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Perceived Traffic Safety Assessment for Pedestrians and Cyclists in Helsinki Using Street View Imagery

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Abstract

Active travel, such as walking and cycling, has significant benefits in promoting human health, mitigating traffic congestion, and eliminating carbon emissions. In many countries, promoting active travel has been listed in various policies. However, there remains a gap that cannot be ignored between current reality and the expected goal. Existing literature indicates that pedestrians' and cyclists' sense of safety from being involved in traffic accidents during travel, i.e., perceived traffic safety, is one of the key factors determining residents' choice of active travel. Additionally, the occurrence of AI tools and novel datasets, such as Street View Imagery, offers promising opportunities to understand perceived traffic safety at the micro-scale. In this context, the primary objective of this thesis was to identify the relationship of perceived traffic safety with various streetscape characteristics, traffic conditions, and population factors by using Google Street View Imagery and Public Participation Geographic Information System (PPGIS) data with machine learning in Helsinki.

The study explored the possibility of combining PPGIS survey datasets on perceived traffic safety collected by the City of Helsinki with GSV images to understand human perception. First, I evaluated the various safety indicators derived from the PPGIS data. Second, I extracted the environmental features information by semantic segmentation and combined these factors with traffic and population factors. Finally, two model-independent techniques—SHAP and PDP—were used to explain the relationship between individual features and perceived traffic safety.

This study identified several key factors contributing to safe or unsafe perceptions during walking and cycling. Among these, population density is the most critical to both travel modes, while traffic factors—road condition, traffic volume, and speed limitation—and several environmental features—vegetation, buildings, sidewalks, people, cars, and traffic signs—also have a major contribution to perceived traffic safety. Moreover, the study compared the different focuses during travel between walking and cycling. The results show that there are subtle differences in emphasis: Pedestrians are more focused on elements that provide security and better visibility, such as lower speed limits, lower value of buildings, sidewalks, and cars, while cyclists are more sensitive to road conditions. In summary, the study offers insights into urban planning and policy making, emphasising the importance of population, urban environment, and traffic features on improving perceived traffic safety during walking and cycling.

Keywords
Perceived road safety, Pedestrian, Cyclist, Machine learning, Street view Imagery, PPGIS

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1 Introduction

With the rapid population growth and accelerated urbanization, a significant concentration of people in large cities has increased transportation demand. In turn, issues such as traffic congestion, noise, air pollution, and urban heat effects have been exacerbated (Murayama & Estoque, 2020; Rahman & Thill, 2023). In this context, promoting sustainable transportation modes, such as walking and cycling, has become increasingly necessary. A major deterrent to both cycling and walking is that vulnerable road users often feel that they are given lower priority than car drivers in shared spaces, potentially causing concerns about their safety (Campos Ferreira et al., 2022; Kaparias et al., 2012; Moody & Melia, 2014; Musselwhite et al., 2014). Research has shown that residents' perceived traffic safety plays a decisive role in their choice of transportation modes (Heinen et al., 2010; Whannell et al., 2012). Another study highlighted the importance of understanding pedestrian safety perception as a key to enhancing the sense of safety, thereby encouraging walking (Aceves-González et al., 2020).

Moreover, pedestrians and cyclists have been identified as vulnerable road users (Hamim et al., 2020), as they are prone to injury in any traffic accidents (Yannis et al., 2020). Pedestrians, who typically lack protective measures on the road, are at a higher risk of severe injury compared to vehicle occupants (Kitali et al., 2017). Research by Schneider et al. (2004) revealed that perceived risk differs from police-reported risk and that perceived information can help identify potential accident hotspots, thereby reducing traffic safety hazards. Therefore, understanding the factors influencing pedestrians' and cyclists' safety perceptions is crucial for increasing active transportation rates and improving overall road safety.

It is widely accepted among policymakers, urban planners, and researchers that the appearance of a city and its perception influence residents' behavior and health (Dubey et al., 2016). Many researchers have found that environmental factors have an impact on human perception (Blöbaum & Hunecke, 2005; Kawshalya et al., 2022; Kim et al., 2023; Lis et al., 2019; Rossetti et al., 2019; Zeng et al., 2023). Specifically, as mentioned by Campos Ferreira et al. (2022), the key determinants of active travel perceived traffic safety include fear of injury, fear of falling, and infrastructure issues, which could be attributed to high traffic volumes and speed, poor road quality, and insufficient dedicated lanes for pedestrians and cyclists. Besides, it has been argued by Hamim & Ukkusuri (2024) that socio-demographic factors such as relative wealth index could influence perceived traffic safety for pedestrians as well. Although extensive research has established various factors influencing perceived traffic safety, research capturing these diverse influences comprehensively remains scarce.

Perception, referring to the understanding and interpretation of different built environments, including natural elements, is challenging to evaluate using traditional measurement methods (Larkin et al., 2022). Common methods for measuring pedestrians' and cyclists' perceptions are divided into quantitative and qualitative approaches, often involving interviews, mailed surveys, and on-site audits. However, these methods are typically time-consuming, labor-intensive, and usually applicable only to limited areas or sample points (Duncan et al., 2018). Moreover, there is often a weak correlation between the ratings of attractiveness by trained auditors and the public; thus, experts' subjective evaluations of pedestrian environments may not effectively represent public perception (Adkins et al., 2012) and there is also a common dissonance between cyclists' perceived risk and the risk assessed by experts (Rivera Olsson & Elldér, 2023).

In recent years, with the development of computer vision, artificial intelligence, and emerging data sources such as Street View Imagery (SVI), more studies have begun exploring the connection between subjective perceptions and objective elements from a human perspective. To quantify specific perceptions, Naik et al. (2014) utilized crowdsourced data and image comparison methods to collect perception data; Hamim & Ukkusuri (2024) used safety perception data assessed by trained evaluators combined with socio-demographic factors to predict safety perceptions. However, the data used by Naik et al. (2014) was not specifically collected to explain pedestrians' safety perceptions of roads, and was not considered the residents' experiences. In contrast, the evaluators in Hamim's study all have similar backgrounds, for example, they are all aged 18-25 and are students from the same university and the same major (Hamim & Ukkusuri, 2024). Therefore, their assessment of the images is potentially influenced by their specialized knowledge and experience. Consequently, to collect data that better represents the general public's perception, it is important to consider both the residents' experiences and the diversity of the participants.

This study aims to investigate the relationship between the perceived traffic safety of active travel and the environment, traffic, and population. Specifically, the following two research questions were answered by this study:

How do environmental and traffic factors impact pedestrians' & cyclists' perceived traffic safety in Helsinki?

What are the strengths and limitations of using Street View Imagery with PPGIS as an ancillary data source when assessing perceived traffic safety?

In summary, this study makes three key contributions and innovations to existing literature. First, previous research utilizing Street View Imagery (SVI) to assess perceived traffic safety quantitatively has seldom incorporated the people's place experiences from Public Participation Geographic Information Systems (PPGIS), such as the spatial distribution of reported points. Instead, most studies typically employed questionnaires that allowed participants or professional evaluators to assess perceptions based on randomly selected SVI images. This study expands the methods of using SVI images and PPGIS to research environmental perceptions.

Second, few scholars have considered the effect of traffic factors on environmental features. This could ignore some potential relationships between them, therefore bringing bias to the results. To address this problem, this study considered the most mentioned factors in perceived traffic safety research to understand the perceived traffic safety for pedestrians and cyclists comprehensively. Additionally, this study analyzed the perceived traffic safety for both cycling and walking and compared the similarities and differences in the perception of traffic safety between these two travel modes.

Third, it remains unclear in the relationships between surrounding characteristics and perceived traffic safety, especially regarding non-linearity and the relative importance of explanatory variables. This was handled by this study by employing model-independent techniques such as Shapley Additive Explanations (SHAP) (Lundberg & Lee, 2017) and Partial Dependence Plots (PDP) (Greenwell, 2017) to reveal the key factors influencing traffic safety perception from both a global and local perspective. These contributions could significantly enhance the precision and practicality of research in perceived environmental safety.

2 Literature review

This section focuses on the current research status of predicting perceived traffic safety in walking and cycling and will discuss it from three perspectives: environmental perception, perceived traffic safety and influence factors, and data and artificial intelligence tools.

2.1 Environmental perception

Environmental perception refers to the process by which individuals perceive, understand, and interpret their surrounding environment through their senses (Ittelson, 1978). This perception extends beyond a mere direct response to the physical environment; it also encompasses the individual's subjective evaluation and emotional reaction to that environment (Ittelson, 1978). The way individuals perceive their environment has a direct impact on their decision-making and behaviour (Saarinen, 1974).

As a core area of research in environmental psychology, the study of environmental perception provides researchers with insights into how people perceive and react to different environments. This understanding could provide helpful insights for improving living conditions (Goodey & Gold, 1987; Smardon, 1988). In urban planning, the concept of environmental perception can be applied to design more liveable and sustainable urban spaces (Douglas et al., 2019; Goodey & Gold, 1987; Smardon, 1988; Zeile et al., 2015). In transportation planning, understanding how road users perceive roads and traffic environments can aid in designing safer and more efficient transportation systems (Amiour et al., 2022; Rankavat & Tiwari, 2016; Rivera Olsson & Elldér, 2023).

Furthermore, research on environmental perception can contribute to advancing sustainable development goals. For instance, by enhancing the perceived quality of the road environment—such as increasing feelings of traffic safety, security, and satisfaction—more individuals can be encouraged to adopt active modes of transportation (Fernández-Heredia et al., 2014; Mertens et al., 2016; Willis et al., 2015).

2.2 Perceived traffic safety and influencing factors

Perceived traffic safety refers to the subjective assessment of traffic safety by individuals while walking or cycling in an environment. Typically, pedestrians perceive the environment during walking from many aspects, such as accessibility, aesthetics, comfort, convenience, attractiveness, safety (traffic safety), and security (personal safety or fear of crime) (Ball et al., 2001; Basu et al., 2022; Craig et al., 2002; Ferrer et al., 2015; Foster et al., 2014; Giles-Corti & Donovan, 2002; Lavrakas, 1982; Moura et al., 2014; Panter et al., 2014; Villaveces Dr. et al., 2012). Similar to pedestrians, cyclists typically perceive the environment from the perspectives of safety, security, accessibility, comfort, etc (Campos Ferreira et al., 2022; Marquart et al., 2020; Mertens et al., 2016).

Many studies have examined the effects of surroundings and socio-demographics on perceived traffic safety during walking and cycling (Aceves-González et al., 2020; Basu et al., 2022; Bustos et al., 2021; Campos Ferreira et al., 2022; Hamim & Ukkusuri, 2024; Moreno-Vera et al., 2021; Naik et al., 2014.; Park & Garcia, 2020; Rivera Olsson & Elldér, 2023; Marquart et al., 2020). The impacted factors can be classified into three categories: 1) environmental factors containing natural and built environment, 2) traffic factors, and 3) socio-demographic factors.

First of all, researchers have found that elements in the natural environment can impact perceived traffic safety. For instance, it is indicated that urban green space and vegetation have a positive impact on both pedestrians' and cyclists' perceived traffic safety (Marquart et al., 2020; Zhao & Huang, 2021). Additionally, an open space layout of landscape elements, low accessibility of water, and more aquatic plants on water can predict a higher overall perceived traffic safety during the daytime (Zhao & Huang, 2021); Kweon et al. (2021) found that trees have a stronger impact on the perception of pedestrian safety when there is a wide buffer between sidewalks and street curbs compared to when the buffer is narrow (Kweon et al., 2021).

The built environment is another critical factor influencing perceived traffic safety, including land use, urban lighting, traffic features, and more (Basu et al., 2022; Hamim & Ukkusuri, 2024; Rivera Olsson & Elldér, 2023; R. Wang et al., 2023). Well-lit streets, for example, generally make people feel safer (Peña-García et al., 2015; Rahm et al., 2021); also, people tend to feel safer in recreational and vacant land compared to residential areas (Basu et al., 2022). Moreover, infrastructure built for pedestrians or cyclists, like sidewalks and bicycle lanes, can impact perceived road safety. For pedestrians, the presence of sidewalks could enhance their perceived traffic safety (Hamim & Ukkusuri, 2024), and for cyclists, adding a bicycle lane together with a clear road marking for bicycles could increase perceived traffic safety (Rivera Olsson & Elldér, 2023). Additionally, one of the most important environmental factors in urban research is population density. Research shows that population density has an opposite effect on perceived crime safety, discouraging walking by increasing the fear of crime (Hong & Chen, 2014). Similarly, Hamim & Ukkusuri (2024) indicate that lower population density could lead to increased perceived road safety. However, Hamim & Ukkusuri (2024) also found that surroundings with fewer people present in walking could cause decreased perceived road safety (Hamim & Ukkusuri, 2024). It may seem paradoxical, but this can be explained by the fact that lower population density nearby reduces the risk of traffic accidents, while fewer people around diminish the sense of social safety.

Traffic factors also play an important role in perceived traffic safety. Rivera Olsson & Elldér (2023) confirms that traffic volume is a decisive factor for the perceived traffic safety of cyclists; Uijtdewilligen et al. (2024) indicates that crowding among cyclists has a negative impact on both route preferences and perceived traffic safety, and also high traffic volume and vehicles approaching a crossing at high speed could negatively influence pedestrians’ perceived traffic safety (Campos Ferreira et al., 2022; Schneider et al., 2022).

Perceived traffic safety also varies due to sociodemographic factors, such as gender and income. Researchers have shown that females tend to feel less safe than males when engaging in active mobility (Basu et al., 2022; Okafor et al., 2023). Individuals with lower incomes have expressed greater concerns about the safety of active transportation modes compared to higher-income earners (Okafor et al., 2023).

2.3 Artificial intelligence tools in perception research

AI tools, such as deep learning and machine learning, have been used widely in quantifying complex urban environments and analysing human perception in recent years (Dubey et al., 2016; Hamim & Ukkusuri, 2024; X. Li et al., 2015; R. Wang et al., 2023). Deep learning based computer vision techniques, such as image segmentation, have been successfully leveraged in extracting information or modeling complex environments from images and videos (Chai et al., 2021). Meanwhile, machine learning approaches have gained a lot of usage and success in extracting the relationship between human perception and influential factors (Hamim & Ukkusuri, 2024; Ito et al., 2024; Lu & Chen, 2024).

Semantic segmentation, one of the most commonly used image segmentation methods, is a technique in computer vision that divides an image into distinct regions or objects, where each region typically represents a specific part or category in the image (Mo et al., 2022).

In recent years, semantic segmentation has become a common approach in urban analytics to extract information from Street View Imagery (X. Li et al., 2015; Lu & Chen, 2024; Rita et al., 2023; Torkko et al., 2023). Through semantic segmentation, each pixel in the image is assigned a category label like "road," "building," or "tree," enabling a clearer representation of image content (Hao et al., 2020).

A growing amount of literature can be found on using semantic segmentation with machine learning models to understand the impact of the environment on human perception. Among these studies, street view imagery was typically used to extract environmental information, which was then combined with perception data to explore the impact of environmental factors. For example, Hamim & Ukkusuri (2024) extracted the proportion of built environmental factors by a semantic segmentation model and explored the impact of factors on the perceived road safety of pedestrians by a machine learning model – random forest; similarly, Ye et al. (2024) extracted 18 features from GSV images by a semantic segmentation model – HRNet and analysed the impact of each feature on cyclists' perceived safety by another machine learning model – XGBoost.

2.4 Explanation of "black box" — Machine learning

Despite the widespread application of machine learning in perceptual research, it is often criticized as a "black box" due to the perceived opacity of its predictive processes. Consequently, the interpretability of machine learning has received increased attention in recent years, leading to the development of numerous methods to explain machine learning models (Z. Li, 2022). Particularly, there are two commonly used methods: SHapley Additive exPlanations (SHAP) (Lundberg & Lee, 2017) and Practical Dependent Plot (PDP) (Greenwell, 2017), which offers an opportunity to understand the contribution of input features on the machine learning output (predictions).

SHAP, based on the cooperative game theory principles, especially SHAP values (Shapley, 2016), provides a comprehensive framework to illuminate the intricate mechanisms of black box models (Shapley, 2016). SHAP values could be used to explain the contribution of each feature to the model's prediction relative to the average prediction. Additionally, SHAP provides many visualization methods to visualize the contribution of each feature, such as beeswarm plot and force plot. The beeswarm plot provides a compact and information-rich summary of how the most important features in a dataset influence the model's output (Lundberg & Lee, 2017). Each dot on a feature row represents the explanation for a single instance, with the dot's horizontal position determined by the feature's SHAP value. Dots accumulate along the row to indicate density, and a sequential color bar is used to show the original feature values.

Another model-explained method is PDP, which is used to show the impact of one or two features on the predictions after averaging out the effects of all other features (Greenwell, 2017). It displays how the average response of the predictions changes when a specific feature is varied. PDP helps to understand the marginal effect of the feature on the prediction, providing insight into whether the feature has a positive, negative, or nonlinear influence on the model’s output.

