UNIVERSIDADE DE LISBOA
INSTITUTO SUPERIOR TÉCNICO

Objective and Subjective Safety Mapping for Urban Cyclists

Miguel Nobre da Costa

Supervisor : Doctor Filipe Manuel Mercier Vilaça e Moura
Co-Supervisors : Doctor Manuel Ricardo de Almeida Rodrigues Marques
Doctor Carlos Miguel Lima de Azevedo

Thesis approved in public session to obtain the PhD Degree in Transportation Systems

Jury final classification: Pass with Distinction and Honour

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Jury

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Use of Generative AI and AI-Assisted Technologies Disclosure

During the preparation of this thesis I used ChatGPT and Grammarly to improve readability and language. After using this tool/service, I reviewed and edited the content as needed and take full responsibility for the content of the publication.

Abstract

Today, cities are seeking to transition to more sustainable transportation modes. Cycling is critical in this shift, including first-and-last-mile links to transit. However, cyclists are exposed to many hazardous circumstances or environments (which can result in accidents, injuries, and deaths), and are exposed to the perceptions of such risks. Thus, analyzing cyclists' safety is critical for planners and decision- makers to improve cycling uptake and reduce the risk of those who cycle. This thesis explores cycling safety and, more specifically, the effects of the urban environment on cyclists' safety. It uses a new framework based on scalable solutions and tools to analyze three components of cycling safety: objective safety (analyzing cycling accidents and their outcomes), subjective safety (exploring perceptions of cycling accidents), and the relation between the two. Its main objective is to "*Combine authoritative and volunteered geographical data to automatically and continuously identify, understand, and draw recommendations to improve urban objective and subjective cycling safety.*" Analyses explored a broad range of methodologies that make use of traditional methods and newer machine learning endeavors to uncover complex relations between urban elements, various built environment typologies, other risk factors and cycling accidents or perceptions of such accidents. Ultimately, the findings highlight the ability to capture heterogeneity in different urban settings, which allows for more direct countermeasures to risky situations or policies to be designed, simulated, and targeted. Additionally, results showed how such an approach facilitates the continuous assessment of changing cycling environments and its use in efficiently assessing different locations with the growing amount of openly available data. In practice, researchers, urban planners, and authorities can employ such methods to actively monitor and identify urban characteristics that either increase or decrease cycling safety at both a micro and macro level.

Keywords

Cycling Safety, Urban Environment, Objective and Subjective Safety, Machine Learning in Transportation, Risk Perception in Cycling.

Resumo

Muitas cidades procuram mudar os seus sistemas de transportes para alternativas mais sustentáveis. A utilização da bicicleta como modo de transporte é fundamental nesta mudança. No entanto, os ciclistas estão expostos a inúmeras circunstâncias ou ambientes perigosos e às perceções desses mesmos riscos. Assim, a análise da segurança ciclável é fundamental para aumentar e melhorar a utilização da bicicleta como modo de transporte e reduzir o risco daqueles que a utilizam. A presente tese aprofunda esta questão, analisando os efeitos do ambiente urbano na segurança dos velocípedes. Esta tese utiliza uma nova abordagem baseada em soluções e ferramentas mais escaláveis para analisar três componentes da segurança ciclável: segurança objetiva (analisando acidentes de bicicleta e a gravidade dos mesmos), segurança subjetiva (explorando as perceções desses acidentes) e a relação entre as duas. O seu principal objetivo é "*Combinar dados geográficos oficiais e dados abertos para identificar, compreender e elaborar recomendações de forma automática e contínua para melhorar a segurança ciclável urbana objetiva e subjetiva*". As diferentes análises exploraram um vasto leque de metodologias que recorrem a métodos tradicionais e a novos métodos de aprendizagem automática para descobrir efeitos entre elementos urbanos, tipologias de ambiente construído, fatores de risco e acidentes de bicicleta ou as perceções desses acidentes. Em suma, os resultados obtidos destacam a capacidade de captar a heterogeneidade em diferentes contextos urbanos, o que permite conceber intervenções para certas situações ou recomendações que permitam a minimização de risco ciclável. Além disso, esta abordagem facilita uma avaliação contínua e eficiente de ambientes cicláveis em diferentes locais com uma quantidade crescente de dados abertos. Na prática, investigadores, planeadores urbanos e autoridades podem utilizar estas metodologias para monitorizar e identificar características urbanas que aumentam ou diminuem a segurança dos velocípedes em diferentes níveis e em diferentes escalas.

Palavras Chave

Segurança Ciclável, Ambiente Urbano, Segurança Objetiva e Subjetiva, Aprendizagem Automática em Transportes, Perceção de Risco Ciclável

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The only true limits are the ones you accept.

Project Iceman

Contents

List of Figures

List of Tables

Acronyms

AET Accident Environment Type. 45
AIC Akaike Information Criterion. 62
ASC Alternative Specific Constant. 67

BMM Bernoulli Mixture Model. 55, 62, 63, 65

CET City Environment Type. 46

EBM Explainable Boosting Machine. 115, 120, 121, 126, 128
EM Expectation-Maximization. 56, 57, 62, 73

GAM Generalized Additive Model. 120
GBM Gaussian-Bernoulli Mixture. xix, xx, 51, 53–55, 64, 65, 69, C-2
GBM-LCDOM Gaussian-Bernoulli Mixture Latent Class Discrete Outcome Model. 53, 54, 56–58, 61, 62, 67, 69, 71–74, 76
GMM Gaussian Mixture Model. 55, 62, 63, 65
GP Gaussian process. 95, 97

LCDOM Latent Class Discrete Outcome Model. 50, 51, 53, 67, 74

OSM OpenStreetMap. 44, 58, 60, 69, 86, B-1
OSM POIs OpenStreetMap Points of Interest. 60, 69

RQ Research Questions. 5

SC Spectral Clustering. 45, B-1
SHAP SHapley Additive exPlanations. 156, 158, 159, 163, 164, 167
SRQ Supporting Research Questions. 5
SVI Street-View Imagery. xv, xvi, 23, 25, 60, 61, 65, 86, 87, 101, 102, 117, 157

TRID Transport Research International Documentation. 141
TS TrueSkill. 97, 98

VGI Volunteered Geographical Information. 7, 50, 72, 135, 158, 178

WoS Web of Science. 141

XGBoost eXtreme Gradient Boosting Tree. 96, 98, 158–160, 164, 167

Chapter 1

Introduction

1.1 Motivation and Research Scope

In the last decades people have been moving towards cities. From 1950 to 2018, the world's population living in cities has increased more than fivefold. Today, 55% of the world's population lives in urban areas, and this number is expected to increase to 68% by 2050 (United Nations, 2018). Under these circumstances, "sustainable urbanization is key to successful development" (United Nations, 2018). Sustainable evolution of cities is one of the seventeen goals proposed by the UN to forge a new platform for urban development (UN General Assembly, 2015), targetting how cities should evolve to be more inclusive, safer, resilient, and sustainable.

This paradigm forces national and local authorities to adapt. Cities need to rethink how housing, public services, energy usage, and other sectors are provided to citizens. A growing need for safer environments, catering to inclusive and accessible spaces, and growing demand for better education and jobs will require cities to strategise how such change occurs. One key sector to where such change is unavoidable is within transportation. More flexible solutions must be created evermore quickly to address the challenges and requirements we now face today. Here, alternatives to replace private fossil-fuelled motorized vehicles is one of municipalities main targets. Looking to foster such change, one alternative authorities look towards is to promoting bicycle usage. Bicycles can be used on their own for short to medium distance trips, or between first- or last-miles to public transportation.

Cycling promotes sustainability by reducing greenhouse gas emissions and air pollutants (Mason et al., 2015; Neves and Brand, 2019). Initiatives led by the Dutch Cycling Embassy and the Cycling Embassy of Denmark continue to increase the number of traveled kilometers and substantially improve the quality of life for those who ride, whether it be in bike parking facilities or sense of safety through infrastructure changes. Bi-annual reports from the City of Copenhagen (I refer the reader to the Bicycle Account reports authored by the City of Copenhagen) further show the evolution the city has experienced in the past years and the economic return of investments made by improving the cycling infrastructure.

Albeit many programs and investments currently being made to improve cycling facilities, both in improving the infrastructure and educating the population to the benefits of cycling, increasing the number of cyclists has proven difficult in several cities. Specifically, cities must target potential-cyclists (those willing to cycle or adopt cycling regularly) and prioritize changes that enable them to cycle (Félix et al., 2017). In other words, mechanisms must be carried out to encourage prospective cyclists to adopt cycling. Félix et al. (2017) explored the behavioral aspects of cycling: motivators and barriers for those who do not cycle or are willing to start cycling (non-cyclists). Among the barriers identified, fear of traffic and safety concerns have been shown to among most significant barriers to cycling for non-cyclists, which has also been identified in multiple other studies (Heinen et al., 2011; Sanders, 2015; Félix et al., 2017; Félix et al., 2019). Cyclists face many adversities in their daily journeys, whether arising from interactions with cars or ill-designed infrastructure which may result in accidents. These interactions affect cyclists' decision to keep cycling and can force them to look for an alternative mode of transportation, if they feel unsafe.

Cycling safety research and practice refers to policies or measures that aim to minimize the number of crashes and/or injuries or increasing the sense of safety for those who cycle. Conceptually, it revolves around measuring risk, exposure to risk, and travel behavior (Schepers et al., 2014). Cycling risk can further be divided into two: **objective risk** (also known as observed or actual risk) and **subjective risk** (or perceived risk). While the former relates to the number of accidents (the count of fatalities, injuries, or material damage resulting from the accident), the latter is the risk that is assumed to exist or the sense of safety regarding a particular environment, route, or behavior. Risk perception is often influenced by near misses, past risky experiences, and the sense of risk exposure felt by cyclists in a given cycling environment. On the one hand, understanding why cycling accidents happen is vital to decrease the number of accidents and minimize their outcomes. On the other hand, understanding subjective safety is vital to developing promotion strategies to increase the number of cyclists.

In recent years, research aimed at decreasing the number of cycling accidents and the number of fatalities has increased. Road incidents are complex events resulting from a combination and interaction of different factors (human, traffic, infrastructure, vehicle-related, and environmental conditions) (Miaou et al., 2003). To decrease accidents and their impacts, researchers have tried to pinpoint and analyze what critical factors have a higher chance of increasing accident frequency and severity. Street elements (Chen, 2015), road network (Marshall and Garrick, 2011), land use (Kaplan and Prato, 2015), cycling volumes and safety-in-numbers phenomenons (Elvik and Bjørnskau, 2017), and personal characteristics (Cripton et al., 2015) are some of the key characteristics to have been investigated and found to have an impact on resulting cycling accidents.

Knowing the impact of such urban characteristics and their correlation to accident causes or contributing factors is vital to propose adequate countermeasures and improving cycling safety. Yet, the availability of such detailed data (specific information on infrastructure elements) where cycling accidents have occurred is often insufficient or missing, although critical for running comparative studies or informed decision-making. To acquire this data, manual inspection of accident sites is usually employed, but this process constantly proves labor-intensive, time and money-consuming.

Likewise, understanding perceived risk has been gaining popularity recently, with infrastructure layout (Wang and Akar, 2018), fear of traffic (Jensen et al., 2007), and usage of safety gear (Lawson et al., 2013) taking center stage. Typical research focuses on conducting *in loco* surveys or post-cycling interviews to cyclists. By and large, previous work has focused mainly on analyzing why cyclists perceive some aspects of their journey as riskier than others. However, a significant downside of such qualitative survey-based methods is that most of them cannot make any inferences about environments where they are not conducted, preventing any attempt of creating a more general or global platform for studying the perception of risk.

