of the traffic will impact the safety level as well, which is not yet considered. Moreover, future research will be developed towards risk management and also models that better address spatial variations, aiming for a more comprehensive and predictive model for cycling safety, eventually to guide urban planning and traffic management strategies better.

CRediT authorship contribution statement

Ying Ye: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Chen Zhong:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Esra Suel:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data used in this research are in public domain.

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Appendix 1

Fig. A1. SHAP summary plot (Cycling Safety Level: risky environment).

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