2.5 Usage of PPGIS data in perception research

Traditional methods to collect human perception data of safety include large-scale surveys, expert evaluation, and on-field surveys (Hamim & Ukkusuri, 2024; Lis et al., 2019; Villaveces Dr. et al., 2012). However, these methods are time-consuming and expensive. To overcome these limitations, web-based crowd-sourcing methods have been developed in recent years and shown great performance (Dubey et al., 2016; Naik et al., 2014; Zhao & Huang, 2021), such as an online survey to obtain the perception of provided images of selected or random locations (Lu & Chen, 2024; Zhao & Huang, 2021), or extraction perception value by ranking provided images (Dubey et al., 2016; Naik et al., 2014).

One of these online and commonly used approaches is the Public Participation Geographic Information System (PPGIS). As defined by Tulloch (2008), PPGIS is a “field within geographic information science that focuses on ways the public uses various forms of geospatial technologies to participate in public processes, such as mapping and decision making.” It is a useful tool for acquiring spatial information grounded in place-based experiences from the public via online mapping tools, supporting the improvement of decision-making processes (G. Brown & Kyttä, 2014). While PPGIS data is usually utilized in the initial stages of planning projects, it can also be valuable for gathering public feedback after project implementation (G. Brown & Kyttä, 2014).

PPGIS can be applied in various fields, such as urban planning, human-environment interaction, value assessment, and more (Bąkowska-Waldmann & Kaczmarek, 2021; G. Brown & Kyttä, 2014; G. Brown & Weber, 2012; Elwood & Ghose, 2001; Kantola et al., 2023). Recent PPGIS studies have focus on capturing human perceptions, such as safety and happiness, by leveraging its ability to collect both qualitative and quantitative information for specific locations from large sample sizes (Davis et al., 2016). For example, Nenko & Petrova (2019) analysed the city's subjective perception by comparing PPGIS and LBSN (location-based social networks) data; Mohamed et al. (2023) evaluated parents' perceived safe and unsafe locations in parks by using PPGIS and photos.

However, while PPGIS data have been widely used to collect public perception data, the usage of PPGIS data and street view imagery to explain the impact of the environmental features on human perception is still lacking. Therefore, based on the existing literature, this study has recognized the research gaps and potential opportunity to combine PPGIS data with street view imagery to advance the understanding of road safety perception of pedestrians and cyclists.

3 Data and pre-processing

3.1 Study area

Helsinki, the capital city of Finland, covers a land area of 217 km^2 with a total population of about 674 thousand (Goals and Guidelines of Traffic Planning in Helsinki, 2016) (Figure 1). This city has extensive walking and cycling infrastructure, with design and maintenance standards that are highly regarded globally (Urban Mobility Readiness Index, 2024). Additionally, the Helsinki city council has a clear strategy for promoting sustainable transportation, particularly walking and cycling (Goals and Guidelines of Traffic Planning in Helsinki, 2016). Studying pedestrian and cyclist safety in Helsinki can inform not only local policy but also provide other cities with valuable insights and a framework for sustainable transportation research.

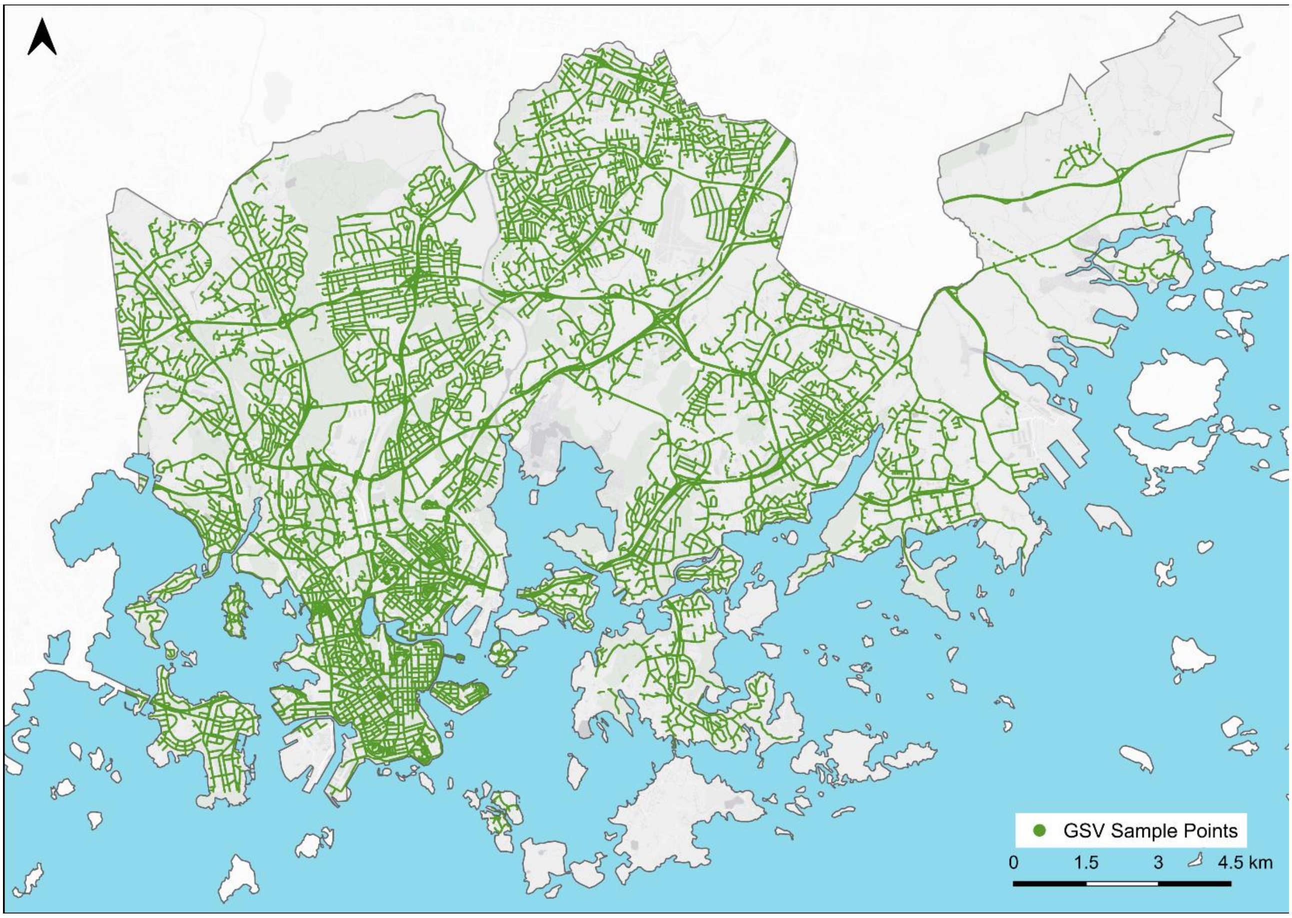

Figure 1. Study area and the sampling points of GSV images

3.2 Data overview

In this study, seven datasets were used to analyze perceived traffic safety, including survey data, traffic data, and street imagery data (Table 1). Detailed descriptions and preprocessing methods for these data will be provided in the next section.

Table 1. Overview of datasets used in this study

Data Name	Source	Date Range	Date Type	Usage in Analysis
Traffic safety survey for citizens of Helsinki	Helsinki City Environment Sector / Traffic and Street Planning (Helsinki City Environment Sector / Traffic and Street Planning, 2020)	2020	Point	To assess Perceived traffic safety
Google Street View	Google (access through Digital Geography Lab) (Anguelov et al., 2010)	2009-2017	Image	To acquire proportion of environmental features
Road Condition	Helsinki City Environment Sector / Property Management (Helsinki City Environment Sector / Property Management, 2022)	2018-2022	Point	To acquire road conditions of main and branch road
Traffic Volumes	Helsinki City Environment Sector / Traffic and Street Planning (Helsinki City Environment Sector / Traffic and Street Planning, 2024)	2024	Line	To acquire traffic volume of vehicles
Speed Limitation	Finnish Transport Infrastructure Agency (Finnish Transport Infrastructure Agency, 2022)	2022	Line	To acquire speed limit of each road
Strava data	Strava Metro (access through Digital Geography Lab) (Strava Metro, 2023)	2023	Line	To normalize perceived traffic safety
Population data	Helsinki Region Environmental Services Authority HSY (Helsinki Region Environmental Services Authority HSY, 2022)	2022	Grid	To acquire population of each sample point

3.3 Data description and preprocessing

3.3.1 Traffic safety survey for citizens of Helsinki

Traffic safety data was obtained from the Helsinki City Environment Sector from September 1 to 27, 2020, and it included both tabular data and a geographic dataset (shapefile). The survey was conducted using a map-based survey tool, and it consisted of citizen feedback on various aspects of traffic safety in Helsinki, including places where respondents had experienced accidents or near misses. Additionally, it suggested measures to improve safety, traffic violations, and dangerous locations.

The shapefile dataset (n=28,939) contains all the risky locations marked by respondents, along with information about the most significant safety issues and the most dangerous modes of transportation at each location. Some examples of the risky points records are presented in Table 2.

Table 2. Examples of risky points records

Respondent	**Issue type**	**Pedestrian**	**Cyclist**	**Car users**	**Public transport**	**Others**
5	Difficult or unsafe intersection or junction	1	0	0	0	0
5	Other problem	0	0	0	0	1
8	High speeds	1	1	0	0	0
12	Difficult or unsafe intersection or junction	0	1	0	0	0
…	…	…	…	…	…	…

This study specifically focused on the risky points that were reported to pose the highest risk to pedestrians (Pedestrian=1; n=13,263) and cyclists (Cyclist=1; n=13,860). Each risky point is characterized by two key features: (1) the most important road safety issue at that location and (2) respondent identification (ID).

As depicted in Figure 2, risky points for pedestrians are widely distributed from the city center to the suburbs. The risky points were reported by 3,253 unique respondents. Among these, 1,800 respondents were aged between 25 and 44, accounting for 55.5% of the total, and 1,024 respondents were aged between 45 and 64, making up 31.6% of the total (as shown in Figure 3).

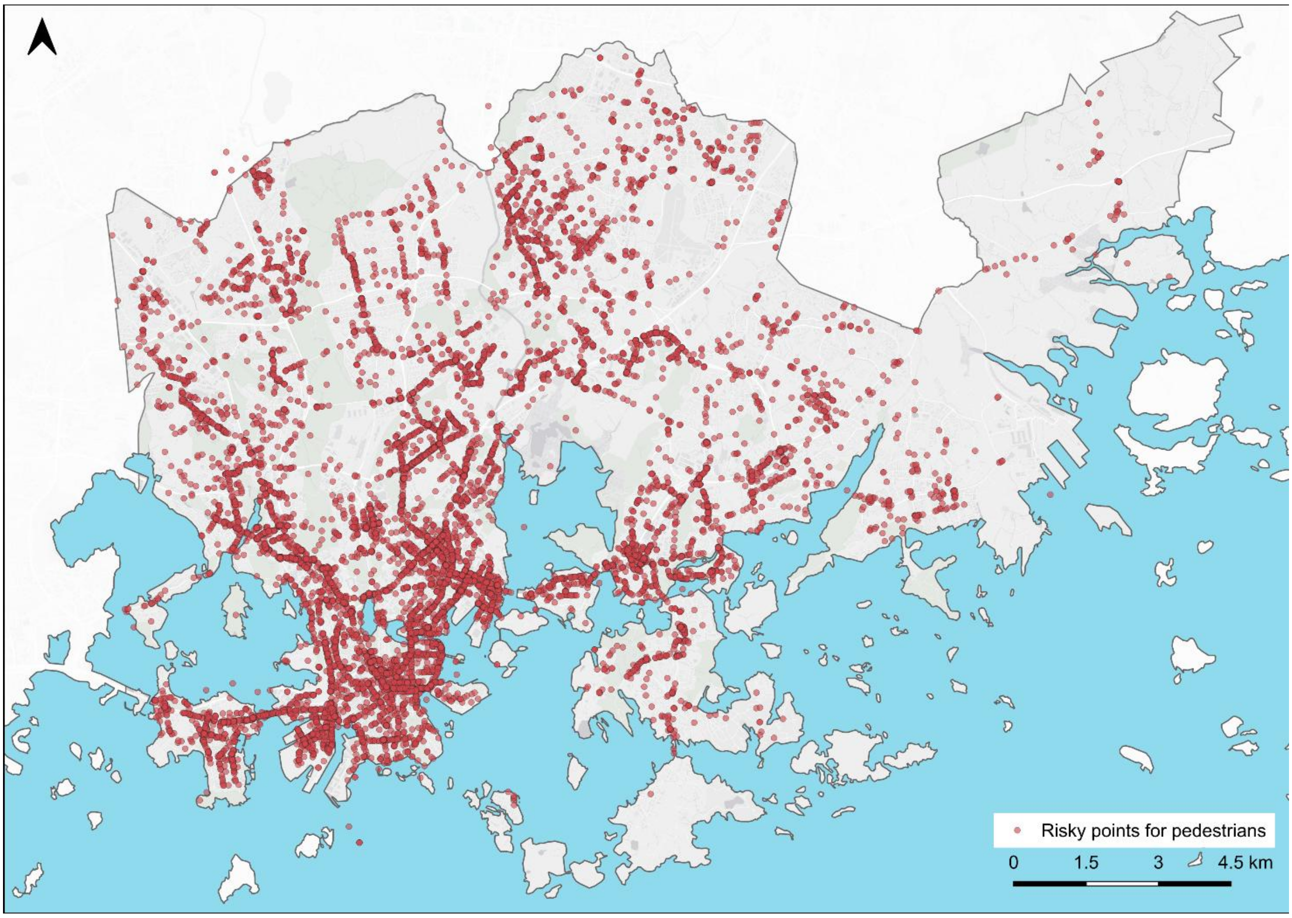

Figure 2. Risky points for pedestrians

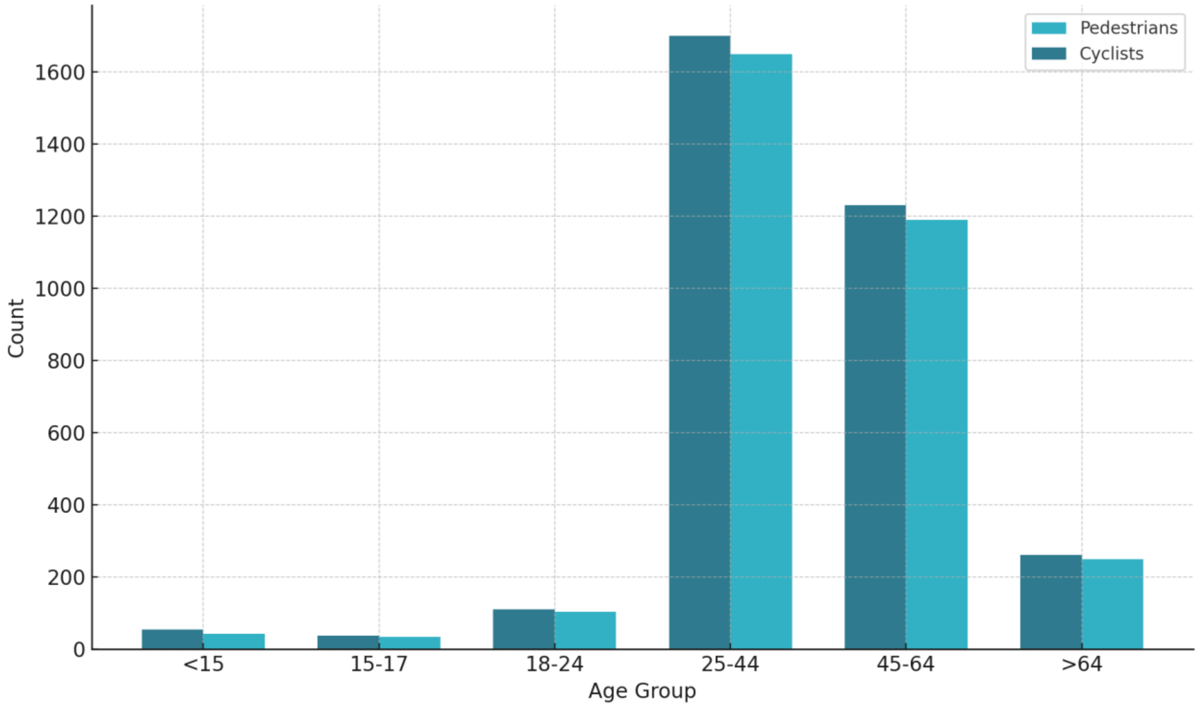

Figure 3. Age distribution of respondents who marked risky points for pedestrians or cyclists

Figure 4 illustrates the spatial distribution of risk points for cyclists, highlighting extensive coverage across the city. The points were reported by 2,901 unique respondents. Among these, 1,621 respondents were aged between 25 and 44, accounting for 56.0% of the total, and 927 respondents were aged between 45 and 64, making up 32.0% of the total (as shown in Figure 3).