More recent works have begun exploring other approaches, such as interviewing and showing videos to cyclists to place interviewees closer to the cycling context. Although these provide valid approaches to studying perceived risk and how different factors influence the perception of safety, these approaches need to be more scalable. Performing interviews or deploying surveys is a lengthy and complex process. More, it does not consider using any new data processing methodologies to make inferences on unknown environments. Automatically understanding human perceptions through wearables, for instance, may provide hotspots where cyclists are negatively aroused (Zeile et al., 2016). In turn, recording such data signals *in situ* serves as a basis for more objectively measuring stress levels and specific emotions such as fear (Vieira et al., 2016; Costa et al., 2017). Combining such data sources with visual inspections of video recordings of the same journeys, researchers may determine which situations lead to stressful events.

However, not only is it essential to analyze both types of safety individually, but understanding what is the relation between the two is also vital. Figure 1.1 depicts a conceptual interaction between objective and subjective safety. Analyzing this matrix and how objective safety relates to subjective cycling safety leads to the following four possibilities:

- **High Objective Safety - High Subjective Safety (Quadrant 1):** This results in comfortable, safe rides, which one can assume will contribute to increasing cycling numbers. This is the ideal scenario that all strive for.

- **Low Objective Safety - Low Subjective Safety (Quadrant 3):** Cyclists will feel unsafe, and the cycling environment will be hazardous for them to ride, potentially leading to accidents. It is also safe to assume that this will lead to a decrease in cycling numbers with individuals ultimately choosing other modes of transport.

- **Low Objective Safety - High Subjective Safety (Quadrant 2):** However, what happens when cyclists feel safe but are subject to many dangerous events ? This particular situation is highly problematic as cyclists will feel safe and therefore disregard many risky possible events, which ultimately can have potentially disastrous consequences (accidents).

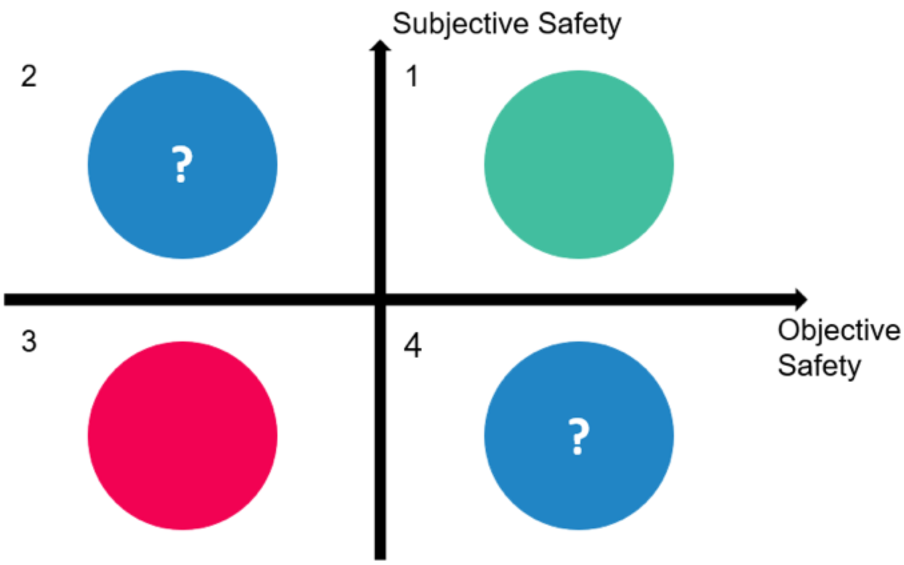

Figure 1.1: Cycling safety matrix: how does objective safety relate to subjective safety?

- **High Objective Safety - Low Subjective Safety (Quadrant 4):** And finally, similar to the previous situation, what happens when the environment is safe but cyclists perceive it as unsafe? Again, if cyclists feel unsafe and uncomfortable riding a bicycle, they will give up and choose another mode of transport. This can hinder any city's strategy that, despite providing safe environments for individuals to ride on, won't see such strategies be successful, laying down all investments made.

With this in mind, this thesis delves into understanding objective safety, subjective safety, and the connection between the two. As will be further detailed in Chapter 2, previous research has been traditionally slow and costly. Overall, approaches for studying observed and perceived cycling safety need to be more scalable and more efficiently repeated over time and space.

I intend to pave the way to overcoming such problems by using newer methods of acquiring data, aligned with processing tools from computer vision, image processing, and machine learning. Using the methodology later enumerated, one can scale inferences and simulate cycling risk and its perceptions under different circumstances, leading to a more general, automatic, and continuous approach. Practical recommendations can be derived from the created framework, driven directly from the results shown, aiming at providing cyclists with safer, more comfortable environments to ride on.

1.2 Objectives and Research Questions

Following the gap pointed out above, I will now present the main objective for this thesis and its associated research questions. This thesis explores cycling safety in its two forms: objective and subjective. The overall objective is then to:

Combine authoritative and volunteered geographical data to automatically and continuously identify, understand and draw recommendations to improve urban objective and subjective cycling safety.

This objective highlights four important components of the research I carried out:

1. **"Combine authoritative and volunteered geographical data"**

   There is little research looking at classifying different levels of objective and subjective safety by combining authoritative and volunteered geographical data. I intend to explore methodologies that can draw from the benefits of combining both data sources.

2. **"automatically and continuously"**

   Objective and subjective safety is pervasive in the sense that all types of cyclists can experience it. Thus, I aim to create something capable of automatically understand both types of risk and that can be easily redeployed continuously over time to re-analyse cycling risk.

3. **"identify, understand and draw recommendations"**

   The usage of new methodologies as tools to identify characteristics that have an impact on cyclists' safety, analyse these impacts, and to devise policies or recommendations that can, ultimately, improve cycling safety.

4. **"urban objective and subjective cycling safety"**

   This work intends to not only improve actual and perceived cycling safety individually, but to explore the relation between the two types of safety as well.

The objective relates to the need of studying and understanding physical and psychological events that urban cyclists face every day and its connection to both observed and perceived cycling risk. This research is positioned at the intersection of two distinct areas of research. This overlap in knowledge is driven by problems of observed risk and perception of safety (from the Transportation Systems side) that will be studied under a data processing approach (from a Data Science perspective), creating added value in how to target the aforementioned problems. Aiming at the laid objective, the methodology in this thesis (which will be later overviewed in Section 1.3) seeks to answer a set Research Questions (RQ) and Supporting Research Questions (SRQ). These are:

RQ1. What is the relation between cycling built environments and cycling accidents?

Although some studies have focused on this question exactly, how such analyses are typically done revolve around costly approaches. This first research question seeks to find the connection and impact of cycling context (and the particular case of built environment) through a scalable approach that can be easily repeated over time.

SRQ1.1. *How can one tackle the lack of data on objective cycling safety?*

SRQ1.2. *Are there built environment differences between cycling accident locations and non-accident locations?*

SRQ1.3. *What is the link between built environment, accident contributing factors, and accident outcomes?*

RQ2. What urban factors impact the perception of cycling safety?

The second research question underlines the one of the fundamental purposes of the proposed research. Perception of risk or safety can be considered a major factor when someone decides to cycle or not. Thus, it is vital to understand what factors influence one's perception of risk, and to do so with a ubiquitous and continuous approach.

SRQ2.1. *Can we capture cycling safety perception through street-view images?*

SRQ2.2. *Can we understand cycling perception of safety in a scalable and continuous manner?*

SRQ2.3. *How do different urban elements influence the perception of risk?*

RQ3. What is the connection between objective and subjective cycling safety?

Research question three focuses on the link between what is evidenced by statistics of crash and injury records among cyclists and the perceptions of safety among those who regularly, occasionally, seldom and never cycle in urban areas. The target is to understand whether actual risk influences or is influenced by a higher or lower perception of safety.

SRQ3.1. *What do we currently know about the objective–subjective cycling safety relation?*

SRQ3.2. *Does an increase in objective risk relate to an increase in perception of risk? Or does the opposite happen, does a decrease in objective risk relate to an increased perception of risk?*

1.3 Research Approach

This section describes the research methodological approach followed throughout this thesis. This approach follows a quantitative-heavy strategy, often using multiple data sources to measure and analyze different aspects related to cycling safety. Being such a pervasive problem in most urban contexts, the multiplitude of dangerous events experienced by cyclists and their associated perception of risk poses a great barrier for cities to increase cycling numbers. In an era where evermore data is available, research has not yet explored faster and scalable tools that can leverage multiple data sources to more rapidly devise measures and changes to improve cyclists' lives.

This dissertation tries to fill this gap, promoting the use of scalable tools to make use of both authoritative records (data officially recorded and published by authorities) and Volunteered Geographical Information (VGI) (data openly collected and contributed by any individual), devising strategies and mapping tools that planners and decision makers can use to make evidence-supported changes to urban environments. Such an approach exploits current machine learning advances, while also contributing to devise how such tools can be used in cycling safety. It should be made clear that the methods we will explore built greatly on previous research and often bridge such knowledge from distinct research areas, making use of them in advancing cycling safety. Regarding the methodology to answer the aforementioned research questions, this dissertation's research can be separated into three parts.

The first part delves into objective cycling research. One main barrier to cycling research is its data, both in terms of accident observations, contributing factors, and surrounding built environment. Yet, these data acts as the foundation for accident frequency and severity models. Here, I intend to tackle this problem by adding data and scalable methods to provide more complete data on cycling accidents, with a particular focus on built environment information. From here, I aim at modeling cycling accident severity using such data, allowing for a better comparison and transferability of models on cycling safety from one location to another.

The second part concerns subjective cycling safety. Fear and concerns over being involved in a cycling accident remain the main deterrent to cycling. Thus, it is vital to understand what factors increase this sense of risk and what can be done to improve cyclists' sense of safety, which in turn can help increase cycling numbers. Research on this typically involves likert-scale surveys and post-riding interviews. In this task, I seek to propose a different, more scalable, approach to understand individuals' perception of safety. Such approach must enable a faster assessment of how different environments are perceived by people and what characteristics of urban spaces impact such perceptions.

The third and final part focuses on the intersection between objective and subjective cycling safety, where very limited research has been carried and little is known about the relation between the two. With this in mind, I seek to draw from the two previous research parts and outline how such relation can be explored and found. Such approach must allow for a better understanding on how practical measures are affected when just considering one type of safety and the implementation harm it can bring when doing so.

1.4 Contributions of this Work

Cycling safety research has been the focus of many in past years because of its direct impact on people's lives. This thesis contributes to advancing this area in different domains, including:

- A new collection of curated cycling accidents containing nearly 1.6 million observations, spanning different geographic scales (city-, district-, or national-level);
- A methodological framework on how authoritative data can be combined with volunteered geographical data (containing both mapping and imagery data) to analyze cycling accidents;
- A methodological approach to model cycling accidents using latent class discrete outcome models, combining the predictive power of machine learning and interpretability of traditional severity-based models;
- Identification and analysis of interactions between cycling built environment and accident contributing factors;
- Proposal of a new framework to study cycling perception of safety using pairwise image comparisons of real-world street-view images;
- A new deep learning model capable of simulating and predicting which environment is perceived as safer for cycling from real-world images;
- Presentation of a perceived cycling safety score as an easy-to-understand and comparable rating of how cycling environments as perceived in terms of safety;
- Modelling and identification of the impact of different built environment elements on the perception of cycling risk;
- Key insights and analysis of the relation between objective and subjective cycling safety.

These contributions and research outcomes were either published in peer-reviewed journals and presented in conferences (with and without published proceedings) or will be submitted for publication. Following is a list of such scientific presentations and publications:

Journal Articles

Costa, M., Marques, M., Roque, C., Moura, F. (2022). CYCLANDS: Cycling geo-located accidents, their details and severities. *Scientific Data*, 9(1), 237.

Costa, M., Azevedo, C. L., Siebert, F. W., Marques, M., Moura, F. (N/A). Unraveling the relation between cycling accidents and built environment typologies: capturing spatial heterogeneity through a latent class discrete outcome model. Accident Analysis & Prevention, 200, 107533.

Costa, M., Marques, M., Azevedo, C. L., Siebert, F. W., Moura, F. (N/A). Which cycling environment appears safer? Learning cycling safety perceptions from pairwise image comparisons. [Manuscript under review in *IEEE Transactions in Intelligent Transportation Systems*].

Costa, M., Siebert, F. W., Azevedo, C. L., Marques, M., Moura, F. (N/A). Understanding perception of cycling safety from street-view images: uncovering non-linear relations to urban factors [Manuscript ready to be submitted].

Christ, A. K., **Costa, M.**, Marques, M., Roque, C., Moura, F. (N/A). Evaluating Cycling Safety: A Systematic Literature Review on Subjective and Objective Measures. [Manuscript in preparation]

Costa, M., Siebert, F. W., Azevedo, C. L., Marques, M., Moura, F. (N/A). The *status quo* of the relation between objective and subjective cycling safety: A scoping review and future directions. [Manuscript in preparation].

Costa, M., Siebert, F. W., Azevedo, C. L., Marques, M., Moura, F. (N/A). How do urban elements influence objective and subjective cycling safety? Using machine learning to analyze congruencies and discrepancies [Manuscript in preparation].

Conferences (with and without procedia)

Costa, M., Marques, Moura, F. (2019). Bike Rider - Sensorial Mapping of Cyclable Paths. *Velo-City 2019*. Dublin, Ireland.

Costa, M., Marques, Moura, F. (2021). Objective and Subjective Risk Mapping for Urban Cyclists. *EIT DTN Annual Forum 2021*. Munich, Germany.

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Karina Christ, A., **Costa, M.**, Marques, M., Roque, C., and Moura, F. (2022). Percebendo a segurança objetiva dos ciclistas urbanos: uma revisão sistemática da literatura. *10º Congresso Rodoferroviário Português*. Lisboa, Portugal.

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Costa, M., Marques, M., Siebert, F. W., Azevedo, C. L., Moura, F. (2023). Scoring Cycling Environments Perceived Safety using Pairwise Image Comparisons. *IEEE Intelligent Transportation Systems Conference ITSC 2023*. Bilbao, Spain.

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1.5 Thesis Structure and Outline

I now describe this dissertation's structure, which follows the methodological approach presented earlier. This thesis is comprised of three main research parts and divided in 12 chapters. The main research parts are dedicated to distinct research aspects and provide unique contributions to the respective research topic. These are framed by the Introduction (Chapter 1), Background (Chapter 2), and Conclusions (Chapter 12). Figure 1.2 presents an overall outline for this dissertation, illustrating the three parts (A, B, , and C) and its corresponding chapters, the research questions addressed in each chapter, with solid arrows representing a logical sequence and dashed arrows showing that Part C builds upon from Part A and Part B.

As highlighted in Section 1.3, each part represents a different research topic (although all within cycling safety). Each part is divided into multiple chapters, each dedicated to distinct concrete methodological strategies to answer a specific research question and provide unique contributions to the respective topic. Broadly speaking, every chapter is subsequently subdivided to provide a concise motivation for the research goals and questions, specific methodology employed within the chapter, corresponding results, and its conclusive insights. This structure was chosen as it enables readers to concentrate on individual chapters, comprehending and assimilating their contents, without necessitating engaging with other chapters that may be of lesser relevance to a specific reader. However, it is important to note that each chapter adheres to an ordered sequence, wherein chapters progressively build upon the outcomes and discoveries of preceding ones.

Part A focuses on the objective aspects of cycling safety and it describes a collection of cycling accidents (Chapter 3) which serves as the basis (data-wise) for the remainder of the dissertation. It then explores accident environment typologies (Chapter 4) and a tool to capture spatial heterogeneity in cycling accident severity modeling (Chapter 5).

Part B is dedicated to the subjective side of cycling safety. Here, I explore a survey using pairwise image comparisons (Chapter 6), how we can score different environments per their perceived safety from pairwise comparisons (Chapter 7), learn these scores directly from real-world images (Chapter 8), and uncover non-linear effects of urban elements on the perception of cycling safety (Chapter 9).

Part C explores the connection between objective and subjective cycling safety. using the results and findings from the two previous parts of this thesis. Here, I explore what is currently known on the connection between the two types of cycling safety (Chapter 10). Lastly, I compare the influence of different urban elements on the objective and subjective safety, both at an individual and environment type level (Chapter 11).

The chapters not included in any of the three research parts support and contextually frame this dissertation. First, this Introduction (Chapter 1) motivates the problem and knowledge gaps in cycling safety which we address later. Chapter 2 reviews current literature, exploring current approaches in objective cycling safety and why cycling accidents occur, how subjective cycling safety is currently explored and how it can make use of more ubiquitous tools and data, and how little is known about the connection between the two types of cycling safety. Finally, Chapter 12 summarizes this thesis's findings, discusses its main limitations, and suggest a few leads for possible future research developments. After, all references used throughout this thesis are listed and supporting materials are provided in the Appendices.

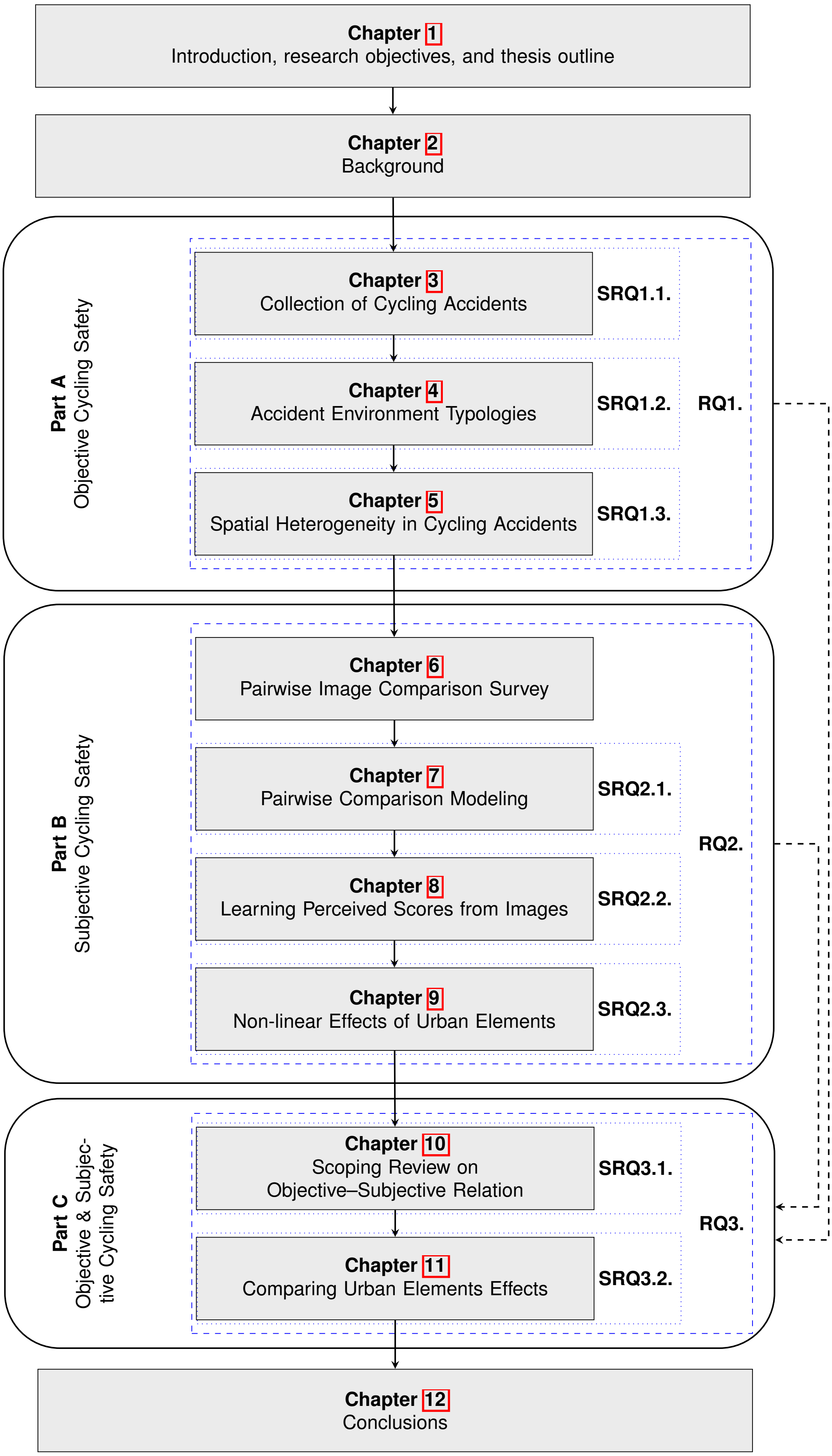


Figure 1.2: Dissertation organization with main parts, chapters, and research questions.

Chapter 2

Background

2.1 Urban Cycling: the Current State

Almost globally, people have been swapping their bicycles to cars from the 1950s as a result of cars' industry evolution and trivialization. Consequently, this led urban planners and decision makers to direct its efforts towards car-oriented urban designs where priority was given to the car.

Much led as a result of the oil crisis and other economic constraints, countries such as Denmark and the Netherlands began trying to revert such car-dependence in the 1970s. For instance, the Dutch government invested heavily in cycling infrastructure (Vandenbulcke et al., 2011) while the Danes were forced to discontinue several projects centered on the automobile (Gössling, 2013).

More recently, many other municipalities have also looked at different strategies to decrease the dependence on cars, with London and Stockholm implementing congestion charges (Tuerk et al., 2012; Börjesson et al., 2012), and with Unites States of America's making funding available to "increase use of bicycling, and encourage planners and engineers to accommodate bicycle and pedestrian needs in designing transportation facilities for urban and suburban areas" (US DOT, FHWA, 2010). Similar investment strategies in bike facilities and policy changes have also had impact in other world cities. Table 2.1 (compended from Goel et al. (2022)) shows the modal share in different cities across the globe. In Portugal, and in the particular case of its capital, Lisbon has invested greatly in cycling network infrastructure since the 2000s. While the municipality first targeted cycling as a leisure activity, expanding the network primarily in leisure areas such as Monsanto and alongside the river Tagus, it began to expand its network in 2015 towards a commuting context. The municipality estimated that the cycling mode share had increased from 0.2% in 2011 to about 1.25% in 2018 (CML, 2018).

Modal share increases can be credited mainly to three different mechanisms: (1) market-based instruments, which include taxes such as rising the cost of travels; (2) control-and-command instruments, who set standards for products and services which affects urban design and land use planning; and (3) soft policy, which relies mainly on distribution of information through education or other ini-

Table 2.1: Bicycle modal shares across the globe. *Source:* Adapted from Goel et al. (2022).

City	Country	Cycling share (%)
Amsterdam	Netherlands	28.7
Munich	Germany	16.3
Cologne	Germany	14.7
Berlin	Germany	14.1
Hamburg	Germany	13.7
Zurich	Switzerland	6.4
Helsinki	Finland	5.3
Delhi	India	4.8
Bangalore	India	4
Santiago	Chile	3.7
Cordoba	Argentina	2.7
London	England	2.6
Philadelphia	USA	1.9
Melbourne	Australia	1.9
Chicago	USA	1.5
Los Angeles	USA	1.3
Lisboa	Portugal	1.25
Brisbane	Australia	1.2
New York City	USA	1.2
Seattle	USA	1.1
São Paulo	Brazil	0.6

tiatives (Gössling, 2013). In all honesty, these changing behavior instruments all have had moderate success in shifting from fuel dependent modes to cycling as a mode of transportation. While some focus on increasing the safety of cyclists through infrastructure changes, seeking to attract more people to this mode, others focus more on changing the perspective of other road users to the benefits of cycling, either environmental, health or economic benefits.

However, as a whole, it is clear that what motivates behavior change is the balance between what are the pros (benefits) versus the cons (barriers) to using a certain mode. In this context, many studies have been carried for the past three decades, but the truth is that in many urban scenarios, the cons still outweigh the pros, which translates into a low adoption of the bicycle as a mode of transport. Next, I begin by briefly enumerating the benefits and motivators for cycling and, then, I list the barriers to cycle, from which risk and perception of risk play a fundamental role.