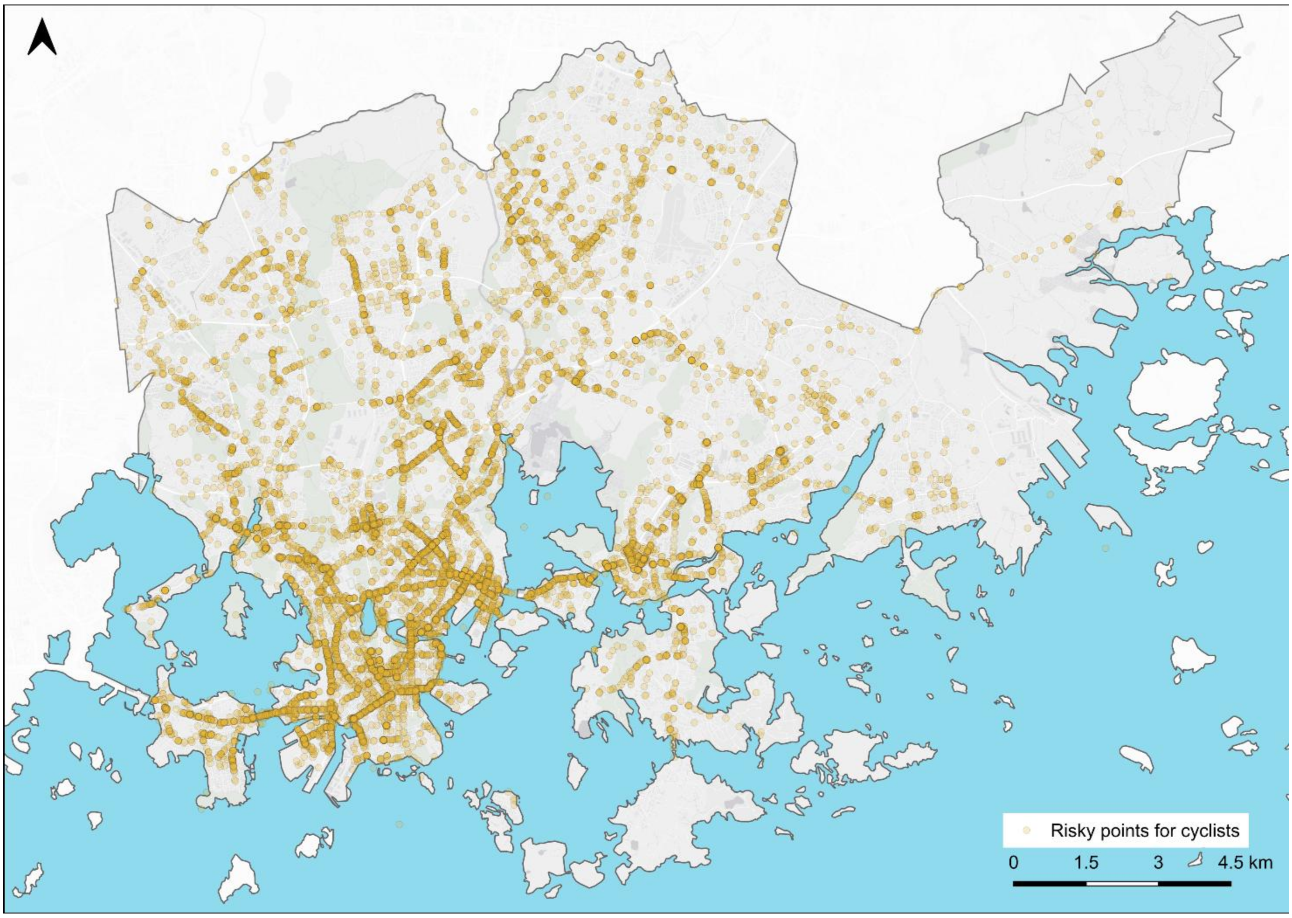

Figure 4. Risky points for cyclists

3.3.2 Google Street View

The GSV data had been purchased by Digital Geography Lab and provided in PNG format. The data is stored and managed according to the General Data Protection Regulation (EU) 2016/679 (the GDPR).

In this study, a total of 688,038 GSV images were collected from 114,673 locations in Helsinki between 2009 and 2017 (shown in Figure 1). GSV images are usually captured by two methods: the Street View car (Figure 5(a)) and the Trekker (Figure 5(b)), which is a lightweight camera mounted on a backpack and carried by an operator. The Street View Car, which uses cameras mounted on the roof of the vehicle, is the most common way to collect GSV images. In some locations inaccessible to vehicles, such as pedestrian streets, and forests, images could be taken by Trekker.

Figure 5. GSV image acquisition methods: (a) Street view car, (b) Trekker

The dataset contained 360°street view panoramas sampled at 20m intervals over the Helsinki Street network. For each location, a GSV panorama was downloaded as six horizontal images from 60-degree intervals (0, 60, 120, 180, 240, and 300), with 640*640 pixels for each image (Figure 6).

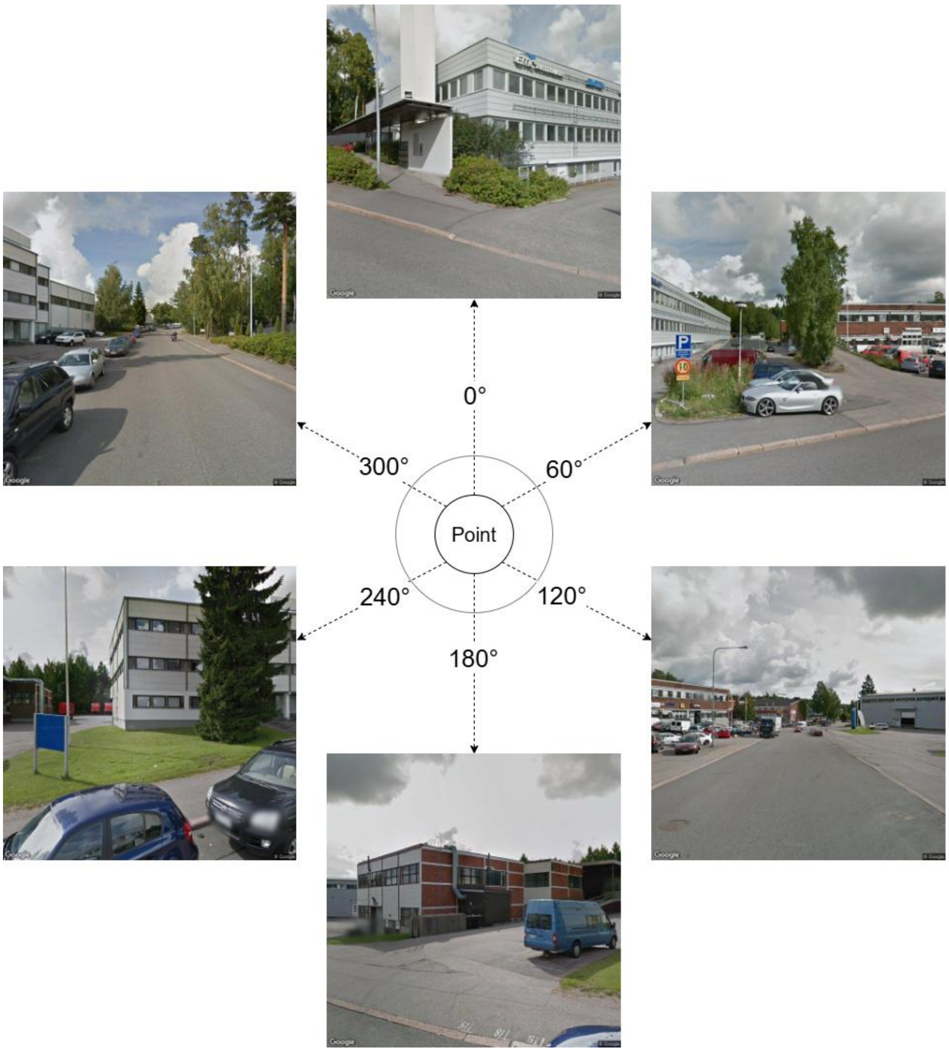

Figure 6. Diagram of GSV Images Divided by Angles

3.3.3 Traffic data

In this study, three types of traffic data were employed to evaluate perceived traffic safety with respect to road quality, vehicle traffic volume, and speed limits.

(1) Road condition

Road condition data was downloaded from Helsinki Region Infoshare (Helsingin kaupunkiympäristön toimiala / Rakennetun omaisuuden hallinta, 2023). It resulted from condition measurements of Helsinki's main street network between 2018 and 2022. It measured the trails, unevenness, and side slope of the coating from the distance data produced by lasers attached to the measuring car and the pavement profile. The field used in this study as general road condition is 'kokonais_l', which means lower value of the measured period average maximum trail depth and mean longitudinal unevenness (classes 1-5, five means best condition).

Since this dataset only covers the main streets and consists of a large volume of point data (n=323,420), Inverse Distance Weighting (IDW) was applied to enhance processing efficiency and estimate values for branch roads. IDW is known as one of the most widely used and successful techniques among interpolation methods. It assumes that the characteristics of an unknown point are related to the characteristics of nearby known points, with this relationship diminishing as distance increases (Chen & Liu, 2012). It could be used to estimate the unknown road condition data from the known points data (Al-Kazaz & Ewadh, 2020; Shao & Jones, 2012). Typically, the weight is the inverse of the distance raised to a power, expressed as follows:

$$w_i = \frac{1}{d_i^p} \tag{1}$$

where w_i represents the weight, d_i is the distance between the known point and the unknown point, and p is the power parameter, typically chosen as 1 or 2. The predicted value for the unknown point is computed using the formula:

$$Z(x) = \frac{\sum_{i=1}^{n}(w_i \cdot z_i)}{\sum_{i=1}^{n} w_i} \tag{2}$$

Where, $Z(x)$ is the predicted value at the unknown point, z_i are the values at the known points, and n is the total number of known points.

(2) Traffic volume

Traffic volume data was downloaded from Helsinki Region Infoshare, and it is a collection of calculations about traffic volumes and estimations of traffic volumes. The data contains volumes per vehicle (passenger car, van, truck, lorry, bus, motorbike, tram) per road and traffic rate per year and so on. The specific field used in this research is ‘autot’, which means the total number of cars.

Traffic volume data covers each road in Helsinki. Since the sample points were obtained along the road network, the traffic volume of the nearest road was assigned as the value for each point. Additionally, to mitigate the impact of the uneven distribution and the large range (from 1 to 118,011) of the traffic volume data, the data was divided into 20 levels based on percentiles.

(3) Speed limit

The speed limit data was downloaded from Digiroad, a national dataset under the responsibility of the Finnish Transport Infrastructure Agency (FTIA) (The Finnish Transport Infrastructure Agency, 2024). Digiroad is an aggregating information system that collects data from many sources, such as the FTIA Velho information system, the Topographic Database of the National Land Survey of Finland (NLS), and the street information systems of municipalities. The data is maintained in the Digiroad system and covers state-owned roads in Finland, and can be accessed via open WMS and WFS interfaces.

The specific field used in this study was ‘arvo’, which means the speed limit of the road. The data consists of discrete values ranging from 20 to 120 in increments of 10. Similar to traffic volume data, the speed limit value of the nearest road was also assigned as the value for each point.

3.3.4 Strava data

Strava Metro data was used in this study to create and test safety indicators normalized by the pedestrian or cyclist volume. The data was collected from the popular fitness app Strava, which is used by cyclists, runners, and other athletes to track their activities using GPS. Therefore, Strava Metro data consists of all recorded Strava trips with both leisure and commuting tags included.

The Strava data used in this study is provided by Strava through the Digital Geography Lab, collected in Helsinki in 2023. There are approximately 22, 000 unique Strava users in 2023 in Helsinki. The data contains (1) shapefile data, which has an ID for each edge and an ID for OSM road, and (2) CSV data, which contains edge ID and trip information like total trips and number of trips in different directions.

For acquiring pedestrians’ and cyclists’ volume for each sample point, I connected shapefile and CSV data based on edge ID first and assigned the nearest one as the value for each point. The maps of pedestrians’ and cyclists’ volume are shown in Figure 7 and Figure 8. It can be noticed that the points with high pedestrian or cyclist volume are alongside coastlines or riversides.

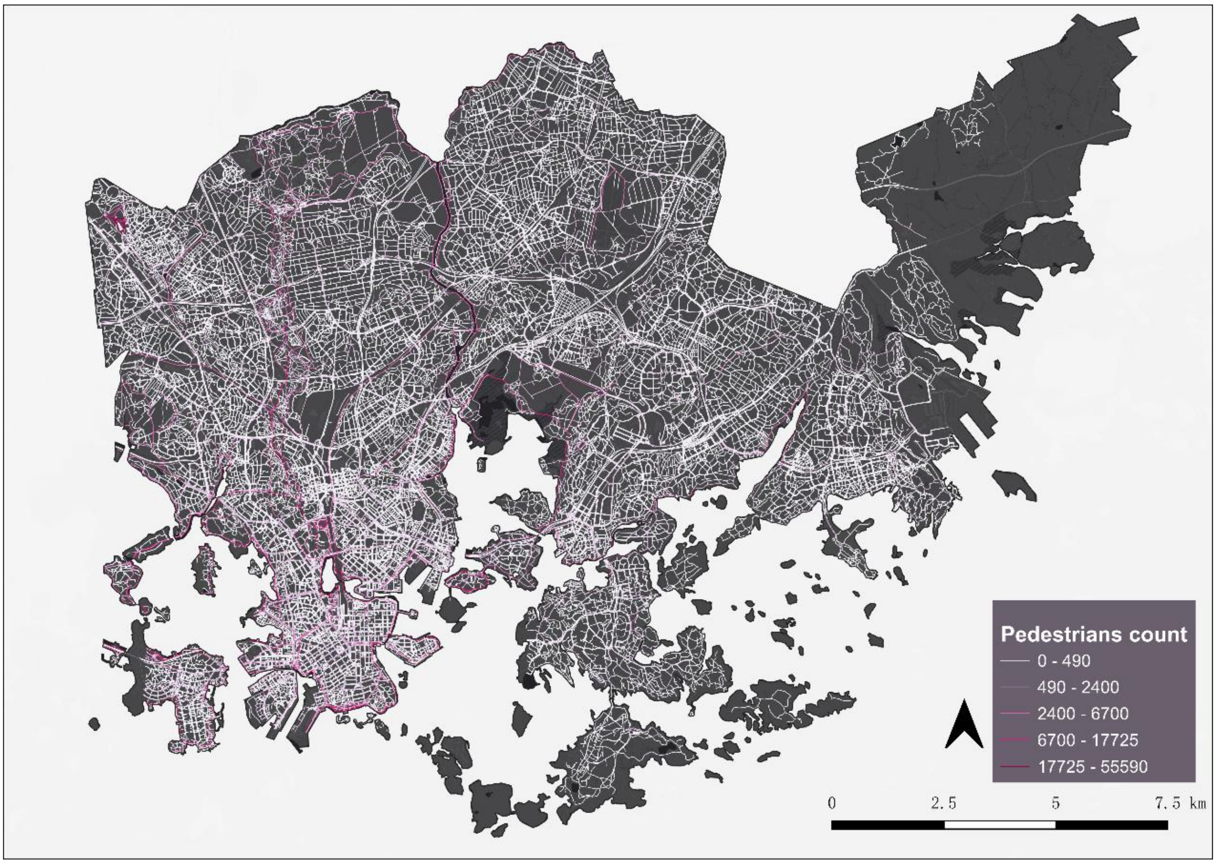

Figure 7. Pedestrians count from Strava data in Helsinki

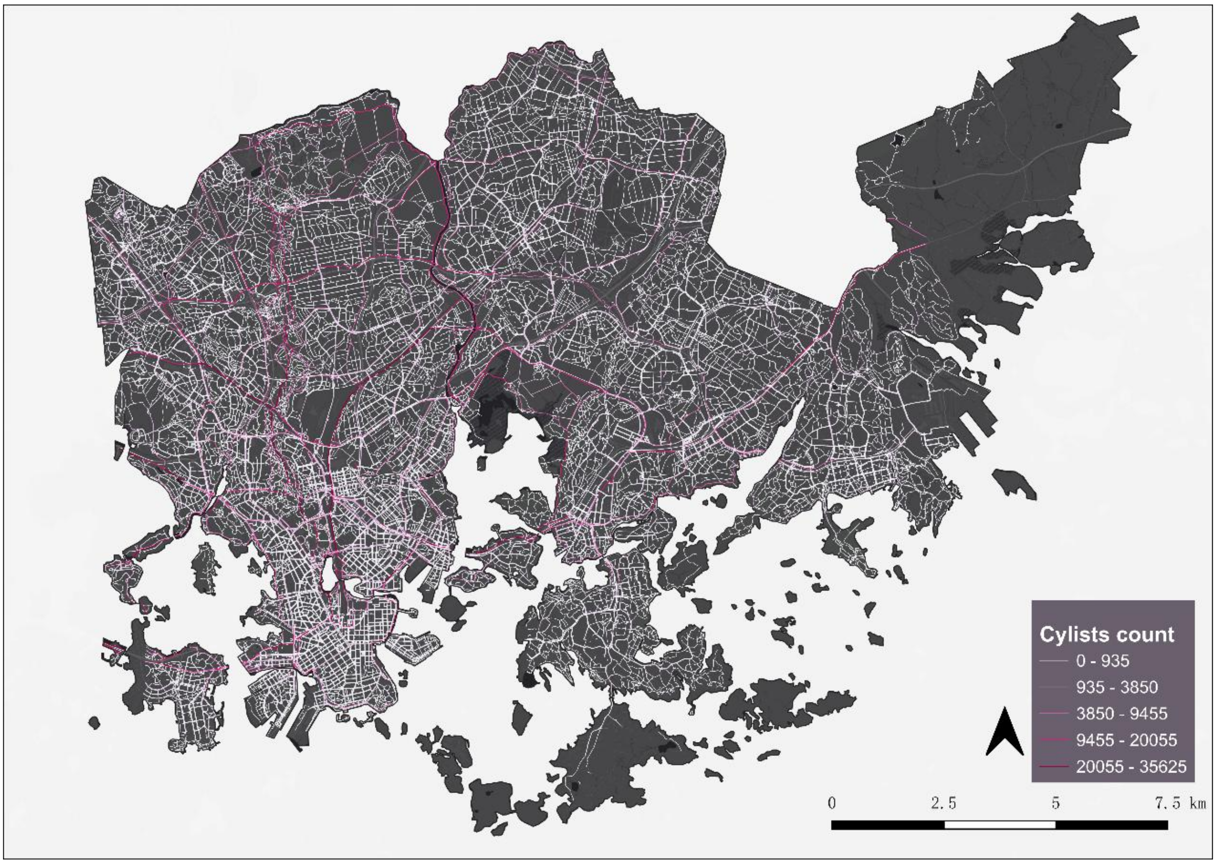

Figure 8. Cyclists count from Strava data in Helsinki

3.3.5 Population data in 2022

The population data is grid data containing the total number of persons permanently residing in the building by grid cell, age distribution, and occupancy rate of Helsinki. The data was updated in 2022, and the cell size was 250m * 250m.