2.2 Benefits of Cycling

Commuting by bicycle or simply enjoying a leisurely ride can have many advantages when it comes to health, economy or quality of life. Many studies have looked at what factors motivate cyclists to take up cycling. I will now overview the three main benefits of cycling in terms of health, economy, and environmental impacts.

The health benefits of cycling are often explored through epidemiological evidence and health impact modelling. While cycling poses additional risks like air pollution exposure and accidents (De Hartog et al., 2010), the benefits outweigh these risks (barriers and risks of cycling are explored in Chapter 2.3). To highlight a few studies, Woodcock et al. (2010) shows that moderate-intensity exercise reduces mortality risk, and the effect is most pronounced when transitioning from no to low activity; Oja et al. (1998) demonstrated improved fitness and cardiovascular strain reduction through cycling or walking to work; Andersen et al. (2000) found a 40% decrease in mortality risk for cycling to work; and, Matthews et al. (2007) noted a 21% mortality reduction in Chinese women who cycled. Kelly et al. (2014) overviewed several studies, concluding that 150 minutes of cycling per week reduced all-cause mortality risk by 10%. Shifting car trips to cycling could prevent cardiovascular diseases, diabetes, and cancer (Rojas-Rueda et al., 2013). In conclusion, cycling offers evident health benefits, with many studies quantifying the associated improvements in quality of life and disease risk reduction. Systematic reviews have also summarized such link between cycling and healt benefits, such as Götschi et al. (2016); Oja et al. (2011a).

Economically, day-to-day bicycling is beneficial, both at an individual and regional-level. First, when trip frequency is accounted for, bicyclists tend to be the ones who spend more on average when compared to pedestrians, public transit users, and drivers, indicating that investments and consequences of mode shifts can be beneficial to local businesses (Clifton et al., 2013). As a result of improved health, it can lead to reduced healthcare costs (League of American Bicyclists, 2011) and prevention of deaths (e.g., equating to $511 million in annual health costs savings for the Colorado economy (BBC Research & Consulting, 2016)). Similarly, it can contribute to boost retail, manufacturing, and events (BBC Research & Consulting, 2016)), job creation (Dean Runyan Associates, 2012), and tourism (Bowker et al., 2004; Grabow et al., 2010; Nickerson et al., 2014)

Under an environmental perspective, cycling can also be beneficial. Increasing cycling may translate in fewer cars being used, meaning cleaner air and less noise pollution if users shift from such motorized modes. Cycling has been found to reduce greenhouse gas emissions and air pollutants (Mason et al., 2015; Neves and Brand, 2019). The City of Copenhagen (2014) expects to save between 10 000 to 20 000 Ton of CO_2/year if 50% of commuter journeys is achieved by 2025 by cyclers. Similarly, other estimates indicate a reduction of 7% reduction in CO_2 emissions under a scenario where cycling/e-bike represents 11% of the worldwide share of urban passenger travel by 2030 and a 11% reduction with a worldwide share of 14% by 2050 (Mason et al., 2015).

Thus, the benefits of bicycling cannot be downplayed. Cycling can lead to health-related improvements, job creation, or environmental sustainability. It has the capability to create jobs or renew rural communities, contributing in many aspects to the economic activities. However, despite its remarkable benefits, one question still arises: why is urban cycling still considered a marginal mode of transport in most urban areas around the globe?

2.3 Barriers to Cycling

Despite its benefits, urban cycling uptake is not without its barriers. Many urban environments do not promote cycling as a mode of transport, which translates into lower number of cyclists. For example, the lack of infrastructure or weather conditions (Félix et al., 2019) are two factors that contribute to the low numbers of bicyclists. In this section I review physical, social, and psychological barriers to cycling, from which safety concerns plays a fundamental role in deterring individuals to cycle.

Physical barriers

Physical barriers relate to physical deterrents in the cycling scene, namely in the built environment (e.g., lack of infrastructure or cycling facilities) and the natural environment (e.g., dissuading climate or topography). Such obstacles to cycle play a fundamental role when choosing to cycle or not, as these are often related to the quality of cycling routes or having to share the space with other road.

Past research have shown that mixed land use (Cervero and Duncan, 2003), work places providing safe bicycle parking, showers, or both (Wardman et al., 2007), denser overall network layout (Litman and Steele, 2012; Cervero, 1996), increased connectivity of bicycle facility (especially for inexperienced riders) (Stinson et al., 2005) tend to increase cycling numbers. Similarly, Pucker (2001) noted a correlation between countries with higher levels of bicycle share and cycling safety and those with higher number of cycling facilities. On the contrary, the presence of traffic signals and stops (Stinson and Bhat, 2003), high intensity traffic (Dill and Voros, 2007), and increasing trip distance (Parkin et al., 2008) have been found to decrease cycling. All in all, its not only the quality of the built infrastructure that motivates or deters cyclists, but cycling infrastructure must also be analyzed under other domains, such as connectivity and sense of exposure to risk. Under this perspective, most design guidelines (see for example Instituto da Mobilidade e dos Transportes Terrestres (2011)) highlight some requirements for cycling, which, when not met, damper any goals of increasing cycling.

Likewise, the natural environment also plays a part in deterring people from cycling. Hilliness has a negative effect on bicycle use (Parkin et al., 2008) and also seasonality, with countries like Canada and Sweden reporting that fewer people cycle during winter and those willing to do so, cycle much shorter distances (Stinson and Bhat, 2004; Bergström and Magnusson, 2003). Lastly, rain is also associated with lower cycling levels (Brandenburg et al., 2004; Parkin, 2004).

Social barriers

Social barriers entail barriers related to societal norms, demographic factors or even the acceptance of the bicycle as a mode of transport (Heinen et al., 2010). Factors like age, class, parental acceptance, or one's living and work conditions can play a role in deterring individuals to cycle.

The Theory of Planned Behavior (Ajzen, 1991) poses that one's intention to perform a behavior is affected not only by one's attitude towards a behavior and its perceived control of the behavior, but also by the subjective norm. Subjective norm can be described as "the perceived social pressure to perform or not to perform the behavior" (Ajzen, 1991). This norm entails the encouragement of people around an individual that affects his or her decision to cycle. For example, Ducheyne et al. (2012) found that parents and friends encouragement to cycle can play a fundamental role for children to cycle to school. Similarly, childrens' peer support as perceiving cycle to be "cool" (Trapp et al., 2011), aversion to driving (Xing et al., 2010), or perceptions of coworkers actively commuting (Bopp et al., 2012) had a positive influence in biking.

Conversely, the descriptive norm refers to the actual behavior of those around an individual (e.g., if friends or close family cycles). As Eriksson and Forward (2011) found, descriptive norm increases the intention to bicycle by about 6% when compared to cars, while Ducheyne et al. (2012) found that parents that walk or cycle to school with their children were always associated with their children always cycling to/from school.

Moreover, age and gender may also impact one's decision to cycle or not. The fact that men cycle more than women is well established in the literature (see for instance (Stinson et al., 2005; Dill and Voros, 2007)). A study conducted in Melbourne, Australia, looked at whether females placed higher value on bicycle routes with separation from motor traffic. Indeed, once distance from the city center was accounted for, they noted that women preferred off-road paths rather than roads with no bicycle facilities (Garrard et al., 2008). This is consistent with other studies, which noted the gender difference in risk aversion (Krizek et al., 2005). As for age, one would expect that elders would mention age as a reason not to cycle as it may require additional physical effort. However, results from Wardman et al. (2007) showed no statistical significance in the age domain.

Psychological barriers

Lastly, psychological factors can also dissuade cycling. These are typically associated with habits or attitudes towards cycling, or with perceived behavioral control. Overall, it is thought that attitudes, habits, and perceptions play a key role when deciding whether or not to cycle in an urban scenario.

In this respect, most consensual modal choice theories put attitudes as a key player in evaluating one's behavior (e.g., decision to cycle or not), such as the Theory of Reasoned Action (Fishbein and Ajzen, 1977), Theory of Interpersonal Behavior (Triandis, 1979), Theory of Planned Behavior (Ajzen,

1991) or the Perception-Intention-Adaptation model (Spears et al., 2013). For example, having a positive expectation of cycling increases the likelihood of commuting by bicycle (Dill and Voros, 2007), which is also simililarly expected from those with views of the health-related benefits of cycling (Gatersleben and Appleton, 2007), and by cyclists which find their commute more relaxing and exciting than other transport modes users (Gatersleben and Uzzell, 2007).

Most theories explored by transport researchers put an emphasis on the behavioral aspect of choices. Fishbein and Ajzen (1977) Theory of Reasoned Action and Ajzen (1991) later Theory of Planned Behavior, explore the psychological factors of travel behavior and modal choice. The former assumes that variables such as attitudes and perceptions play the key role in driving a certain behavior. The latter puts perceived social norms and perceived behavioral control at center stage. Such models are, however, often contested on the grounds that they almost completely overshadow structural and contextual factors that also modulate one's behavior. As a result, more recent models, such as Spears et al. (2013) Perception-Intention-Adaptation model put both perceptions and the physical environment with a direct effect on travel behavior.

When conducting surveys to uncover reasons to cycle, most answers cover the topics of: health benefits, fitness, flexible, convenient or attractive mode (Stinson and Bhat, 2004; Gatersleben and Appleton, 2007). In contrast, when enumerating reasons not to cycle, most include: being too dangerous, too much traffic, bad weather, or inconvenient (Bergström and Magnusson, 2003; Gatersleben and Appleton, 2007; Wardman et al., 2007). In fact, safety (whether real or perceived) is regularly mentioned as one of the main deterrents to cycle (Pucher and Dijkstra, 2000; Sanders, 2015; Félix et al., 2019). If someone has a sense of heightened risk of having an accident, then the supposition is that he or she will not cycle (Pucher et al., 1999; Pucher and Buehler, 2006). Such remark entails the need to understand and look at causes such dangerous perceptions to the cyclist.

So, on the whole, there may be many reasons as to why individuals do not take cycling. For a deeper review on such factors and determinants I refer the reader to Heinen et al. (2010). Deterrents range from other individuals' perceptions of them, to their own fears and attitudes towards other road users, or even infrastructure problems. However, one key aspect that many studies touch upon is the feeling of insecurity, or lack of safety that cyclists are subject to in their journeys. Increasing cycling safety and the perception of such safety seems to be a vital factor to raise cycling numbers.

2.4 Objective Cycling Safety

Definition

Risk Analysis characterizes hazards based on: their attributes, the knowledge people have about it, if it is a source of dread (potentially severe, uncontrollable and catastrophic event) and the perceived exposure to said hazard (McDaniels et al., 1992). Similarly, risk is often specified as the probability that some event outcome will happen accounting the event's exposure. In cycling, risk can be defined as the probability of some incident happening given the cyclist's exposure to traffic and/or other factors during a period of time (Vandenbulcke et al., 2014). Past research has focused on identifying such factors (risk factors) associated with increasing or decreasing the probability of occurring a incident and which can be, sometimes, modified by changes to the infrastructure or vehicle design.

Traditional cycling risk (or its counterpart, cycling safety) can be objectively evaluated by measuring one (or more) of the following quantities:

- *Injuries* and *Fatalities*: relating to the resulting severity of a given accident;
- *Crashes or collisions*: events where the bicycle hits, or was hit, by another object, no matter where the fault can be attributed to;
- *Falls*: instances where the bicycle hit the ground and was not caused by a collision, such as tripping in tram rails for instance; and
- *Conflicts*: which are usually interactions between the cyclist and other road users, pedestrians or other cyclists, oftentimes resulting in crashes or near misses.

In this thesis, I will try to use such specific vocabulary where applicable, but note that typically accidents are analyzed (i.e., crashes and/or falls) in terms of the resulting outcome (severity). In such sense, objective cycling safety in this thesis does not delve into exposure of cycling accidents due to missing data related to such frequency of events (this is further detailed below).