To ensure a more concentrated distribution of the data, I applied a logarithmic transformation to the population variable. In subsequent analyses, p_log was used as an input variable for the models.

4 Methodology

4.1 Study design

The study consists of three steps: data preprocessing, model training, and feature contribution analysis. There are four types of data in this study: traffic survey data, Google Street View (GSV), traffic data, and population data.

Initially, the study area was defined, followed by the extraction of GSV imagery. The most appropriate image segmentation model for feature identification was selected through a comparative evaluation of the accuracy and computational efficiency of four distinct models. Subsequently, six methodologies for assessing perceived traffic safety were applied to process traffic safety survey data from Helsinki.

In the second phase, twelve machine learning regression models were constructed for each safety indicator to systematically identify the factors influencing pedestrians' and cyclists' perceived traffic safety. These models incorporated population density, traffic-related variables, and features derived from semantic segmentation.

Lastly, two model-agnostic techniques, SHAP and PDP, were utilized to interpret the contribution of each feature to the predictive outputs of the best-performing model for both pedestrians and cyclists.

The conceptual framework used in this research is presented in Figure 9.

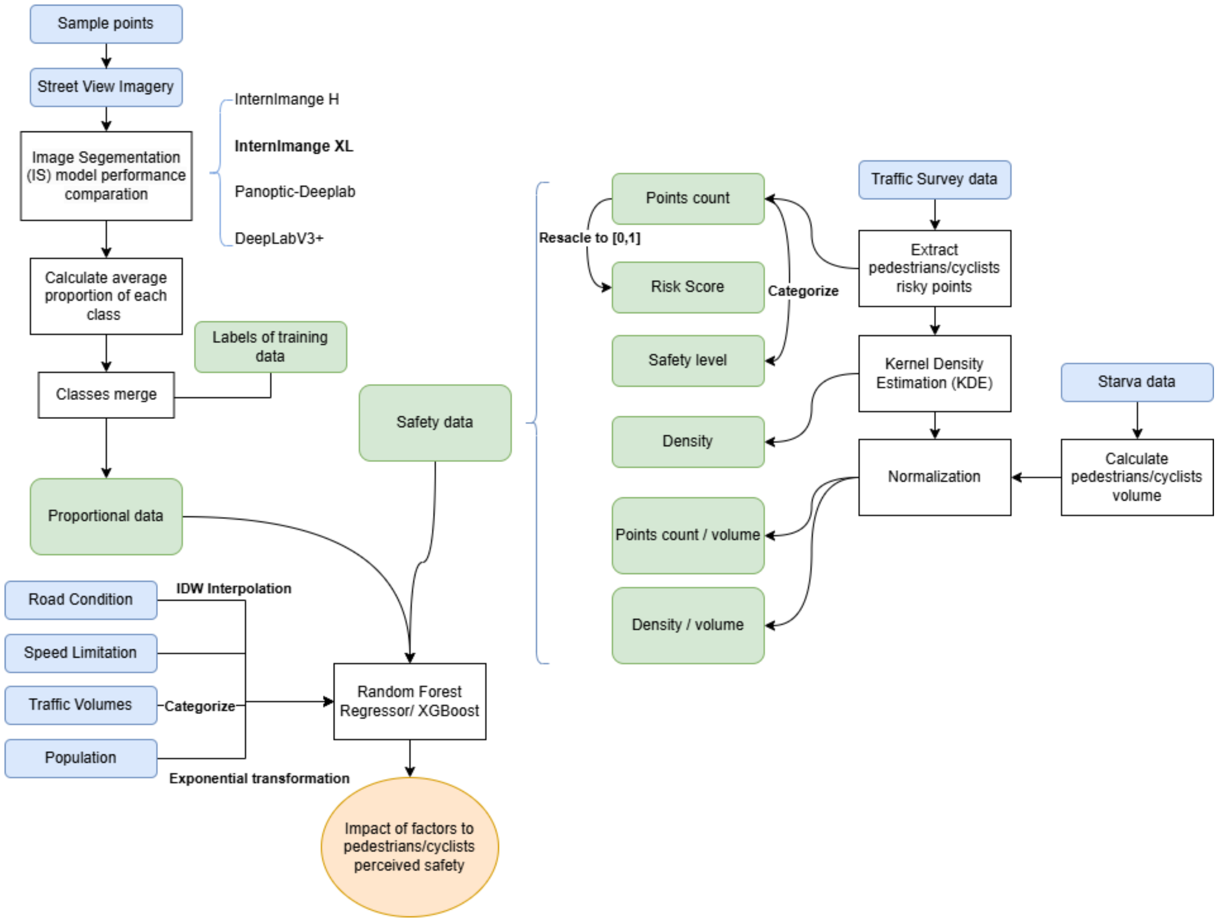

Figure 9. Conceptual framework describing the processes of this study

4.2 Image Segmentation

4.2.1 Semantic Segmentation Model

To detect the streetscape image components accurately, I employed the InternImage model, which has been trained and validated on the ADE20K dataset (B. Zhou et al., 2017), a large-scale dataset containing diverse scenes and fine-grained semantic labels. InternImage is a large-scale model based on conventional neural networks (CNNs), and it can provide a strong representation for versatile vision tasks, such as image classification, object detection, and semantic segmentation (W. Wang et al., 2023). Compared to previous semantic segmentation models, such as CNNs and ViTs (vision transformers), InternImage has a higher segmentation accuracy and demonstrated the world's best performance on 16 other important visual benchmark datasets (W. Wang et al., 2023).

In this study, I obtained the InternImage XL model from the official page on GitHub (https://github.com/OpenGVLab/InternImage/tree/master), which is available for download with specific configuration files (cfg) and pre-trained weights (ckpt). The model combining both InternImage and UPerNet architectures and frameworks uses InternImage architectures as a backbone and Unified Perceptual Parsing Network (UPerNet) (B. Zhou et al., 2017) as the head. The InternImage could enhance the ability of the model to capture high-resolution details (W. Wang et al., 2023). UPerNet employs a feature pyramid structure to aggregate multi-scale features, enabling precise segmentation across diverse categories and resolutions. Therefore, this architecture is well-suited for tasks requiring high accuracy in understanding and labeling intricate environments, such as streetscapes. Samples of segmentation results are shown in Figure 10.

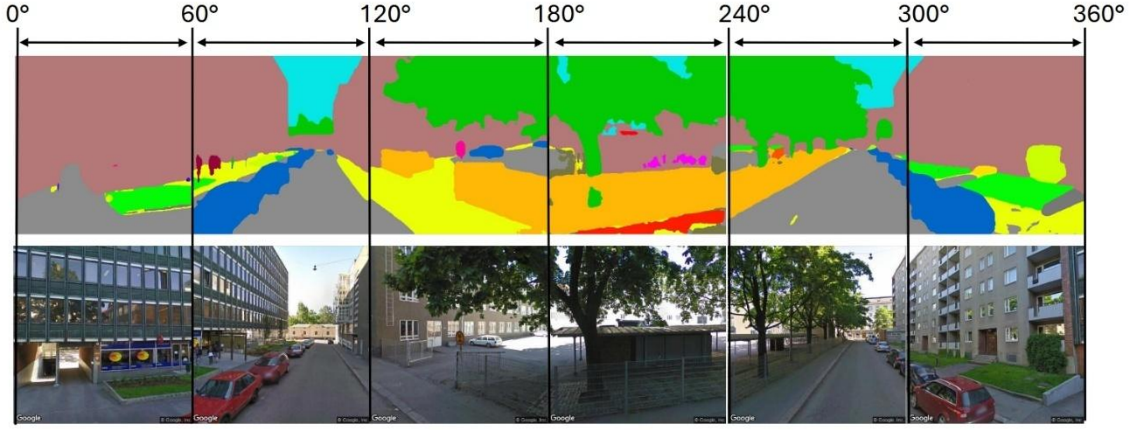

Figure 10. Segmentation result sample

4.2.2 Image segmentation

Since the InternImage XL model which has been trained by ADE20K dataset produces 150 categories in its classification results, many of which have minimal impact or are highly similar, I consolidated these categories into 18 based on their similarity (Table 3) and used the merged results as proportional data. The final proportional data samples are shown in Table 4.

Table 3. Merged categories

Category	Include Items
road	road, route, path, dirt track
sidewalk	sidewalk, pavement
building	building, edifice, house, grandstand, covered stand
wall	wall
fence	fence, fencing
pole	pole
traffic_light	traffic light, traffic signal, stoplight
traffic_sign	signboard, sign, poster, posting, placard, notice, bill, card, trade name, brand name, brand, marque
vegetation	tree, grass, plant, flora, plant life, flower
terrain	earth, ground, sand, rock, stone, hill, mountain, mount
sky	sky
person	person, individual, someone, somebody, mortal, soul
car	car, auto, automobile, machine, motorcar
truck	truck, motortruck, van
bus	bus, autobus, coach, charabanc, double-decker, jitney, motorbus, motorcoach, omnibus, passenger vehicle
bicycle	bicycle, bike, wheel, cycle, minibike, motorbike
water	water, sea, river
rail	railing, rail, bannister, banister, balustrade, balusters, handrail

Table 4. Samples of final proportional data (precision 0.001)

road	**sidewalk**	**building**	**wall**	**…**	**water**	**rail**
0.298	0.000	0.009	0.000	…	0.000	0.000
0.295	0.000	0.008	0.001	…	0.000	0.000
0.085	0.003	0.027	0.001	…	0.000	0.045

4.3 Variable correlation and distribution analysis

After data pre-processing, feature values have been assigned to each sample point. The explanation of all features except image segmentation features is listed in Table 5.

Table 5. Description of input features (except image segmentation features).

Feature name	**Description**	**Data range**
p_log	Population data after logarithm transformation	0.778 – 3.351
trafficVolume_group	Levels based on the percentiles of traffic volume of the nearest road.	1-20
speedLimit	Speed limit of the nearest road.	20-120

roadCondition	Road condition interpolated using KDE and rounded.	1-5

To reduce redundancy and improve model efficiency, correlation analysis was conducted to examine the relationships between features, allowing for the identification and removal of highly correlated variables that may not contribute additional predictive power to the model.

It can be observed from Figure 11 that none of the features has a high correlation coefficient (>0.70) among them; therefore, it can be concluded that no multicollinearity issues exist.

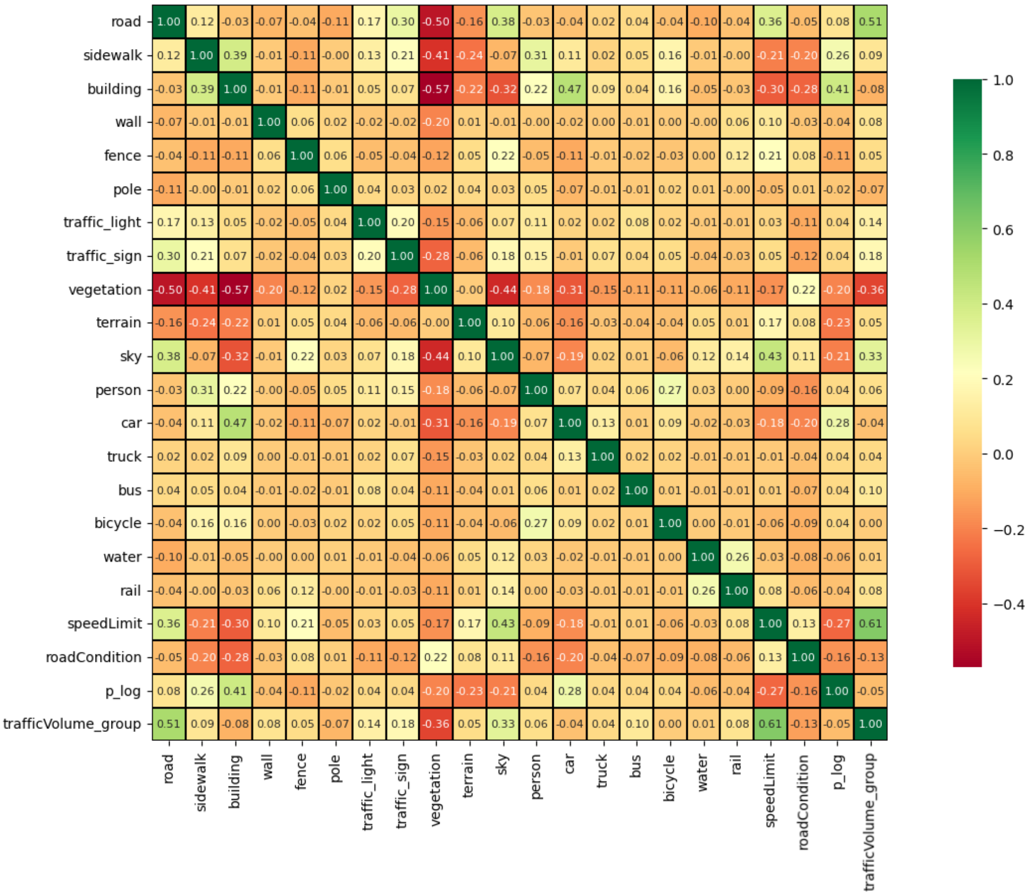

Figure 11. Correlation coefficient matrix of the features used in regression models

To understand the distribution of the features, boxplots are used to show the minimum, first quartile, median, third quartile, and maximum values for each feature (Figure 12).