That being said, road incidents are complex events which usually result from a combination and interaction of five different factors: human factors (e.g., driver, cyclist or pedestrian behavior), traffic conditions (e.g., traffic density or velocity), infrastructure factors (e.g. roadway design, signalization), vehicle related factors (e.g., characterization of the vehicle and its shape), and environment conditions (e.g., weather) (Miaou et al., 2003). Although some factors cannot be controlled (e.g., weather), other factors might be manipulated to reduce the probability of a given event happening. Thankfully, considerable accident research has been conducted in the last decades and significant improvements have been achieved. For instance, New York City, when comparing the period of 1996-2000 to 2011-2015, saw a decline of 71% of cyclist fatalities per 100 million bicycle trips (Getman et al., 2017). Similarly, in Copenhagen the number of cyclist fatalities have been steadily decreasing since 1996 (City of Copenhagen, 2017). However, despite all the efforts carried by municipalities, bicycle advocates, and education programs, the number of killed or seriously injured (KSI) cyclists is still considerable, hence the need to further understand how to minimize accidents and their outcomes.

Data

In this sense, accident or crash records play a critical role in cycling safety research. They serve as the basis for any analysis to be made, enabling researchers to understand what can be changed to improve the safety of those who cycle. However, they are rather hard to collect, often being recorded on police reports or hospital admissions. Moreover, most accidents are often not reported (or underreported) Winters and Branion-Calles (2017); Gildea et al. (2021), resulting in underestimates in gauging how (un)safe cycling is. A survey in North America revealed that about 2 in 5 individuals report their crashes to the police and that about half require a visit to the doctor or the emergency room (Moritz, 1997), denoting that most accidents end up missing from official statistics.

This under-reporting problem has serious consequences, hindering results of studies or other interventions. Even when accident records are available, researchers face many other challenges. These include: data being fragmented over multiple files, often containing different data characteristics; publishing specifications vary between authorities; and data observations must be carefully curated as samples often contain unfeasible characteristics (Costa et al., 2022). More, if researchers are particularly interested in studying the impact of specific factors (e.g., impacts of lighting conditions, built environment, or weather), acquiring such data at the time of accident occurences can be particularly hard, as accident context is not often captured in records, obstructing their analysis in cycling accidents.

Another important aspect in risk analysis relates to how exposure is measured. A review of literature (Vanparijs et al., 2015) denoted that there is no consensus when it comes to comparing exposure and frequency of incidence and risk rates. Some track the distance traveled in one type of infrastructure and compare it to distance cycled in other types, some focus on frequency of cycling, while others measure it in time or number of passages in a location and number of conflicts. This problem, aligned with a lack of proper and workable datasets that capture bicycle traffic flow hinders frequentist approaches to study cycling accidents.

Overall, these hurdles have hampered the comparison and transferability of models and findings between locations. To circumvent these problems, many have tried to perform and apply multiple data mining techniques to gather a more complete set of characteristics on how and where accidents have occurred. This need for using data mining techniques arises from the multitude of complex data on cyclist accidents (Scarano et al., 2023). Seeking to untangle such large and complicated datasets, results have shown that these data-mining methods may be preferred to more traditional econometric models by requiring relatively short data preparation time and providing good accuracy (Mannering et al., 2020; Rella Riccardi et al., 2022).

Methods

Nevertheless, researchers have used whatever data is available to analyze the impact of diverse factors on accidents outcomes. To conduct such studies many approaches have been proposed, ranging from a traditional use of discrete outcome models, to more recent approaches using various machine learning techniques.

Traditional research approaches have mostly been done using discrete (both ordered and non-ordered) outcome models (Kaplan et al., 2014; Chen and Shen, 2016a; Behnood and Mannering, 2017; Chen et al., 2017), generalized linear models (Chen and Shen, 2016a; Pedroso et al., 2016), spatial models (Chen et al., 2017; Osama and Sayed, 2017), collision tests (Kang et al., 2011), or probability damage models (Cantisani et al., 2019). Other approaches have used latent classes (subgrouping accident types, individuals, or infrastructure characteristics) to analyze and identify common risk factors that impact similar cycling accidents (Heydari et al., 2017; Prati et al., 2017; Myhrmann et al., 2021; Sekiguchi et al., 2022), or to perform spatial clustering on urban factors at different levels (Labetski and Chum, 2020). In particular, latent class discrete outcome models have seeked to perform such type of subgroup clustering at population-level (Myhrmann et al., 2021), together with different accident characteristics, to model cycling accident severities. Latent class discrete outcome models are finite mixture approaches where mixtures arise from distinct subgroups with consistent features within each group. It differs from other random mixture approaches (e.g., mixed logits) as unobserved heterogeneity is not captured by a continuous mixture, but rather a discrete distribution that is represented by a specified number of classes. In turn, this frees the analyst from distributional assumptions on distribution parameters (Eluru et al., 2012). Comparisons between random parameters and finite mixtures have been conducted (Greene and Hensher, 2003; Shen, 2009), with results varying from case to case. Hybrid models to account for group and observation heterogeneity have been proposed (e.g., Greene and Hensher (2013); Xiong and Mannering (2013)), but, again, these require assumptions on random parameter distributions and can be structurally complex to model (Xiong and Mannering, 2013).

More recently, a rise in the use of machine learning models in cycling safety research has been witnessed. Researchers resort to methods such as deep neural networks (e.g., fully connected networks, convolutional neural networks, or generative adversarial networks) (Jeong et al., 2018; Zhao et al., 2019; Janstrup et al., 2022; De Bock and Verstockt, 2022) or other traditional models (e.g., random forest, logistic regression, nearest neighbor) (Cara and de Gelder, 2015; Jeong et al., 2018; Goldhammer et al., 2020; Fischer et al., 2022; Eriksson et al., 2022). Uniquely, these approaches combine conventional hospital and police accident records with other data sources to complement such records, enabling more contextual information about the accident to be examined, stepping away from traditional research strategies. Yet, to the best of my knowledge, little research on cycling safety has tried combining machine learning and econometric approaches, thus exploiting the good predictive power of the former with the conventional explainability capacity of discrete outcome models.

Factors Influencing Objective Safety

Although many approaches have been put forth, the general aim of cycling safety researchers is to pinpoint and analyze what critical factors have a higher chance of increasing accident severities. Street elements (Chen, 2015), road network (Marshall and Garrick, 2011), land use (Kaplan and Prato, 2015), cycling volumes and safety-in-numbers phenomenons (Elvik and Bjørnskau, 2017), and personal characteristics (Cripton et al., 2015) have been investigated and found to have an impact on cycling accidents. Again, understanding whether these factors increase or decrease the risk cyclists face is the main concern of cycling research Vanparijs et al. (2015), which, ultimately, can guide planners and decision-makers to devise urban changes that lead to safer environments.

Within these factors, a particular interest has been put on how the built environment (i.e., infrastructure) and different behaviors (both cyclists' and drivers') may increase or decrease accident severity outcomes (Salmon et al., 2022). For one, planners can learn and plan how future infrastructures may help to prevent or minimize accident outcomes, or education programs can be taught to promote less risky behaviors. Several elements have been studied, such as intersections (Zahabi et al., 2011; Hu et al., 2018), urban and building density (Chen and Shen, 2016a; Branion-Calles et al., 2020), bus and metro stops (Bi et al., 2023), road types and hierarchies (Bi et al., 2023), roadside elements (Wang et al., 2021), existence and types of bike lanes (Morrison et al., 2019), to name a few. However, I note that studies typically select one type of infrastructure layout, urban characteristic, or contributing factor and analyze how it correlates to cycling accidents, to the detriment of investigating multiple hazards at once as is typically done in risk analysis (Yang et al., 2021). Understanding relations between different contributing factors is a critical provision in any research attempting to understand cycling accident causation (Salmon et al., 2022).

2.5 Subjective Cycling Safety

Definition

Subjective (or perceived) cycling safety relates to the feeling of safety of an individual while cycling. Subjective risk perception can be defined as cyclists' process to perceive the existence of hazards and risks when cycling () which includes different components (Haworth et al., 2005; Sørensen and Mosslemi, 2009; von Stülpnagel and Binnig, 2022). It is often considered the most critical deterrent to urban cycling (Pucher and Dijkstra, 2000; Sanders, 2015; Aziz et al., 2018; Félix et al., 2019) and it is hypothesized that perceptions of cycling safety may be more significant than objective reality in increasing bicycle use (Manton et al., 2016). Thus, understanding what increases or decreases the sense of cyclists' risk is vital to adequately provide them with environments in which they feel safe to cycle. Fortunately, considerable efforts have been made recently to understand individuals' perceptions of safety better. These include different data collection approaches, new modeling strategies, and the creation of various indices to facilitate the comparison of different cycling environments.

Data

Data collection typically assumes the use of qualitative and quantitative surveys, *in loco* or post-riding interviews to collect data on individuals' perceptions to identify elements that negatively arouse individuals (Sanders, 2015; Aldred and Woodcock, 2015). These approaches usually rely on on-ride, immediate post-ride, on-ride plus post-ride, ride-along, ride-along plus post-ride, or intercept survey methods to capture users' subjective experiences and perceptions (Anjani Kalra and Beck, 2023). Questionnaires and surveys effectively serve as a strategy to evaluate existing or conceptual cycling environments and contexts and derive cause and effect relations in safety assessments (Fuest et al., 2023). Researchers frequently use such methodologies to assess whether or not specific changes to an environment increase the sense of safety or evaluate specific infrastructure typologies and elements. Evaluating perceived hazards through education programs can also help improve awareness and perception skills (Rosenbloom et al., 2008; Zeuwts et al., 2018).

In recent years, however, led by new technologies and the availability of open data in cities, newer approaches have explored how to collect data on individuals' perceptions. Naturalistic and semi-naturalistic approaches are often used, focusing on more quantitative methods to capture human responses to risky environments. These include using physiological data from wearable sensors (Zeile et al., 2016), cycling videos (Parkin et al., 2007), drawings from mental maps (Manton et al., 2016), virtual reality environments (von Stülpnagel and Krukar, 2018), or gaze behavior via eye tracking devices (Schmidt and von Stülpnagel, 2018). Yet, these approaches are often not scalable as they are time-consuming and resource-intensive, require precise preparation and monitoring of special devices, or may require individual training. Recently, some methods have been proposed to counter this. For example, von Stülpnagel and Binnig (2022) used a Likert-scale-based survey using 1900 images of semi-realistic cycling environments to generalize recommendations regarding best practices regarding subjectively safe cycling lanes. Ito and Biljecki (2021) has used computer vision to index bikeability utilizing several automatically extracted features from SVI to compare Tokyo and Singapore. However, despite whatever strategy is used to collect data on individuals' perceptions, approaches usually require critical preparation and control over what stimuli are presented to individuals. This manual task of carefully calibrating what is shown and enquired to users often limits the scalability and complexity of environments explored. Ultimately, this hinders the repeatability and transferability of results.

Methods

Multiple statistical modeling tools have been used to analyze the data collected. For example, Branion-Calles et al. (2019) used logistic regression to measure perceived safety and individual characteristics associated with bicycle infrastructure availability. von Stülpnagel and Lucas (2020) and von Stülpnagel et al. (2022) used Poisson regressions to investigate how perceived safety is correlated with road attributes, public transportation elements, and cycling volume. Other common approaches use hypothesis testing using ANOVA or Chi Squate tests (Møller and Hels, 2008; Sanders, 2015; Useche et al., 2019), principal component analysis (Lawson et al., 2013), ordered logistic regression (Lawson et al., 2013; Wang and Akar, 2018), linear regression (Møller and Hels, 2008), structural equation models (Chataway et al., 2014), general linear mixed-modeling (Ng et al., 2017), clustering techniques (Graystone et al., 2022), or other survey qualitative tools (Aldred and Woodcock, 2015; Useche et al., 2019), to name a few.