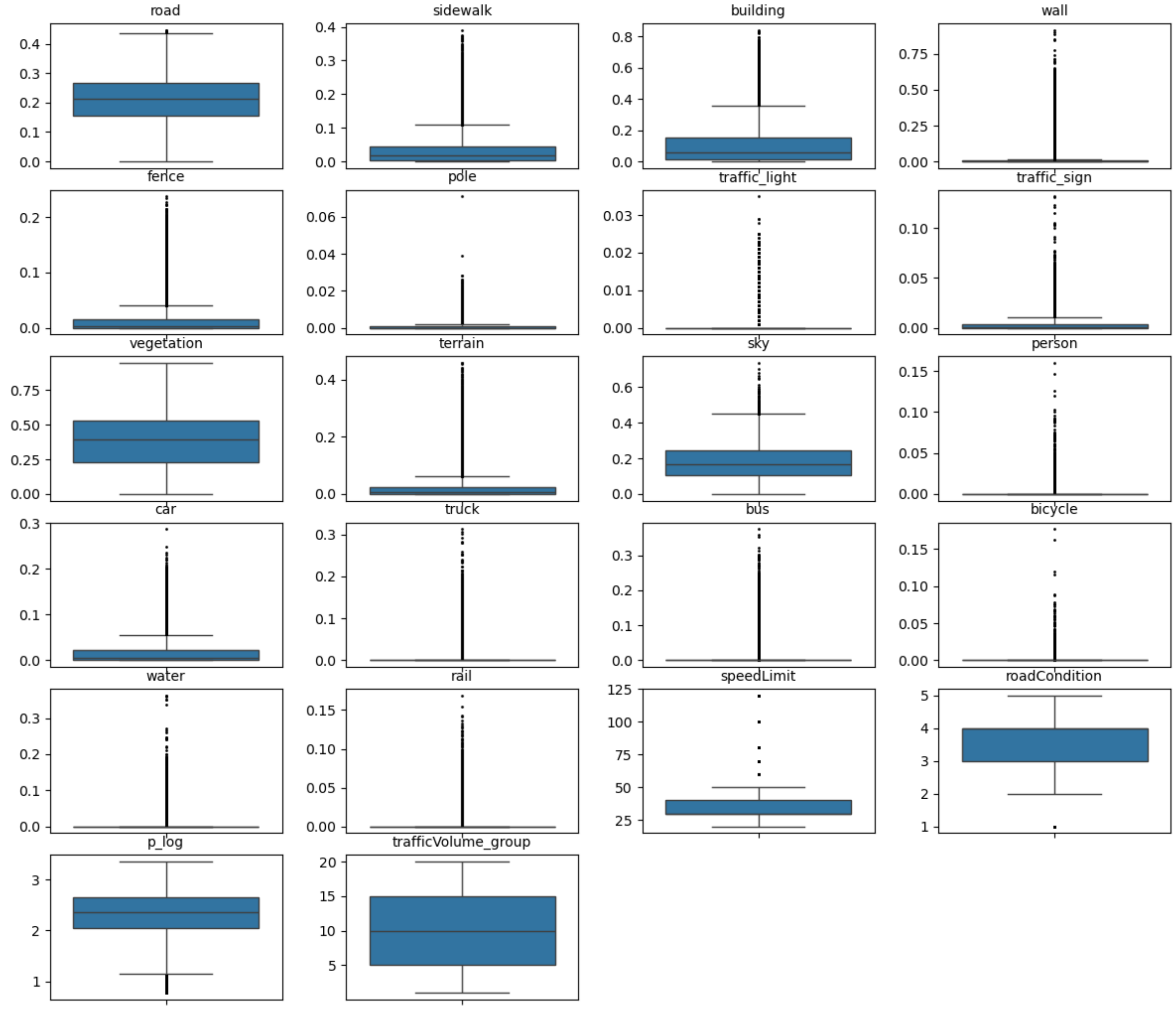

Figure 12. Boxplots showing the distribution of the features used for regression models

Additionally, it has been mentioned by many studies that sidewalk plays an important role in the perceived safety of pedestrians (Aceves-González et al., 2020; Campos Ferreira et al., 2022; Hamim & Ukkusuri, 2024; Kim et al., 2023; Park & Garcia, 2020). Therefore, I checked the distribution of sidewalks (Figure 13) and the images with a high proportion of sidewalks in Helsinki (Figure 14). It can be noticed that the points with a high proportion of sidewalks are mostly located in the city center areas, which are typically inaccessible for vehicles. Therefore, as observed from Figure 14, most of the images with a high proportion of sidewalks are likely taken by Trekker. The mixed-perspective method of image collection could potentially impact the results. Therefore, subsequent sections will consider these variations when discussing the influence of sidewalks on perceived traffic safety.

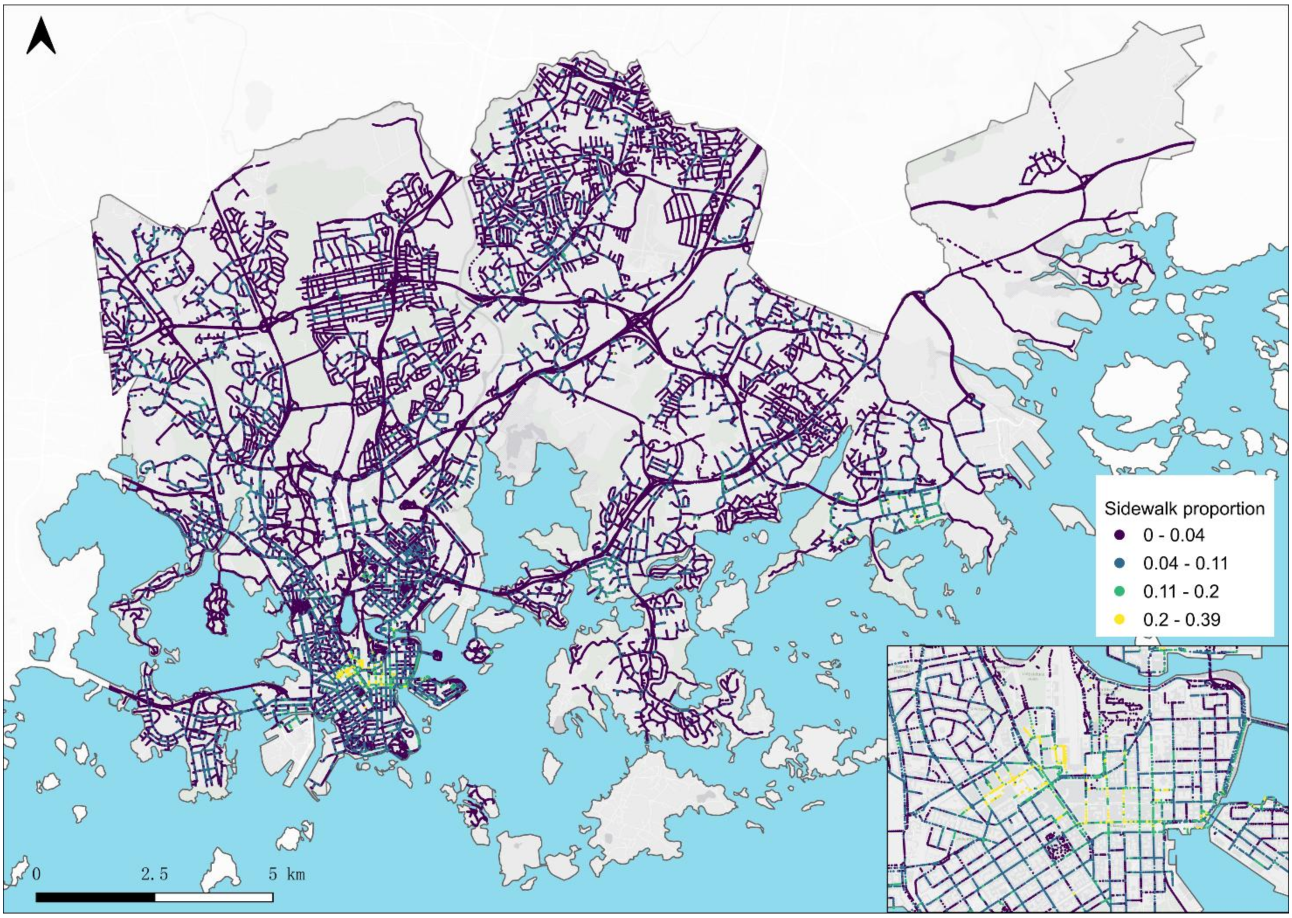

Figure 13. Map of sidewalk proportion in Helsinki and the City center (bottom right)

Figure 14. Location with a high proportion of sidewalks

4.4 Perceived traffic safety assessment

Perceived road safety indicators were assessed based on the density of reported risky points from the traffic safety survey. For determining the assessment method that has the best performance and representativeness of perceived road safety, six perceived traffic safety indicators were utilized for each mode of transportation, including (1) unsafe points count, (2) safety score (ranging from 0 to 1, 1 means safest), (3) density calculated by Kernel Density Estimation (KDE) which is a method that smooths point data to estimate the concentration of events across an area. Higher KDE values indicate areas with a higher frequency of risky points, signaling lower perceived safety, (4) risk level, (5) points count normalized by pedestrian/cyclist volume, and (6) reported risky points density normalized by pedestrian/cyclist volume. The final two assessment methods are designed to mitigate the bias introduced by pedestrian or cyclist volume on perceived traffic safety. Additionally, after evaluating the performance of different buffer distances (50m, 100m) in machine learning regression models, the buffer distance was set as 100m for the calculation of each indicator. Each indicator is described in Table 6, and the distribution of one of the safety indicators - safety scores (0-1) for pedestrians and cyclists is shown in Figure 15 and Figure 16 as an example.

Table 6. Safety indicators assessment methods

Safety indicator	**Description**
Unsafe points count	Number of reported points
Safety Score (0-1)	Rescale points count to 0-1
Density	Value of KDE
Risk Level	Category based on points count Very safe (0 points) Medium safe (1-5 points) Medium dangerous (6-20 points) Very dangerous (>20 points)
Volume-Normalized Points	Points count divided by pedestrians'/cyclists' volume
Volume-Normalized Density	Density divided by pedestrians'/cyclists' volume

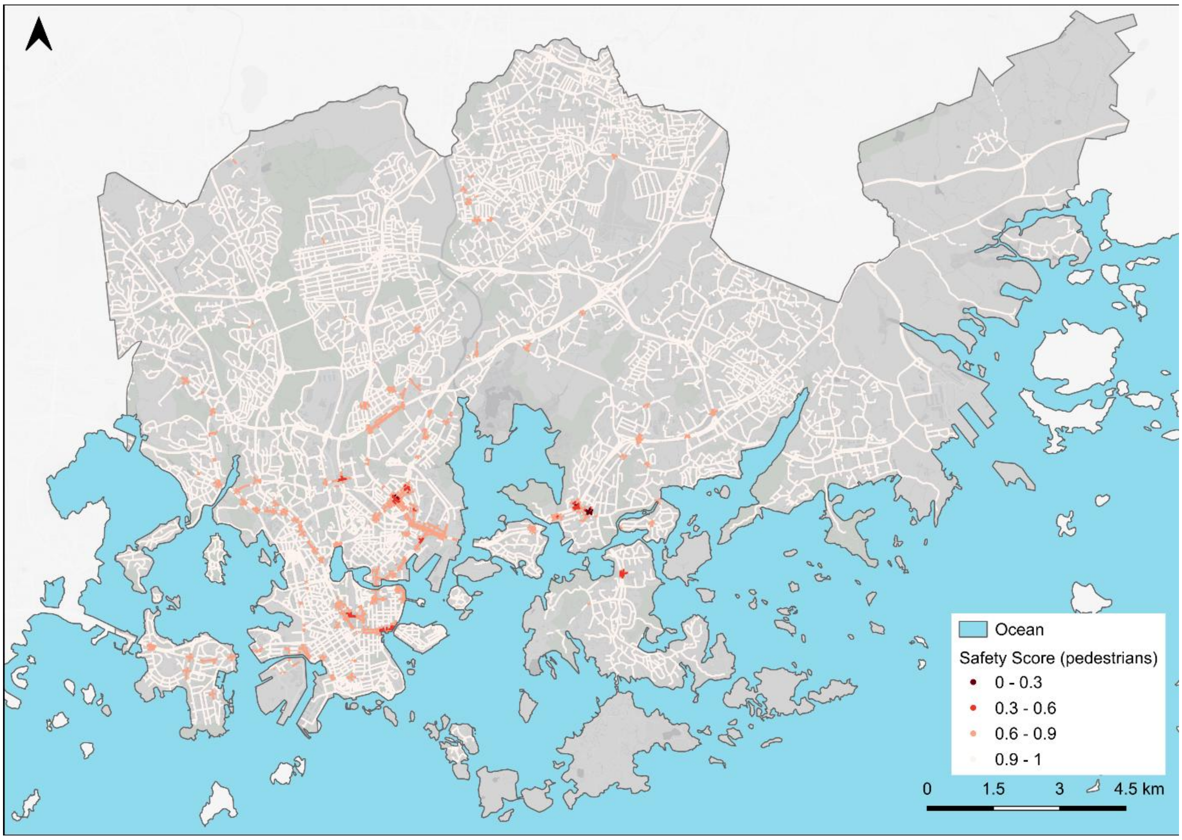

Figure 15. Distribution of safety score for pedestrians in Helsinki

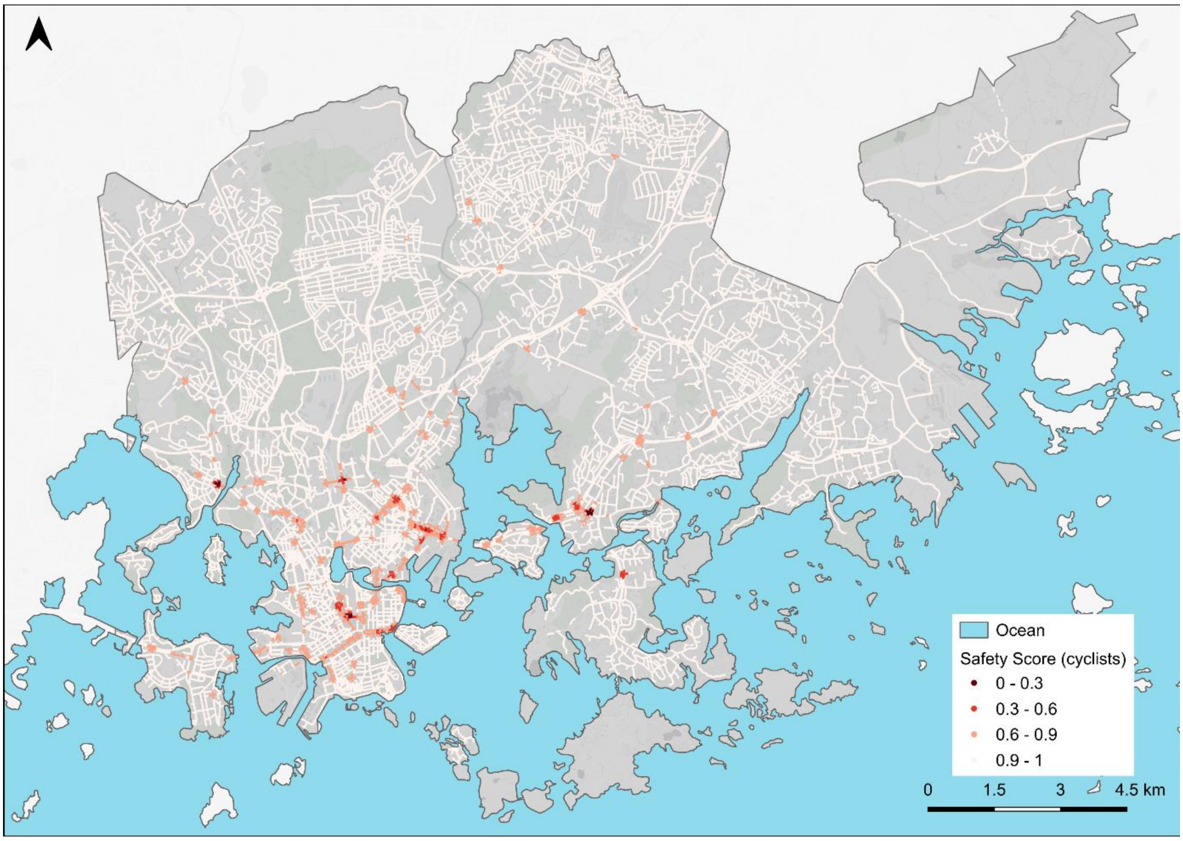

Figure 16. Distribution of safety score for cyclists in Helsinki

4.5 Regression Analysis: XGBoost and Random Forest

For estimating the association of surrounding environments, traffic factors, and population on perceived road safety, two machine learning models, XGBoost (T. Chen & Guestrin, 2016) and Random Forest (Breiman, 2001) were used in this study for each safety indicator. The performance of each model was evaluated by R-squared, the mean squared error, and the mean absolute error of both training and test sets. The results are shown in the Comparison of Safety Assessment in XGBoost and Random Forest Models (Table 7 and Table 8).

4.5.1 XGBoost

In this study, XGBoost was selected as one of the models for regression analysis due to its scalability and effectiveness in handling complex relationships within data. XGBoost is a widely used, end-to-end tree-boosting system that data scientists often rely on to achieve state-of-the-art results in machine learning. The algorithm is based on Gradient Boosting, and its core principle is to reduce model errors by gradually adding new decision trees. In each update, XGBoost includes a regularization term in the loss function to control the complexity of each tree. This prevents overfitting and ensures the model generalizes well to new data.

Twelve XGBoost regression models were built to examine the association of features on the perceived traffic safety of pedestrians and cyclists based on six safety indicators, respectively. 70% of the data served as the training set, while the remaining 30% of the data served as the test set. The optimal parameters for training each model were identified based on the GridSearchCV method (Pedregosa et al., 2011) and the five-fold cross-validation methods (Seraj et al., 2022) were applied to evaluate the model's performance. GridSearchCV is a method in machine learning used for hyperparameter tuning. GridSearchCV exhaustively tests combinations of specified hyperparameters and evaluates model performance using cross-validation to identify the optimal parameter set. In this study, the GridSearchCV method was applied twice for each model. The first application was used to determine a broad range of optimal parameters, such as an initial estimate of 0.1 for the learning rate. The second application then focused on refining the search around this initial value by subdividing the range into smaller intervals, for example, testing 0.05 and 0.15 for the learning rate, to pinpoint the most optimal value. The cross-validation method is a technique used to assess the performance of statistical learning models (Seraj et al., 2022). In the five-fold cross-validation process, the whole data is divided into four subsets randomly. Four of the subsets are used as training data to train the model, and the remaining subset is used as the test data to evaluate the model's performance. This process is repeated five times, with each subset having a chance to serve as the test set once (Seraj et al., 2022). Therefore, the usage of cross-validation method helps prevent overfitting and ensures the stability and reliability of the model.

The first parameter grid was defined as follows: { "n_estimators": [200,300,400,500], "learning_rate": [0.05,0.06,0.07,0.1,0.15], "max_depth": [7,8,9], "subsample": [0.6,0.8], 'colsample_bytree': [0.6,0.8], 'min_child_weight': [2,3], 'scale_pos_weight': [0.6,0.8], 'reg_alpha':[0.15,0.2], 'reg_lambda':[0.7,1.0] }. The second parameter grid was defined by the results of the first parameter grid search. After at least 19200 iterations, optimal parameters for each model were acquired.

4.5.2 Random Forest (RF)

Another automated machine learning approach, random forest, was used to evaluate perceived road safety. Random Forest is an ensemble learning method that is derived from the modification of decision trees (Breiman, 2001). It combines multiple decision trees by randomly sampling data and features, which reduces overfitting and enhances prediction stability.

Twelve RF models were built to evaluate perceived road safety for each safety indicator and the dataset was divided into training and testing sets at a ratio of 70:30. Same as XGBoost regressor, the optimal parameters were also determined by usage of GridSearchCV and five-fold cross-validation. The first parameter grid was defined as follows: { 'n_estimators': [300,400,500], 'max_features': ['auto','sqrt', 'log2'], 'min_samples_leaf': [3,4,5, 6,7], 'max_depth': [5,6,7], 'bootstrap': [True, False], 'min_samples_split': [3,4,5] }. After at least 4050 iterations, optimal parameters for each model were acquired.

4.5.3 Model evaluation indicators

The performance of the models with different safety indicators was evaluated by three indicators – R^2 (A. Brown, 2022), Root Mean Squared Error (RMSE) (Nevitt & Hancock, 2000), and Mean Absolute Error (MAE) (Sammut & Webb, 2010) which are commonly used to evaluate the performance of machine learning models (Chicco et al., 2021; Hamim & Ukkusuri, 2024; Kouadri et al., 2022).

R^2 measures the proportion of variance in the dependent variable that is predictable from the independent variables. Its value typically ranges from 0 to 1, where R^2 = 1 indicates the perfect prediction of all dependent variable values and R^2 = 0 indicates the model performs no better than using the mean of the dependent variable (A. Brown, 2022).

RMSE measures the standard deviation of prediction errors, describing how concentrated the data is around the line of best fit (Nevitt & Hancock, 2000). The smaller the RMSE, the higher the model's predictive accuracy.

MAE is the average absolute difference between observed and predicted values, providing an average size of the prediction errors (Sammut & Webb, 2010). MAE is less sensitive to large prediction errors. The smaller the MAE, the higher the model's predictive accuracy.

Many previous studies used R^2 as the standard indicator to evaluate the performance of machine learning regression analysis (Cai et al., 2022; Hamim & Ukkusuri, 2024; Ki & Lee, 2021; Kouadri et al., 2022). Additionally, the value of RMSE and MAE could range between zero and +infinity; therefore, a single value of RMSE or MAE is not enough to describe the performance of the regression (Chicco et al., 2021). Therefore, in this study, R^2 was used as the main standard metric to evaluate machine learning models' performance, and RMSE and MAE were used to measure the size and distribution of models' prediction errors.

4.6 SHAP and PDP

SHAP and PDP were used in this study to explain the contribution of each feature to model input from both local and global perspectives.

Firstly, SHAP values could help to evaluate the effect of each feature by comparing what a model predicts with and without the feature (Shapley, 2016). It is very suitable for explaining the impact of different factors on perceived safety.

Additionally, different from SHAP's precise explanations for individual predictions, PDP focuses on explaining the overall behavior of models. Therefore, in this study, these two methods were used in a complementary manner to provide a comprehensive understanding of the model output. However, it is essential to note that SHAP values do not explicitly indicate which factors are sufficiently important to warrant further exploration. Therefore, in this study, the top six factors with the highest SHAP values were subjectively selected to create PDP plots, and factors with significant contributions were discussed in depth.

5 Results

5.1 Comparison of Safety Assessment in XGBoost and Random Forest Models

5.1.1 Pedestrians' Perceived Traffic Safety

Table 7 presents the performance of each model based on different perceived traffic safety indicators for pedestrians. The results indicate that the XGBoost model outperformed the RF model across all safety indicators. Notably, the model achieved the highest R² value with the safety score as the dependent variable, suggesting that it explains 73.1% of the variance in the safety score within the test dataset. Besides that, the R² value, RMSE, and MAE values are close between the training and testing sets, suggesting that the model generalizes well and can effectively predict pedestrian safety on new data.

Although the performance difference between the safety score and unsafe point count was minimal, I chose the safety score as the final method for assessing pedestrians' perceived traffic safety due to its more intuitive interpretation (i.e., values closer to 0 indicate higher risk).

Another notable observation was that the safety indicator normalized by Strava data showed the poorest performance in both the XGBoost and Random Forest models, with R² values less than half of those obtained with other safety indicators.

Table 7. Model performance in pedestrians' perceived traffic safety indicators

Safety indicator	**Training sets**			**Testing sets**			**Model**
	R^2	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	
Safety score	0.693	0.034	0.018	0.731	0.032	0.017	XGboost
Unsafe points count	0.688	6.282	3.17	0.725	5.828	3.023	XGboost
Density	0.655	3.238	1.489	0.696	3.014	1.432	XGboost
Risk Level	0.627	0.324	0.197	0.656	0.312	0.189	XGboost
Volume-Normalized Points	0.354	0.428	0.127	0.459	0.412	0.121	XGboost
Volume-Normalized Density	0.338	0.192	0.053	0.402	0.193	0.050	XGboost
Safety score	0.323	0.051	0.025	0.336	0.05	0.025	RF
Unsafe points count	0.323	9.256	4.471	0.336	9.062	4.472	RF
Risk Level	0.323	0.436	0.288	0.325	0.439	0.291	RF
Density	0.301	4.613	2.019	0.314	4.527	2.038	RF
Volume-Normalized Points	0.113	0.503	0.139	0.147	0.518	0.139	RF
Volume-Normalized Density	0.102	0.225	0.056	0.132	0.232	0.056	RF

5.1.2 Cyclists' perceived traffic safety

Table 8 presents the performance of each model based on different perceived traffic safety indicators for cyclists. Similar to the results for pedestrians' perceived traffic safety, the XGBoost models outperformed the RF model across all safety indicators. The safety score from the XGBoost model, which achieved the highest R² value and demonstrated stable performance on both training and testing sets, was selected as the final assessment method for cyclists' perceived traffic safety in the subsequent study.

Among the cyclists' safety indicators, the indicator normalized by Strava data also showed the poorest performance in both the XGBoost and Random Forest models.

Table 8. Model performance in cyclists' perceived traffic safety indicators

Safety indicator	**Training sets**			**Testing sets**			**Model**
	R^2	**RMSE**	**MAE**	**R^2**	**RMSE**	**MAE**	
Safety score	0.707	0.038	0.018	0.744	0.035	0.018	XGBoost
Unsafe points count	0.705	7.215	3.448	0.740	6.784	3.303	XGBoost
Density	0.666	3.749	1.613	0.705	3.538	1.553	XGBoost
Risk level	0.655	0.331	0.196	0.678	0.324	0.190	XGBoost
Safety score	0.345	0.056	0.026	0.354	0.056	0.026	RF
Unsafe points count	0.344	10.771	4.988	0.354	10.690	5.047	RF
Volume-Normalized Points	0.218	3.060	0.749	0.338	2.807	0.715	XGBoost
Density	0.324	5.335	2.234	0.337	5.301	2.272	RF
Volume-Normalized Density	0.224	1.300	0.290	0.333	1.163	0.277	XGBoost
Risk level	0.335	0.461	0.297	0.331	0.467	0.301	RF
Volume-Normalized Points	0.081	3.320	0.768	0.095	3.283	0.780	RF
Volume-Normalized Density	0.066	1.427	0.281	0.092	1.356	0.283	RF

5.2 Key Factors Influencing Perceived Traffic Safety

5.2.1 Feature Contribution for Pedestrians

(1) Feature Contribution on Model Output (Safety Score)

Figure 17 presents the impact of the top twenty features on pedestrians' perceived traffic safety (higher output value means safer), with the population identified as having the greatest influence. Other significant features, in descending order of their impact on the model output, include traffic volume, vegetation, speed limit, building, road condition, sky, person, road, sidewalk, terrain, car, traffic sign, fence, bus, traffic light, wall, truck, rail, and pole.

From the figure, it can be observed that a higher value for road condition (indicating better condition) and lower values for speed limit, buildings, cars, and traffic signs are associated with increased perceived traffic safety for pedestrians. Conversely, higher values for population, traffic volume, person proportion, sidewalk area, road area, rail presence, and truck presence, along with lower values for vegetation and terrain, contribute to decreased perceived traffic safety. Additionally, features such as sky, fences, buses, traffic lights, walls, and poles have mixed impacts on pedestrians' perceived traffic safety.

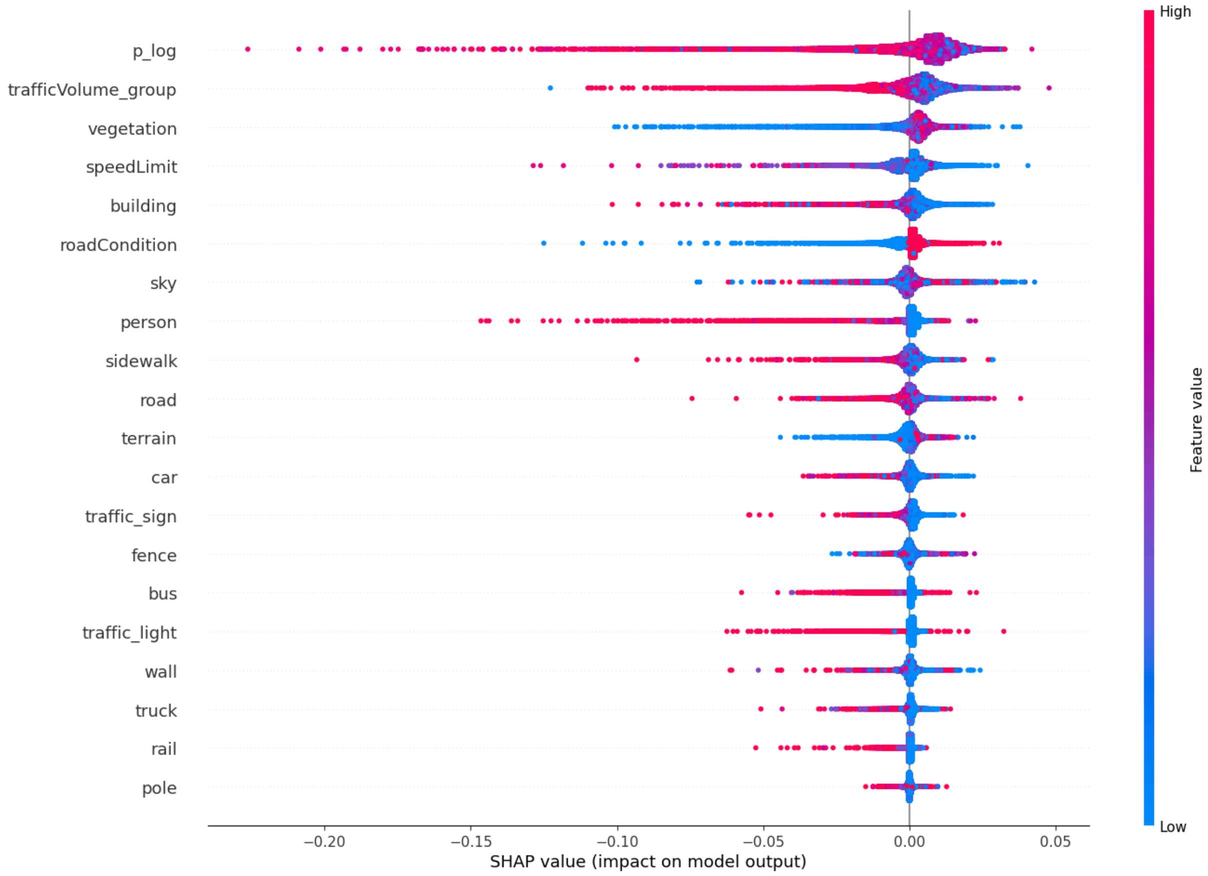

Figure 17. SHAP value of different features of pedestrians' perceived traffic safety used in XGBoost regression

(2) Analyzing Feature Impact with Partial Dependence Plots (PDP)

Figure 18 shows that, overall, as population density, traffic volume, speed limit, and building proportion increase, perceived traffic safety noticeably decreases. In contrast, an increase in vegetation and better road conditions lead to an improvement in perceived traffic safety.

In addition, the figure reveals subtle changes that are not evident in the SHAP plot. For instance, in areas where vegetation coverage exceeds 0.5, there is a noticeable declining trend in perceived traffic safety, and a sharp decrease in perceived traffic safety is also observed in a speed limit range from 60 to 75.

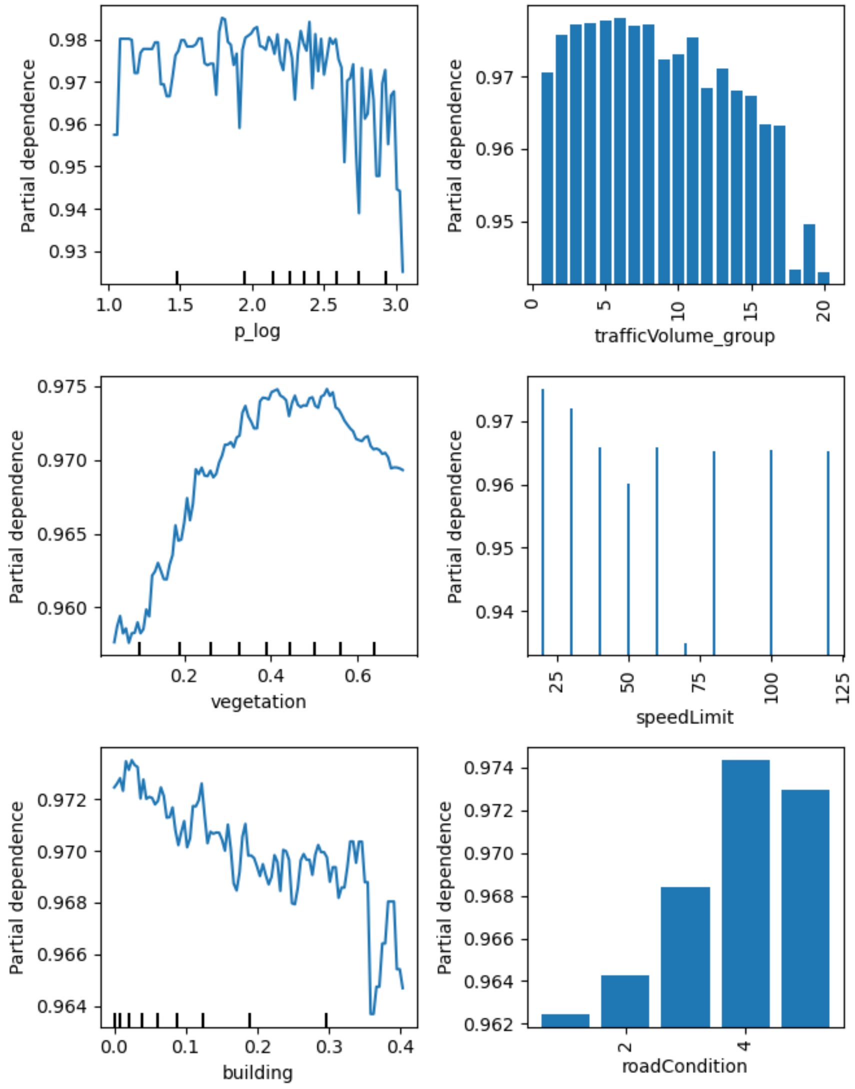

Figure 18. PDP of first six features of pedestrians’ perceived traffic safety used in XGBoost regression

5.2.2 Feature Contribution for Cyclists

(1) Feature Contribution on Model Output (Safety Score)

The contribution of features on cyclists' perceived traffic safety is shown in Figure 19. Same as pedestrians, the population was identified as the feature having the greatest influence. Other significant features, in descending order of their impact on the model output, include traffic volume, vegetation, road condition, speed limit, building, sky, person, road, sidewalk, terrain, traffic sign, car, wall, traffic light, fence, truck, bus, rail, and pole.