Factors Influencing Subjective Safety

Ultimately, whatever method is used, researchers seek to uncover what factors impact one's perception of cycling risk. Research has found that several aspects contribute to this perception, including socio-demographic characteristics and urban elements. For the former, Branion-Calles et al. (2019) has found that younger cyclists, male, who have lower income, have young children, have a high-school education, and cycle more frequently are more likely to perceive bicycling as safer. Similar studies have evidenced that perceived safety is influenced by gender (Møller and Hels, 2008; Chataway et al., 2014; Manton et al., 2016; von Stülpnagel and Binnig, 2022), age (Parkin et al., 2007; Chataway et al., 2014), cycling frequency (Parkin et al., 2007; Chataway et al., 2014), cycling experience (Lawson et al., 2013; Chataway et al., 2014; Manton et al., 2016), and use of cycling helmets and clothing (Chataway et al., 2014; Aldred and Woodcock, 2015).

Like these factors, urban structure and its elements also impact how cyclists subjectively experience accident risk. These are often investigated as they contain components or features where urban planners and designers can intervene to present cyclists with environments they feel safer to cycle in. Here, multiple characteristics have been found to be linked with subjective safety, including traffic (Chataway et al., 2014; Sanders, 2015), interactions with drivers and compliance with road rules (Lawson et al., 2013; Graystone et al., 2022), road and cycling infrastructure (Chataway et al., 2014; Ng et al., 2017), urban roads and compliance with road rules (Lawson et al., 2013), infrastructure layout (Chataway et al., 2014), intersection density (Wang and Akar, 2018), bicycle lanes (Ng et al., 2017; Wang and Akar, 2018), roads hierarchies and number of lanes (Chataway et al., 2014), lack of cycling network connectivity (Félix et al., 2019), cycling facilities (Useche et al., 2019), presence of median refuge island (Wang and Akar, 2018), and roundabouts typologies (Møller and Hels, 2008). Most studies' approach is to choose a small set of factors and understand their effect on individuals' perceptions. Such a choice reduces the chances for colinearity and allows researchers to focus on a few aspects. Yet, urban environments are often complex and heterogeneously composed of many elements altogether, making it difficult to study such environments in their entirety.

Subjective Safety Indices

In turn, the knowledge gained from understanding how different factors impact perceived cycling safety can be used to create metrics and indices where authorities, planners, decision makers can compare contexts and analyze various cycling environments. Such indices typically model perceived risk objectively, assigning different scores or levels to distinct environments based on their compositions. To this end, the Bicycle Stress Level (Sorton, Alex and Walsh, Thomas, 1994) and the Level of Traffic Stress (Mekuria, Maaza C and Furth, Peter G and Nixon, Hilary, 2012; Furth, 2017) remain the most well-known indices that attempt to measure bikeability and perceived risk. Yet, to compute such metrics, manual labor is usually employed, requiring individuals to annotate environment elements manually. Ito and Biljecki (2021) approach fills this gap, deriving a bikeability index from computer vision-extracted features from SVI, facilitating an automatic and scalable methodology to score environments effortlessly, which can eventually replace more traditional techniques. Nevertheless, this index covers five bikeability aspects, of which perceptions are one, which can be inadvertently mischaracterized if appropriate supervision is not employed. Another typical restriction of such indicators is that they are typically built in a linear format. While this is frequently a way to simplify and extract meaningful insights into safety perceptions, the effects of various factors may not be entirely linear, and thus, understanding a factor's influence may be over-simplified or not be wholly captured in its entirety.

2.6 Summary and research gap

So far, we have introduced and reviewed the importance of analyzing and understanding cycling safety in the context of urban cycling. For cities that seek to improve and increase cycling numbers, providing citizens with environments where they can both cycle safely and feel safe is vital. Cycling safety is usually considered to be made up of two parts: objective safety and subjective safety.

Objective cycling safety analysis involves understanding cycling accidents, including injuries, fatalities, falls, and crashes. We have explored the importance of understanding various factors contributing to such accidents. These include human behavior, traffic conditions, infrastructure design, vehicle characteristics, and environmental conditions.

A substantial challenge highlighted revolves around the scarcity and fragmentation of accident data, coupled with difficulties in obtaining context data and exposure data. To overcome these limitations, the adoption of data mining techniques as a means to extract valuable insights from large and intricate datasets can be helpful, thereby contributing to a more comprehensive understanding of cycling accidents. This approach, rooted in analyzing accident data, location, and context, can provide a foundation for identifying patterns and retrieving insights about modifiable risk factors associated with cycling incidents.

On the other hand, subjective cycling safety encapsulates individuals' subjective experiences and feelings of safety while cycling. The methodologies employed for data collection in this area are diverse, ranging from qualitative and quantitative surveys to innovative approaches such as cycling videos, mental maps, virtual reality simulations, and eye-tracking devices. These methodologies seek to unravel the intricate relationships between various factors and the subjective experience of safety. Factors influencing perceived safety extend beyond the individual level (e.g., socio-demographic characteristics and cycling habits) to different urban elements (e.g., traffic dynamics, infrastructure, and road design).

However, challenges persist despite notable progress in understanding the factors impacting perceived safety. These include labor-intensive data collection and analysis, limited scalability of methodologies, and potential oversimplification in linear modeling. To this end, a reevaluation of the approaches used, emphasizing the need for methods that balance scalability with the attainment of meaningful insights, can better understand perceived safety holistically. In turn, this can lead to designing urban spaces that prioritize the safety and well-being of cyclists.

After reviewing the relevant background on cycling safety and why it is a major barrier to individuals cycling, I will now present this thesis's contributions to the body of knowledge in this area. Part A will explore contributions to objective cycling safety research, Part B will present the work to advance subjective safety, and Part C will delve into the relation between the two.

Part A

Objective Cycling Safety

What have we learned so far

Today, cyclists are exposed to many hazardous circumstances or environments, resulting in accidents, injuries, or deaths. While improvements have been observed, the number of seriously injured or killed cyclists is still considerable. Hence, transport researchers and authorities must understand why accidents occur to reduce the risk of those who cycle. At a time when cycling is gaining popularity, this is even more important, indisputably enforcing the need for more detailed data about accidents' contexts. Likewise, for such a growing amount and complexity of data, faster approaches ought to be developed to retrieve vital insights to foster safer conditions for those who cycle.

What we will explore next

Acknowledging the need for more accessible cycling accident records, I will start by curating an indispensable worldwide database of cycling accident records. Next, we will see how such records can be complemented nowadays using open data, effectively enriching the information available about the locations where these accidents have occurred. Using these augmented records, I will showcase how a new joint machine learning and traditional severity model can analyze the complex relation between the built environment and accident circumstances. As will be shown, such a framework captures the holistic influence of different cycling environments, which can be used to analyze cycling safety at a city level.

Research Questions

1. *What is the relation between cycling built environments and cycling accidents?*

1.1. *How can one tackle the lack of data on objective cycling safety?*

1.2. *Are there built environment differences between cycling accident locations and non-accident locations?*

1.3. *What is the relation between built environment, accident contributing factors, and accident outcomes?*

Cycling safety research aims to comprehensively analyze the level of safety associated with cycling while understanding the factors linked to individuals, bicycles, and the surrounding environment that significantly influence cycling safety. The overarching objective is to cultivate a safer cycling environment, aiming to reduce the occurrence and severity of accidents. The present part of the dissertation, Part A, presents my contributions in this domain, highlighted in Figure A. In view of the fact that this problem is inherently complex, we begin from the basis of cycling safety research: cycling accident records. From here, I build on these to analyze the intricate relation between cycling, built environment context, and cycling accidents. In this sense, I divided this process into three chapters.

Chapter 3 addresses the pressing need for a meticulously curated compilation of cycling accident data. I curate a comprehensive dataset of cycling accidents called CYCLANDS, which encompasses nearly 1.6 million records. While various cities and countries already publish their datasets on cycling accidents, this compilation is motivated by the need for a standardized and unified repository of cycling crash information. As will subsequently elucidated, cycling safety researchers encounter numerous challenges when dealing with publicly available data from different cities. The resulting database is unprecedented in cycling research, containing thirty individual cleaned, validated, and curated datasets, which covers 42 years in some cases and up to six severity outcomes. The creation of CYCLANDS aims to lower the difficulty barrier, enabling any individual less proficient in data processing tools to access and explore such valuable resources and laying the ground for more accident severity modeling research, which can lead to evidence-based improvements to cyclists' safety.

Chapter 4 delves into the data augmentation process of authoritative accident records, such as those contained within the CYCLANDS collection above. This augmentation involves incorporating built environment data initially absent from the original accident records. Here, I explore the use of volunteered geographic data to complement cycling accident records, thereby providing crucial attributes about the built environment in which these accidents occurred. I employ this methodology to comprehensively describe circulation spaces, encompassing the network infrastructure surrounding cycling accident locations. Furthermore, I compare these environment types with city-wide typologies, highlighting noteworthy disparities. These findings underscore the potential of data augmentation procedures to identify significant city areas where cycling accidents are prone.

Chapter 5 expands upon the findings above and employs an accident severity model to investigate the relationship between the built environment and cycling accidents. Specifically, I use a novel modeling framework that combines the power of unsupervised machine learning and econometric models, allowing for more complex representations while retaining interpretability. This is achieved through a latent class discrete outcome model, wherein latent classes are derived from a Gaussian-Bernoulli mixture. Model components are simultaneously estimated, enabling the quantification of risk factors in terms of their contribution and impact, contingent upon the location and specific built environment typology in which accidents occurred. Consequently, researchers can account for such heterogeneity by indexing and analyzing city locations using simulated accident features, thereby being able to look deeper at the inherent risk associated with accidents occurring in such particular settings.

Lastly, I finalize Part A by providing a comprehensive summary, highlighting its primary scientific contributions, discussing their implications in advancing objective cycling safety research, and associated limitations.

Part A: Objective Cycling Safety
(Chapters 3, 4, and 5)

Collection of Cycling Accidents
(Chapter 3)

- ⇒ A new collection of curated cycling accidents covering 5 countries, 7 regions, and 18 cities.
- ⇒ The collection contains nearly 1.6 million observations;
- ⇒ The collection is openly available to foster more widespread transferability and comparisons of findings in objective cycling research.

Accident Environment Typologies
(Chapter 4)

- ⇒ New methodological framework on how volunteered geographical mapping data can be used to augment built environment data in accident locations;
- ⇒ Clustering of circulation spaces around accident locations to uncover main types of infrastructure surrouding accident locations;
- ⇒ Comparison between typical cycling accident environment locations and typical city environment locations.

Spatial Heterogeneity in Cycling Accidents
(Chapter 5)

- ⇒ A methodological framework on how authoritative data can be combined with volunteered geographical data (containing both mapping and imagery data) to analyze cycling safety;
- ⇒ A methodological approach to model cycling accidents using latent class discrete outcome models;
- ⇒ Identification and analysis of interactions between cycling built environment and accident contributiong factors;
- ⇒ A simulation tool to understand city's location context and how accident factors impact accident outcomes.

Figure A: Summary of research for Part A: Objective Cycling Safety. Part A is divided in three chapters and main research highlights are listed for each chapter.

Chapter **3**

CYCLANDS: A Collection of nearly 1.6 Million Cycling Accidents

This chapter is partially published as a journal article as: "Costa, M., Marques, M., Roque, C., Moura, F. (2022). CYCLANDS: Cycling geo-located accidents, their details and severities. Scientific data, 9 (1), 237."

3.1 Introduction

Cycling safety is often measured by the number of injuries or fatalities cyclists suffer. It is usually recorded on police reports or hospital admissions. However, most incidents are often not reported (or go underreported) Winters and Branion-Calles (2017); Gildea et al. (2021), resulting in underestimates in gauging how (un)safe cycling is. Nevertheless, accident or crash records are vital because they form the basis for cycling safety research. Researchers use these cycling accident records to analyze how factors such as demographic data, built environment, weather, and behavior increase or decrease cyclists' risk of being involved or injured in an accident Vanparijs et al. (2015). For instance, accident records act as the foundation for accident frequency and severity models, where researchers analyze and quantify which factors impact the outcome of accidents and what measures should be taken to protect cyclists.