From the figure, it can be observed that a higher value for road conditions and lower values for speed limit and traffic signs are associated with increased perceived traffic safety for cyclists. Conversely, higher values for population, traffic volume, building, person proportion, sidewalk area, wall, and car, along with lower values for vegetation and terrain, contribute to decreased perceived traffic safety. Additionally, features such as sky, road, traffic lights, fences, trucks, buses, rail, and poles have mixed impacts on cyclists' perceived traffic safety.

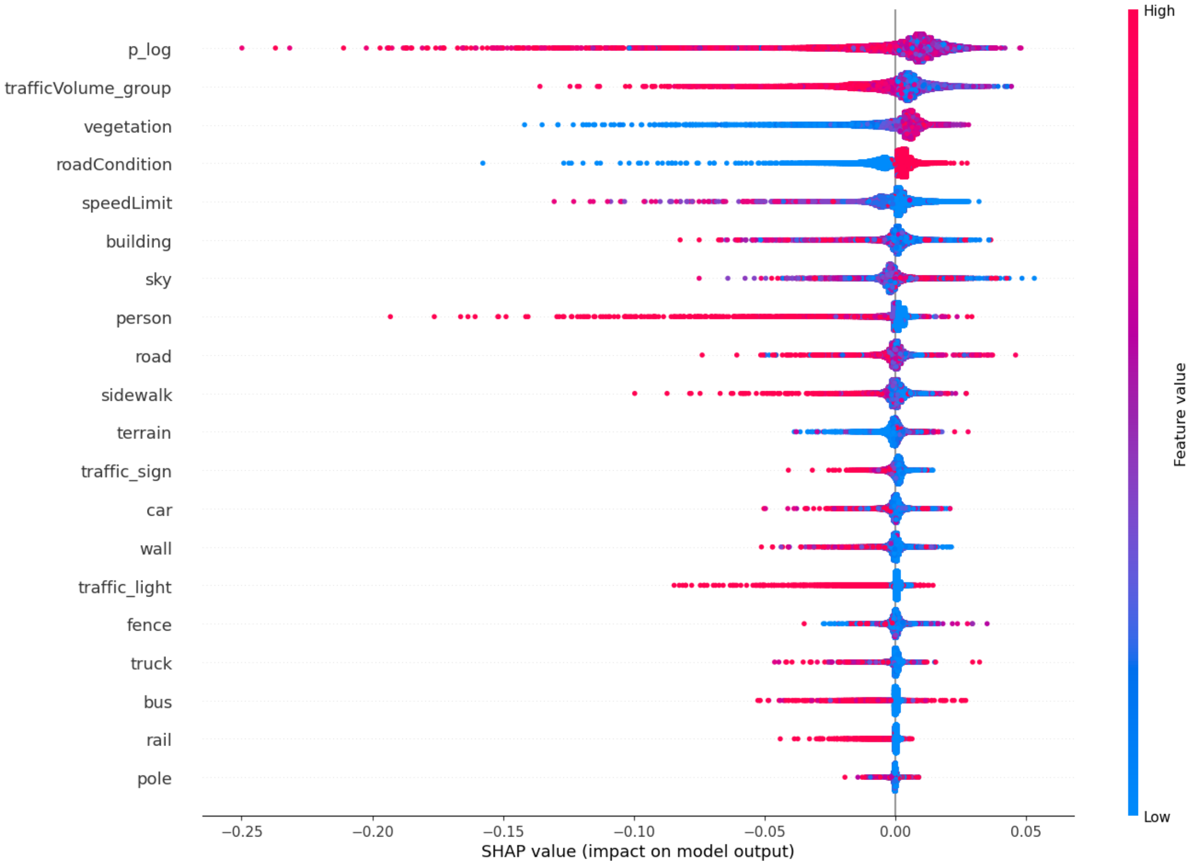

Figure 19. SHAP value of different features of cyclists' perceived traffic safety used in XGBoost regression

(2) Analyzing Feature Impact with Partial Dependence Plots (PDP)

It can be observed from Figure 20 that, overall, an increase in population density, traffic volume, speed limit, and building proportion is associated with a decrease in perceived traffic safety. In contrast, higher vegetation coverage and improved road conditions contribute to an increase in perceived traffic safety.

Moreover, similar subtle changes observed in pedestrians' perceived traffic safety also appear in cyclists' perceived traffic safety PDPs for vegetation and speed limit. Specifically, there is a noticeable decline in perceived traffic safety in areas where vegetation coverage exceeds 0.5, and a sharp decrease in perceived traffic safety is also observed within the speed limit range of 60 to 75.

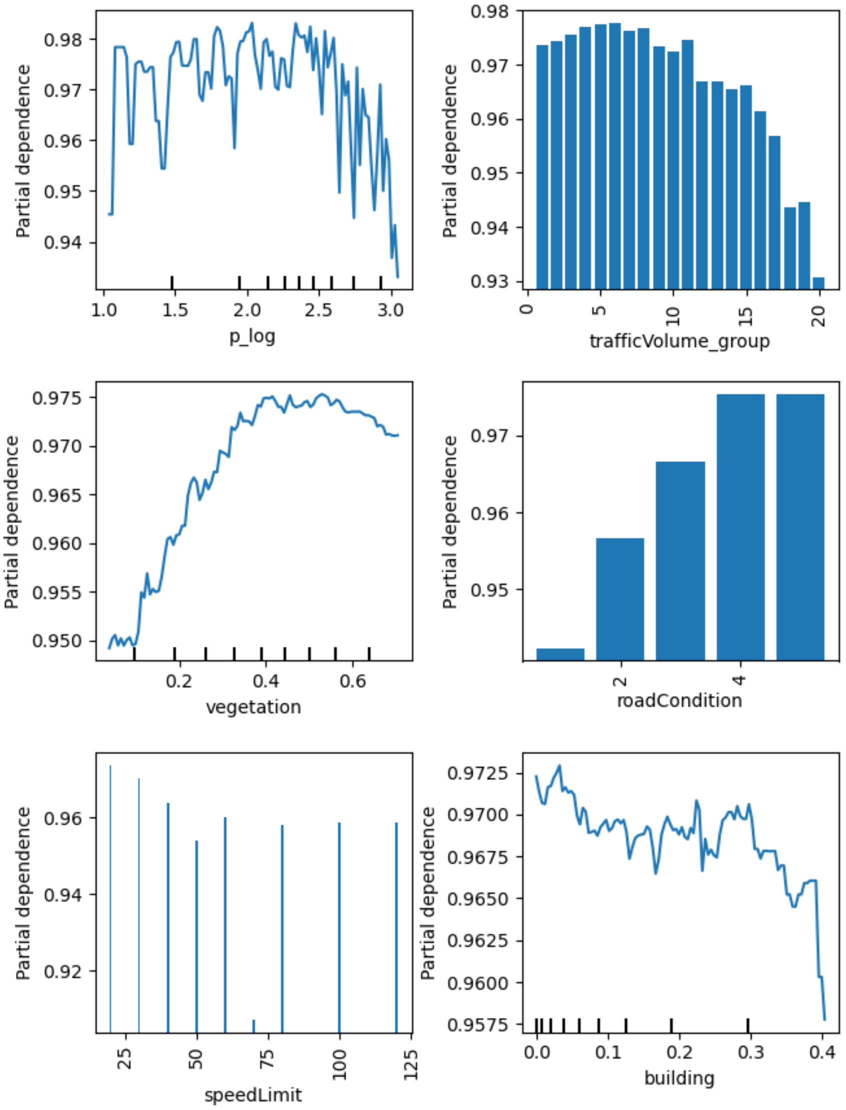

Figure 20. PDP of first six features of cyclists' perceived traffic safety used in XGBoost regression

5.2.3 Comparison of the features' importance between pedestrians and cyclists

It can be noticed from Figure 21 that population, traffic volume, vegetation, speed limit, building, and road condition have higher importance than other features in both travel modes. Notably, the SHAP values of the top three features—population, traffic volume, and speed limit—exhibit a significant increase compared to others, suggesting their dominant contribution to perceived traffic safety for pedestrians and cyclists.

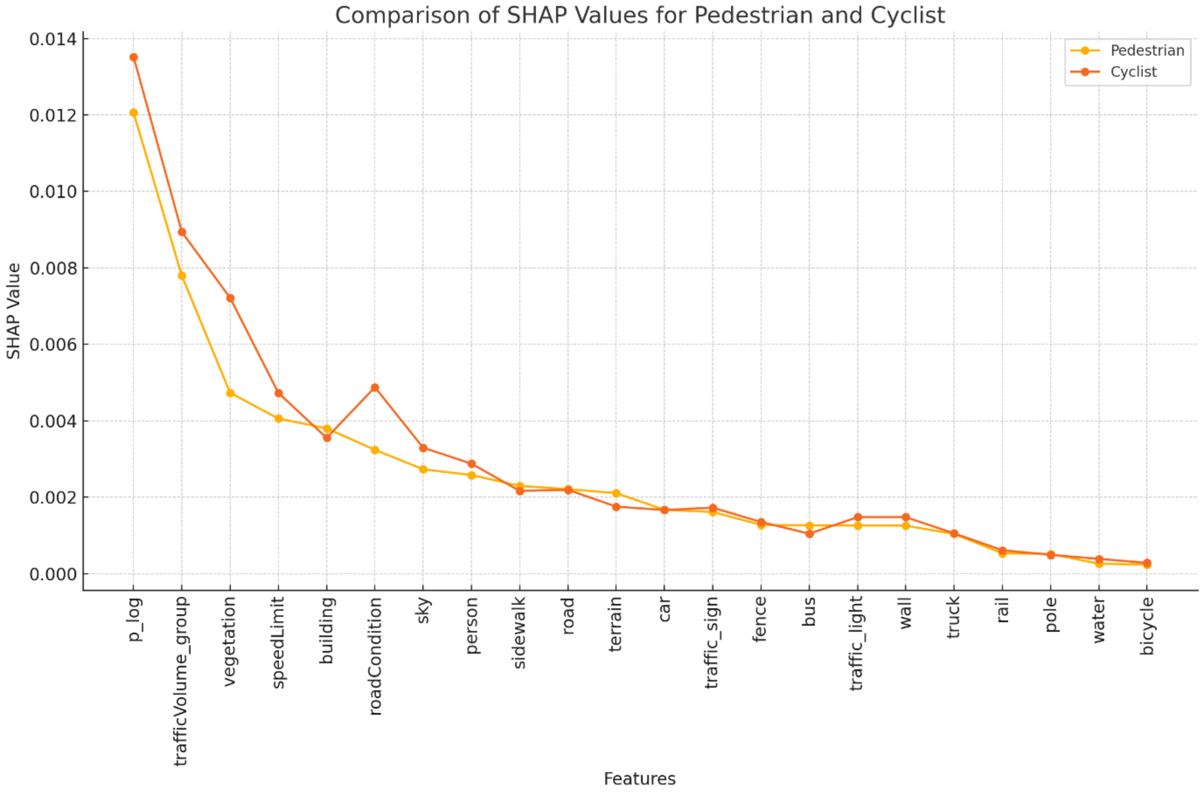

Figure 21. SHAP value comparison between pedestrians' and cyclists' perceived traffic safety

However, although the overall impact is similar, distinct emphases between the two modes of transportation were found in this study. Figure 22 illustrates the differences in feature importance for cyclists' perceived traffic safety compared to that of pedestrians. The importance difference refers to the discrepancy in the ranking of importance for elements between pedestrians and cyclists. For example, for the element "road condition," if it ranks sixth in importance for pedestrian perceived safety and fourth for cyclist perceived safety, then the importance difference for the "road condition" element is 6 - 4 = 2. In the results, a positive number indicates greater importance for cycling, while a negative number indicates greater importance for walking.

It is evident that among the features with a clear impact on both modes, road conditions and traffic signs have a greater influence on cyclists, while speed limit, buildings, sidewalks, and cars have a lesser impact compared to pedestrians.

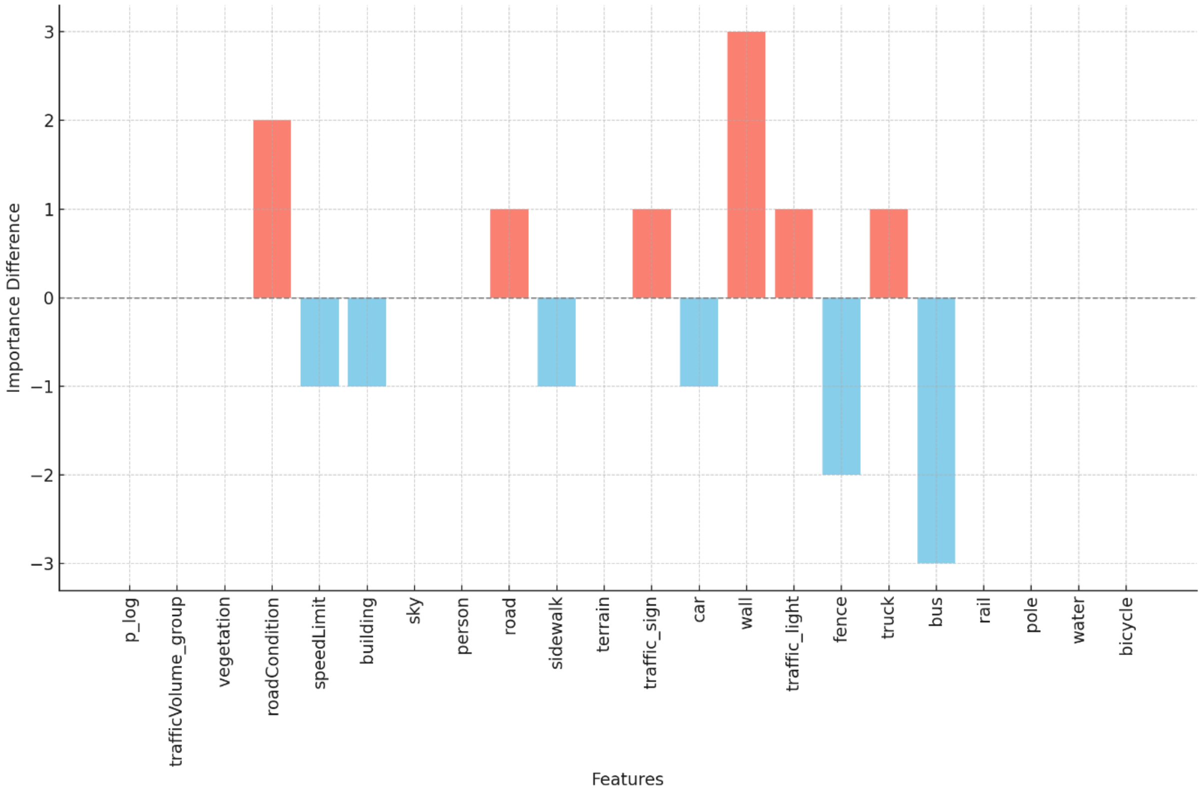

Figure 22. Importance difference of cyclists' perceived traffic safety compared with pedestrians' perceived traffic safety; red means that the feature is more important to cyclists, and blue means that the feature is more important to pedestrians.

6 Discussion

Nowadays, one of the most urgent problems that urban planners are facing is determining the factors and the mechanisms through which they contribute to the growing unsafe feeling (Zeng et al., 2023). Many previous studies have found that perceptions of traffic safety are highly correlated with the built environment (Blöbaum & Hunecke, 2005; Rossetti et al., 2019; Ye et al., 2024; Zeng et al., 2023). The results of this study revealed the correlation between environmental features, traffic factors, population density, and perceived traffic safety for active travel, identifying the most significant factors and priorities for each mode that should be emphasized in building cities where pedestrians and cyclists feel secure. The following discussion focuses on the interpretation and practical implications of the findings.

6.1 Regression models and safety indicators comparison

6.1.1 Random Forest and XGBoost

It can be observed from Table 7 and Table 8 that the XGBoost models significantly outperformed the RF models across each safety indicator. In each safety indicator, XGBoost models could explain over 20% more data than RF models. This difference may stem from the algorithmic structures of the two models.

The XGBoost algorithm is based on the idea of boosting trees, which iteratively trains the model through gradient boosting and includes regularization terms (T. Chen & Guestrin, 2016). It also supports parallel processing and distributed computing, making it highly effective on large-scale datasets and capable of handling missing values (Peng et al., 2024). On the other hand, the RF model is based on the principle of ensemble learning, which constructs multiple decision trees and integrates them to produce a more robust and accurate predictive model (Breiman, 2001). Therefore, Random Forest is more suited to handle high-dimensional feature data (Peng et al., 2024), a kind of data with a very high number of features per sample (Verleysen, 2003).

In this study, with a total of 22 features and sample numbers in the hundreds of thousands, the data does not represent typical high-dimensional feature data but rather a large-scale dataset. Therefore, the performance of XGBoost models surpasses that of Random Forest models.

6.1.2 Safety indicators

The study selected six evaluation methods to establish six safety indicators for each travel mode. Among the two models and two travel modes, the best-performing safety indicator was the safety score normalized for unsafe points (0-1), and the least effective was the indicator standardized using Strava data. This may be because the normalized data is more uniform and standardized, reducing the scale differences between different magnitudes, thus helping to enhance model performance.

Previous research indicated that Strava's user base is likely comprised mostly of sports enthusiasts, with data predominantly recording walking and cycling activities aimed at leisure and recreation (K. Lee & Sener, 2021; Sun et al., 2017; Venter et al., 2023). The characteristic can be observed in the Figure 7 and Figure 8, where high values for cycling and walking are mostly along coastlines or in forests. Therefore, the pedestrian or cyclist volume provided by Strava data may differ from reality, thereby introducing errors into the model.

6.2 Common influencing factors and differing emphases in active transportation modes

6.2.1 Influence of factors summary for active transportation modes

Results in 5.2.1 suggest that pedestrians tend to feel safer in environments with well-maintained roads and fewer buildings, cars, and traffic signs. In contrast, areas with high population density and heavy traffic volume contribute to a sense of unsafety from traffic. Furthermore, environments with less vegetation and terrain and a higher proportion of roads, rails, and large vehicles are also perceived as less safe by pedestrians.

Similarly, results in 5.2.2 suggest that cyclists tend to feel safer in environments with well-maintained roads, fewer traffic signs, and lower vehicle speeds. In contrast, areas with high population density, heavy traffic volume, and a high proportion of cars and persons contribute to a sense of unsafety. Furthermore, environments with less vegetation and terrain and a higher proportion of buildings, walls, and sidewalks are also perceived as less safe by cyclists.

6.2.2 Common influencing factors

Overall, comparing beeswarm plots of two transportation modes (Figure 17, Figure 19), two common points can be noticed: first, there are ten features (population, traffic volume, vegetation, road condition, speed limit, building, sidewalk, person, car and traffic sign) having same and clear impact on both transportation modes; second, among these common features, population, traffic volume, vegetation, speed limit, building and road condition are the most important six features with highest average SHAP values, indicating the crucial influence on perceived road safety.

(1) Population

Firstly, population was identified as the most important determinant of perceived road safety in this study. It was found that higher population density would hurt the perceived traffic safety of pedestrians and cyclists. The impact may result from the fact that high population density increases the likelihood of collisions or traffic accidents (Stoker et al., 2015), thereby causing a sense of tension among people. A similar impact on the population has been found in the previous study (Hamim & Ukkusuri, 2024), while the impact of population in this study is considered together with traffic factors. Also, this study complemented the gap that few papers have considered the influence of population on cyclists' perceived traffic safety.

(2) Traffic factors

Secondly, three traffic factors were found to have a major impact on perceived traffic safety. The results show that roads with high speed limits, high traffic volumes, and poor road conditions decrease the perceived traffic safety of active travellers. This impact may stem from the fact that poorer traffic conditions are more likely to lead to accidents, thereby causing uneasiness among people. Moreover, high traffic volumes hinder pedestrians from crossing intersections, which contributes to a sense of insecurity (Campos Ferreira et al., 2022; Gadsby et al., 2022).

(3) Environmental factors

Finally, the results showed that six environmental factors (i.e., vegetation, building, sidewalk, person, car, and traffic sign) were important in both active travel modes. Notably, vegetation, buildings, and sidewalks have a more crucial impact.

In recent years, more and more studies have focused on the effect of vegetation on human-perceived traffic safety, and it has been indicated by many studies that people perceived the environment as safer when vegetation was present (Basu et al., 2022; Park & Garcia, 2020). The same tendency could be observed from Figure 18 and Figure 20. Combined with the average distribution of vegetation shown in Figure 12, the tendency can be concluded that the medium and high proportion of vegetation can improve perceived traffic safety for pedestrians, but there probably exists a threshold for the vegetation proportion beyond which perceived traffic safety begins to decrease. The negative impact of a high proportion of vegetation on perceived traffic safety may result from dense vegetation obstructing views and offering concealment (Lis et al., 2019). The findings of this study add quantitative insights to previous research, highlighting that an increase in vegetation proportion enhances perceived traffic safety when vegetation occupies less than 50% of the visible area of the environment. However, when vegetation exceeds 50%, further increases in its proportion reduce perceived traffic safety.

On the other hand, the impact of buildings is more complex, typically related to their density and structure (e.g., cross-sectional facades and height) (Asgarzadeh et al., 2012; Harvey et al., 2015; Kawshalya et al., 2022). This study indicates that a higher percentage of buildings in the surrounding environment correlates with lower perceived traffic safety for pedestrians and cyclists, supporting the findings of R. Wang et al. (2023) and Rossetti et al. (2019). However, Harvey et al. (2015) suggest that a greater number of buildings may enhance perceived traffic safety by creating more enclosed spaces. There are three potential reasons for the result. First, urban environments dominated by high-rise buildings can create psychological pressure for urban residents; reduced sky visibility and shorter distances between people and building facades may add psychological stress (Asgarzadeh et al., 2012). Second, a higher building density may obstruct visibility and create shadows, forming areas of “entrapment” and “concealment” that lower perceived traffic safety (Blöbaum & Hunecke, 2005). Finally, perceptions of buildings may vary based on cultural and geographical contexts, as well as respondents’ backgrounds (Harvey et al., 2015), which should be considered when analyzing the impact of buildings.

As discussed, sidewalks are another crucial environmental factor affecting perceived traffic safety, especially for pedestrians. However, the results of this study reveal that a higher sidewalk proportion negatively impacts perceived traffic safety, while a lower proportion has a positive influence, which contrasts with most previous studies (Aceves-González et al., 2020; Campos Ferreira et al., 2022; Hamim & Ukkusuri, 2024; Kim et al., 2023; Park & Garcia, 2020). After analyzing various image perspectives, three possible explanations emerge. Firstly, there may be an interaction between sidewalk and traffic factors. As noted by Kim et al. (2023), sidewalk width can negatively affect perceived traffic safety because sidewalks are wider along high-traffic main roads. In this study, locations with high sidewalk proportions are concentrated in downtown areas with complex traffic conditions, which may lead the model to associate an increase in sidewalk proportion with heightened insecurity. Secondly, the mixed perspectives from which images were taken may introduce bias. As shown in Figure 13, many locations with high sidewalk proportions were located away from the main roadways, captured by the Google Trekker system. Additionally, images captured by Trekker are typically located in pedestrian squares or car-free walkways, where safety concerns differ significantly from sidewalks adjacent to roadways and from images captured from vehicle perspectives. In areas with a high sidewalk proportion that are close to roadways, pedestrians may feel less safe due to their proximity to traffic. Lastly, in Finland, sidewalks are commonly shared by both pedestrians and cyclists, which may lead to more conflicts between the two groups. Therefore, pedestrians in Finland may tend to associate sidewalks with a lack of safety.

Finally, in this study, the "traffic_sign" category includes a broader range of sign types beyond traditional traffic signs, encompassing elements such as signboards, notices, posters, and brand names. These signs are often found in high-density pedestrian areas, commercial zones, and intricate intersections, where the environment is more complex. As mentioned by M. Lee et al. (2021), in environments that require the identification of excessive information, pedestrians often have a weaker perception of potential hazards around them. Therefore, in complex and hazardous environments, it is essential to minimize unnecessary information and provide appropriate signage. Moreover, in the study of Kawshalya et al. (2022), users of the urban streets of Colombo indicated that a moderate level of visual complexity felt safest. Additionally, Müggenburg et al. (2022) found that cyclists feel safer on streets with a clear separation of travel modes and well-planned designs. Consequently, an increase in the proportion of "traffic signs" may raise visual complexity, thereby reducing the perceived traffic safety of pedestrians and cyclists.

6.2.3 Differing emphases

Although minor, the results still demonstrated that pedestrians and cyclists have different focused points when perceiving their environment. The results showed that cyclists are more sensitive to changes in road conditions, which also verified the findings of Gadsby et al. (2022) that road conditions have a substantial to moderate influence on cyclists' perceived traffic safety and comfort. Besides, road class is also one of the factors that had the greatest impact on the safety level of riding (Ye et al., 2024).

By comparison, pedestrians tend to focus more on elements that provide a sense of security and enhance visibility, such as a lower proportion of buildings, sidewalks, and cars, and lower speed limit. As noted by Campos Ferreira et al. (2022), high-speed vehicles make pedestrians feel unprotected, especially when vehicles are not clearly visible. Therefore, ensuring open visibility and lower speed limits is particularly important for enhancing pedestrians' perceived traffic safety.

6.3 Usage of PPGIS as auxiliary data in perception evaluation

Conventionally, perception data are obtained by three methods – investigation, expert evaluation, and field survey (Lu & Chen, 2024; H. Zhou et al., 2019). For instance, Lu & Chen (2024) collected perceived walkability data by online survey, which asked participants to evaluate the perceived walkability of given GSV images; Hamim & Ukkusuri (2024) obtained perceived road safety by 38 individual raters to rate each image on a scale of 0 to 10. The findings of this study provide new insights into the application of combining PPGIS and GSV images for understanding human perceptions.

In this study, perceived traffic safety is evaluated based on the density of PPGIS data, which were reported as risky locations, and GSV images, offering an alternative approach to understanding the perceived danger. Compared to traditional approaches, this density-based evaluation allows participants to consider a broader range of factors in marking locations, taking real-life conditions into account rather than relying solely on static visual information. Additionally, this method enables data collection over a wider geographic area, allowing participants to mark any location within the study region, thus reducing bias that may arise from manually selected images. Finally, this perception-based density approach captures spatial distribution and reveals differences in perceived traffic safety across various regions.

Nevertheless, there are also three challenges in density-based evaluation. First, the traffic safety data was collected by a map survey tool, which allowed participants to choose or mark specific locations on the map. However, the abstract and often imprecise spatial and locational concepts held by the public are not always easily simplified into traditional points, lines, polygons, and attribute data (Huck et al., 2014). Additionally, in participatory mapping, if participants do not dedicate sufficient time and effort to the mapping activity, the quality of the spatial information may suffer. Therefore, the first challenge in PPGIS applications is spatial accuracy. Moreover, Density-based methods focus on aggregated data, which means that individual significant events may be overlooked if they occur in areas with an otherwise low density of danger.

The second challenge is data representativeness; in addition to the potential biases of participatory mapping, voluntarily contributed spatial data may differ from randomly sampled data, often leading to the overrepresentation of certain groups (Brown & Kyttä, 2014). For example, in this study, participants aged 25-44 accounted for over 55% of the sample, far exceeding other age groups (Figure 3), which may lead to insufficient representation for other demographics.

Additionally, the density of reported hazardous points may be affected by pedestrian or cyclist traffic volume. High-traffic areas may inherently generate more reports simply due to the larger number of users rather than a higher inherent level of danger.

6.4 Policy implications for road traffic safety and urban planning

The findings of this study could provide valuable insights for urban planners and policymakers seeking to improve perceived traffic safety for pedestrians and cyclists. Based on the findings, the following aspects could be considered.

Firstly, the results indicate that people tend to feel unsafe when walking or cycling in areas with high population density. However, this finding is inconsistent with many previous studies, which generally suggest that people typically feel safer in densely populated areas (Ermagun et al., 2016; Jacobs, 1982). These two perspectives are not necessarily contradictory, as the sense of safety mentioned in many studies includes not only the perception of safety from traffic accidents but also perceived personal security. Therefore, the positive impact of population density on perceived safety in many studies may involve its influence on perceived security. Additionally, the areas with high population density have a higher likelihood of collisions and traffic accidents (Stoker et al., 2015). Thus, areas with high population density should be prioritized when formulating policies to enhance perceived traffic safety.

Secondly, relevant infrastructure should be scheduled maintenance or improved. Since road quality significantly affects perceived traffic safety, the roads should be kept smooth and even, minimizing potholes and irregular surfaces to reduce the sense of unsafety for pedestrians and cyclists.

Additionally, high traffic speed not only causes unsafety of pedestrians and cyclists but is a key risky factor for pedestrian traffic injury (Who, 2013). Therefore, some specific measurements should be conducted to reduce the exposure of active travellers to vehicular traffic by creating separation between active travellers and vehicles or reducing traffic volumes (Stoker et al., 2015), for example, separating motor vehicle lanes from sidewalks and bicycle lanes using green buffers or barriers or ensuring the connectivity of sidewalks and bicycle lanes.

Thirdly, as Kawshalya et al. (2022) mentioned, there is an inverted U-shaped relationship between perceived safety and visual complexity, indicating that an environment with high visual complexity may decline general safety perception for people. Therefore, traffic signs should be reasonably placed in high-foot traffic areas, reducing unnecessary signage to prevent information overload.

Lastly, spatial enclosure could influence perceptions of fear and danger, and people tend to feel safer in an environment with low or moderate spatial enclosure than high spatial enclosure (Baran et al., 2018). Therefore, vegetation proportion and building density should be controlled to ensure adequate visibility, creating friendlier, more open streets that alleviate psychological stress.

6.5 Limitations and future directions

This study is significant in that it broadens the knowledge base regarding the impacts of environmental, population, and traffic factors on perceived traffic safety. However, five limitations are noted. First are the challenges associated with using PPGIS data, such as spatial accuracy, volume effects, and data representativeness, as discussed in 6.3. Secondly, GSV images were taken from two perspectives—pedestrians and vehicles—and it isn't easy to separate them as there has not been an automatic method to identify the perspectives. Therefore, the mixed perspectives may bring bias to the results. Thirdly, GSV images do not cover some areas, such as parks or forests, where people may walk or cycle for recreation. This incomplete coverage may introduce bias into the results. Therefore, it is necessary to clarify the geographical coverage of the dataset and to explore alternative datasets to supplement the analysis. Fourthly, in this study, the interpolation of road condition data from major roads was used to estimate the conditions of minor roads. However, because the conditions of minor roads may differ from those of nearby major roads, this approach might introduce bias into the results. Lastly, in this study, the best safety indicator was determined based on the proportion of variance explained by the independent variables. However, this does not necessarily mean it is the best safety indicator in an objective sense, as the model's variance is also related to the independent variables. This implies that the introduction of factors not considered or included in the model could alter the results. Therefore, future research could explore more influencing factors to enhance the explanatory power of the model.

Based on the findings, future research could focus on two directions. First, it has been indicated that after dark, physical and social environmental factors interact in a way that makes a place appear unsafe (Rahm et al., 2021). Additionally, environmental factors change with the alternation of seasons. Therefore, the temporal and seasonal change of features’ impact on perceived traffic could be considered. Second, the study suggests the possible interactions between traffic or population factors and environmental factors. Based on these findings, future research could explore the impact of environmental factors on perceived safety in different traffic conditions, such as high vehicle volumes versus low vehicle volumes.

7 Conclusion

The study aimed to identify the factors influencing perceived traffic safety for pedestrians and cyclists, considering not only environmental factors but also traffic and population factors. This study explored and implemented the integration of PPGIS data and GSV imagery to assess human perception, demonstrating the feasibility of this approach. In this study, a traffic safety survey was used to obtain perceived traffic safety value and GSV images, and traffic and population data were used to extract urban environment, traffic, and population information. Two machine learning regression models were then employed, and to gain insights into the significance of each feature in determining perceived traffic safety, two model-independent techniques—SHAP and PDP—were utilized to explain the contribution of individual features to the overall model output. Moreover, four points were discussed based on the results: (1) the impact of each feature on perceived traffic safety for pedestrians and cyclists; (2) similarities and differences in the factors influencing perceived traffic safety for pedestrians and cyclists; (3) the strengths and weaknesses of usage of PPGIS as auxiliary data in perception evaluation; (4) policy implications for road traffic safety.

In summary, the results demonstrate that population density has the most significant impact on perceived road safety, and the three traffic factors—road condition, traffic volume, and speed limit—also play important roles. Additionally, six environmental factors—vegetation, buildings, sidewalks, people, cars, and traffic signs—clearly influence perceived traffic safety. Moreover, although these factors affect both modes of transportation in generally similar ways, there are subtle differences in emphasis: Pedestrians are more focused on elements that provide security and better visibility, such as a lower proportion of buildings, sidewalks, and cars, and lower speed limit. while cyclists are more sensitive to road conditions. Besides, the results suggest to policymakers and urban planners that perceived traffic safety for active travel should be ensured by considering both the built environment and traffic factors.

Ensuring perceived safety for pedestrians and cyclists is not only a measure to promote active travel but also a fundamental prerequisite for establishing a well-functioning urban transportation network. Overall, this study highlights the potential of integrating PPGIS data and GSV imagery to assess perceived traffic safety and examines the influence of various factors on it. I hope this study helps to provide a more comprehensive understanding of the factors influencing perceived safety in active travel.

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