Fortunately, a growing number of cities are publishing road accident data. However, this data is often published for all transport modes, making it difficult for researchers who only want to focus on vulnerable road users and the particular case of cyclists. Moreover, cycling safety researchers face many other challenges when working with the provided data. First, accident data is often fragmented into different files, where separate files contain location information, anonymized personal characteristics, involved vehicle attributes, weather, and road conditions, among others. All additional files must be compiled and merged to account for all the accident attributes captured. Second, data specifications differ for each authority publishing the dataset, with even injury severity levels specific to a single country or region. The third and final challenge is that the published data often must be corrected (e.g., unfeasible accident locations). Thus, researchers ought to perform a series of validation steps before even being able to study what makes an accident happen. Furthermore, all these challenges also hamper the comparison and transferability of models on cycling safety from one location to another, hindering knowledge transfer from one place to another.

Hence, validated datasets are required to lower the barrier to cycling safety research. Such an extensive compilation of curated cycling accident records is non-existent today. Thus, I publish CYCLANDS: CYCling geo-Located AccideNts, their Details and Severities. CYCLANDS is a collection of 30 datasets on objective cycling safety (i.e., based on accidents and crash counts), comprising 1.58M cycling accident records with geographical scales ranging from country, region, or city-level data. I present this data in different easy-to-access formats. This data will particularly benefit researchers working with severity models (such as discrete outcome models) or similar. A worldwide effort is needed to improve and standardize accident data collection to monitor the evolution of cycling safety plans and policies and implement the most effective safety countermeasures. This collection provides a solid contribution to fulfill this need.

3.2 Methodology

In general, I begin by searching for publicly available data on road accidents (including accidents involving cars, cyclists, pedestrians, and other road users). After downloading the original data, I filtered the collected datasets, resulting in geo-located observations with severity outcomes of accidents where any number of cyclists are involved. I further curate and validate the collected data to ensure that the corresponding datasets are easy-to-use and researchers do not need much validation work, essentially lowering the barrier on cycling safety analysis. I detail each step to achieve the final collection of cycling accident datasets.

3.2.1 Downloading data

To make a collection of cycling accident data, we began by searching for traffic accident data, as national authorities and cities more commonly publish these. Traffic accidents include observations of accidents involving all road users: cars, public transportation, pedestrians, and cyclists, among others. I focused on looking for data from cities with different sizes, distinct continents, different cycling modal shares, and with different cycling maturities. However, our final collection was greatly influenced by the data available, as most cities worldwide do not yet publish any data or statistics on traffic safety. Thus, I included and downloaded data for different geographic scales (ranging from city, region, or country-wide data) and for which their licensing or usage conditions do not hinder its usage for research purposes. Hence, to the best of our knowledge, at this point, all datasets in this collection are available under the public domain, allow for reuse for scientific purposes, or have no licensing terms. Table 3.1 enumerates all 30 datasets in this collection, alongside some basic information for each, including the number of cycling accidents. Figure 3.1 depicts the geographical ranges and locations of the datasets in this collection.

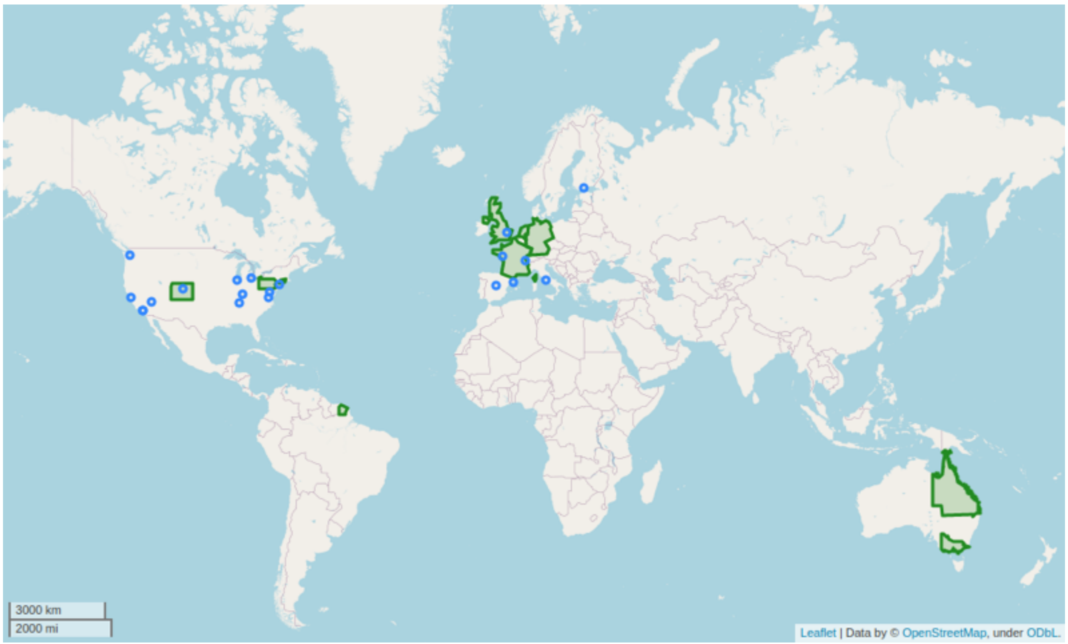


Figure 3.1: Location of the collected datasets. Datasets range from city level (in blue) to region or country-wide (in green) cycling accident observations.

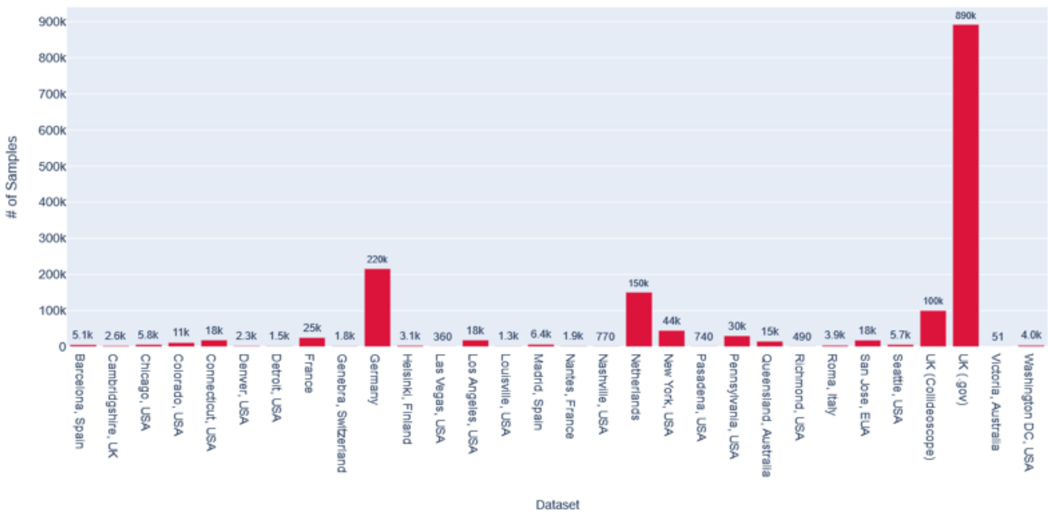


Figure 3.2: Number of cycling accident records in each dataset.

Table 3.1: Datasets in the collection. Additional information on the original dataset size, size of the cycling accident sample, the dataset date, and its geographical coverage and scale are reported.

Location	Original Size	Cycling Accidents		Dataset Date	Geog. Scale
Barcelona, Spain	86 701	5 144	(5.93%)	2010–2018	City
Cambridgshire, UK	11 954	2 647	(22.14%)	2012–2017	Region
Chicago, USA	384 200	5 784	(1.51%)	2013–2020	City
Colorado, USA	995 203	11 192	(1.12%)	2004–2018	State
Connecticut, USA	18 169	18 169	(100%)	1995–2020	State
Denver, USA	176 958	2 298	(1.3%)	2013–2020	City
Detroit, USA	214 469	1 477	(0.69%)	2009–2018	City
France	958 471	24 813	(2.59%)	2005–2018	Country
Genebra, Switzerland	25 493	1 792	(7.03%)	2010–2018	City
Germany	827 140	215 566	(26.06%)	2016–2019	Country
Helsinki, Finland	48 101	3 078	(6.4%)	2000–2018	City
Las Vegas, USA	37 086	363	(0.98%)	2015–2017	City
Los Angeles, USA	520 699	18 190	(3.49%)	2010–2020	City
Louisville, USA	255 541	1 273	(0.5%)	2010–2017	City
Madrid, Spain	304 805	6 365	(2.09%)	2010–2019	City
Nantes, France	7 551	1 851	(24.51%)	1998–2018	Region
Nashville, USA	296 826	773	(0.26%)	2010–2020	City
Netherlands	1 070 263	150 678	(14.08%)	2003–2018	Country
New York, USA	1 674 490	44 384	(2.65%)	2013–2019	City
Pasadena, USA	17 027	739	(4.34%)	2008–2017	City
Pennsylvania, USA	2 596 801	29 742	(1.15%)	1999–2018	State
Queensland, Australia	32 8247	14 747	(4.49%)	2001–2018	State
Richmond, USA	492	492	(100%)	2009–2015	City
Roma, Italy	1 093 040	3 933	(0.36%)	2006–2019	City
San Jose, EUA	584 085	17 701	(3.03%)	1977–2021	City
Seattle, USA	201 549	5 666	(2.81%)	2005–2020	City
UK (Collideoscope)	100 053	100 053	(100%)	2013–2020	Country
UK (.gov)	8 394 089	892 644	(10.63%)	1979–2018	Country
Victoria, Australia	1 358	51	(3.76%)	2016–2019	State
Washington DC, USA	222 087	3 978	(1.79%)	2009–2020	City

I searched traffic accident data on different platforms, such as cities' open data portals and maps, national statistics bureaus, and national open data platforms. Typically these platforms aggregate the data collected by police authorities and hospitals about traffic accidents, their locations, severity outcomes, and the conditions in which accidents happened. After reviewing the data to ensure it could be reused for research purposes, it was downloaded in Excel, CSV, GeoJSON, or any other format.

3.2.2 Cycling data filtering

Next, after downloading each dataset, I filtered the data such that, in the end, only accidents where cyclists were involved were included. This step is needed because cities' accident and collision data include accidents for all transport modes (motorized vehicles, bicycles, and pedestrians). Since most cycling safety research relies solely on cycling observations or accidents involving cyclists, I filtered the original dataset only to have observations concerning bicycles.

I scrutinized each observation to identify whether a bicycle or cyclist was involved in the accident. I scout such information from the user or vehicles involved, matching cases for which information is scattered across several sources. If a positive match is found, the observation is filtered and added to the final version of the cycling dataset.

3.2.3 Data curation

The third and final step consisted of curating the cycling accident data. Once filtered, I curate the data, ensuring that the data can be easily handled by any researcher and consistent across the collection.

I begin this curation process based on the geographical location of accidents. Knowing the location of accidents is vital in safety research. Many use this information as the foundation to analyze the built environment in such locations and how it impacts accidents. Although all added, datasets include the location to some degree, the description of accident locations varies greatly across datasets. Accident locations on each dataset can be found in one of four formats. Some describe locations based on geographic coordinates under the WSG 84 coordinate system, while others use specific coordinate systems or projections for the particular referenced region. Other datasets' accident location information is not as straightforward or accurate, and crashes are instead located using an address, the closest intersection to the location, or a description of the location (i.e., 200 meters west of the intersection of streets A and B). Given the importance of crash locations, I standardize crash locations when feasible to a single format. Given its wide use across many applications worldwide, I chose the WSG 84 coordinate system. Thus, for datasets whose crash locations are in a projection system different from the WSG 84, I automatically project all accident locations to the WSG 84 coordinate system. This projection was applied to the following datasets, where the original coordinate system is detailed in parentheses: Barcelona (UTM), Helsinki (EPSG:3879), Netherlands (EPSG:28992), Queensland (GDA94), and UK (.gov) (OSGR) datasets. No projection is applied for the datasets that do not contain any geographic coordinates and are instead located using an address or description (Detroit, Las Vegas, and Madrid datasets). Ultimately, this allows for locations to be more easily discoverable and circumvents researchers' needs to identify and project the original dataset's coordinate system for those datasets that use a specific coordinate system to the related area.

Next, I standardize the date and time details of each observation. Knowing when an accident has happened allows researchers and urban authorities to identify the frequency of accidents and any related trends. Consequently, I standardize the format of how accident dates are enumerated across datasets, easing the analysis of accidents over time.

Finally, I filtered accident observations to ensure that critical fields (accident severity, location, and date) do not contain any erroneous or missing elements. Localized accident severity models vastly rely on knowing accidents' location and outcomes. With this in mind, I iterate over all observations and filter entries where these variables are either 0, NaN, None, empty, or correspond to an Unknown value. Equally important, these variables' observations with incorrect or invalid data are also filtered. This means that observations with unfeasible locations or annotated outside their respective geographic boundaries are removed (e.g., accidents outside the state of Colorado are removed for the Colorado dataset, or accidents with location [0.0, 0.0] for the Barcelona dataset are also excluded). This step enables the inclusion of only observations which contain critical information for cycling safety research.

3.3 Results

For each dataset, I provide the curated data on cycling accidents enumerated in Table 3.1. A copy of all data is provided at Zenodo (Miguel Costa, Manuel Marques, Carlos Roque, Filipe Moura, 2021a) and at an online repository (Miguel Costa, Manuel Marques, Carlos Roque, Filipe Moura, 2021b). Additionally, an online site (`https://ushift.tecnico.ulisboa.pt/cyclands`) can be used for easy exploration and interactive visualization of the datasets. Figure 3.3 showcases the collection in some European countries.

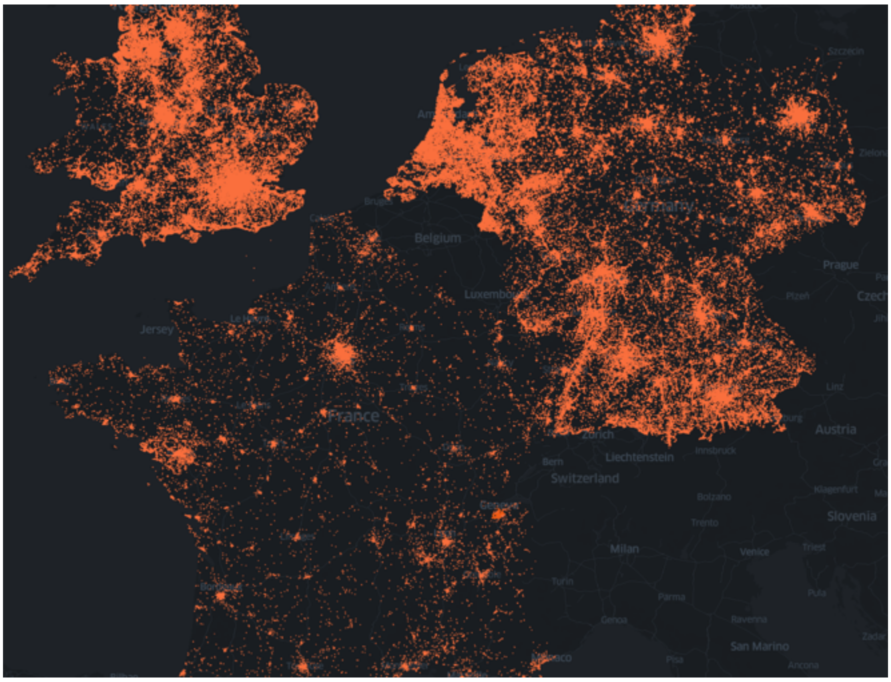


Figure 3.3: Cycling accidents' locations. Data included in CYCLANDS from France, Germany, the Netherlands, and the United Kingdom on where cycling accidents occurred.

Table 3.2 shows some essential information about the contents of each dataset. Table A.1 and Table A.2 in the Appendices expand Table 3.2 by providing more detailed information about the data contained in each dataset. For each dataset, the following files are provided, where $\{name\}$ corresponds to a given dataset's name:

- `cycling_safety_{name}.csv`: The data for each dataset is available as a comma-separated value (CSV) file to allow easy use and exploration, regardless of the software used. This file contains all variables available for the data, including the accident severity, location, and date, among other variables.
- `cycling_safety_{name}.geojson`: I also provide the data as a GeoJSON file to facilitate the usage of this data in GIS-based software and other mapping tools by reducing the need for researchers to transform the data into readable formats for such tools.
- `cycling_safety_{name}_summary.txt`: A summary of the available variables for the dataset, together with some descriptive statistics of each variable.
- `cycling_safety_{name}_license.txt`: The license or terms of use for each dataset. The details for the license are provided in `cycling_safety_{name}_legalcode.txt`.
- `cycling_safety_{name}_legalcode.txt`: The legal code for the license under which the data is provided.

Table 3.2: Summary of information available in each dataset of this collection. The number of outcome (severity) classes of the accident in each dataset is reported, along whether other types of information are also disclosed, such as light conditions, road conditions, weather, personal features of those involved, vehicle features, and location coordinates.

Dataset Location	**Outcome Classes[1]**	**Light Cond.**	**Road Cond.**	**Weather Cond.**	**Personal Feat.**	**Vehicle Feat.**	**Lat/ Long**
Barcelona, Spain	4				✓	✓	✓
Cambridgshire, UK	4	✓	✓	✓	✓	✓	✓
Chicago, USA	3	✓	✓	✓	✓	✓	✓
Colorado, USA	5	✓	✓	✓	✓	✓	✓
Connecticut, USA	5	✓	✓	✓		✓	✓
Denver, USA	3	✓	✓		✓	✓	✓
Detroit, USA	5	✓	✓	✓		✓	
France	4	✓	✓	✓	✓	✓	✓
Genebra, Switzerland	4	✓	✓	✓		✓	✓
Germany	4	✓	✓			✓	✓
Helsinki, Finland	3						✓
Las Vegas, USA	6	✓	✓	✓	✓	✓	
Los Angeles, USA	3				✓	✓	✓

Louisville, USA	3	✓	✓	✓		✓	✓
Madrid, Spain	3		✓	✓	✓		
Nantes, France	4						✓
Nashville, USA	3	✓		✓		✓	✓
Netherlands	3			✓	✓	✓	✓
New York, USA	3					✓	✓
Pasadena, USA	3	✓	✓	✓	✓	✓	✓
Pennsylvania, USA	5	✓	✓	✓	✓	✓	✓
Queensland, Australia	3	✓	✓	✓		✓	✓
Richmond, USA	1						✓
Roma, Italy	3	✓	✓		✓	✓	✓
San Jose, EUA	5	✓	✓	✓	✓	✓	✓
Seattle, USA	4	✓	✓	✓		✓	✓
UK (Collideoscope)	4						✓
UK (.gov)	4	✓	✓	✓			✓
Victoria, Australia	1				✓		✓
Washington DC, USA	5						✓

[1] Outcomes vary per datasets and include some of the following classes: Property Damage Only, Injury, Serious Injury, Fatality, and others.

Cycling accident datasets can be analyzed using different tools or software. For each dataset, additional formats are provided to facilitate data import into various tools or pieces of software, such as Python, R, NLogit, or others, typically used in cycling safety research when using discrete outcome modes, ordered probability models, or any machine learning approach.

3.4 Conclusions

CYCLANDS is a curated collection of 30 datasets on cycling accidents aimed at lowering the barrier in objective cycling research. CYCLANDS contains nearly 1.6M cycling accidents, which includes accident severities and locations. Substantial efforts were undertaken to verify and validate the collection quality presented here. Individual datasets were found, selected, and obtained from reliable sources linked with cities, municipalities, statistical bureaus, or police records. Then, a series of automated data validation steps were undertaken from the original data to validate each dataset's correctness further. Datasets were individually checked for key missing features (e.g., crash severity outcome or location), and invalid observations were removed from the final curated data. In effect, this ensures that researchers can readily use the data available under this collection to expedite research in cycling safety, potentially helping planners design policies and implement the most effective safety countermeasures to help protect cyclists.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/U-Shift/cyclands. All code has been written for Python3. I present the code under Jupyter notebooks, which provide step-by-step instructions on how to reproduce the results here presented. The code is available under MIT license (https://opensource.org/licenses/MIT).

The collection of cycling accidents is available at https://doi.org/10.5281/zenodo.5603036 . Each dataset under this collection is available under a specific license, detailed in the above link.

Additionally, an online website published at https://ushift.tecnico.ulisboa.pt/cyclands can be used for easy data exploration and interactive visualization of the datasets.

Chapter 4

Uncovering Accident Environment Typologies

This chapter was partially presented at and is available as: "Costa, M., Roque, C., Marques, Moura, F. (2022). Cycling Safety Data Augmentation in the Urban Environment: A Barcelona Case Study. International Cycling Safety Conference 2022. Dresden, Germany."

4.1 Introduction

Despite the creation of a comprehensive collection of cycling accidents, it is evident that the information gathered within each subset exhibits significant variations. While some subsets contain details encompassing accident circumstances, individuals and vehicles involved, and characteristics of the built environment in which the accidents occurred, others provide only limited attributes for each accident.

With this in mind, I aim to enrich the available accident data by exploring and incorporating additional data pertaining to the built environment surrounding each accident location. Specifically, the focus of this section lies on augmenting the available accident information by incorporating infrastructure data in which accidents occurred, particularly circulation spaces (i.e., network infrastructure) such as roads, sidewalks, and cycleways, among others.

To illustrate the methodology employed to achieve this goal, the Barcelona subset of the CYCLANDS dataset is utilized, which comprises 7,047 accidents that occurred in Barcelona, Spain, between 2010 and 2021. This subset encompasses information such as the severity of the resulting accident outcomes, dates, locations (latitude and longitude), vehicles involved, age, and gender. However, it is important to note that minimal or no information is provided regarding accident context, contributing causes, or the built environment in which the accidents took place. An additional experiment using CYCLAND's subset of cycling accidents occurred in New York is presented in Appendix B.

4.2 Methodology

I begin by using the geographic coordinates (latitude and longitude) for each accident to download and extract data from OpenStreetMap (OSM)[1]. OpenStreetMap data contains geographic information about the world contributed by users who voluntarily add to its creation, edition, and expansion. Data elements represent physical characteristics (e.g., roads, trees, buildings, or traffic signals) and their location. Elements are often categorized into specific groups (e.g., primary roads, lamp posts, fences) and may include many details (e.g., type of road, number of lanes, type of traffic signal).

I use accident locations as a starting point to extract information about the built environment where cycling accidents happen. I use Overpass[2] to query OSM data (pertaining to December 31st, 2021) given a set of parameters. Since I am interested in the immediate surroundings of cycling accidents, I extract all available information within a 25-meter radius of accident locations, including the existence of, for example, roads, street furniture, shops, trees, or plants. Figure 4.1 shows how data is extracted from OSM given an accident location.

(a) (b)

Figure 4.1: Cycling accident location and area around accident location where data is extracted from OpenStreetMap (a) such as urban elements including buildings, land use, bus stops, and network infrastructure (b).

Next, I filter this data to extract only relevant elements related to network infrastructure, i.e., circulation spaces. Totalling 15 different infrastructures extracted, these attributes refer to:

- Road hierarchies: motorways, primary, secondary, tertiary, streets, bridges, or others;
- Road lanes dedicated to public transportation;
- Sidewalks: footways and crossings;

[1] https://www.openstreetmap.org
[2] https://overpass-turbo.eu/

- Cycling infrastructure: dedicated cycleways, shared lanes with buses, and shared lanes; and
- Rail infrastructure: rails and subways.

After extracting data on circulation spaces for the 7.047 accidents, I aim to typify the usual environments where accidents occur. I employ a clustering algorithm to group accidents' circulation spaces (i.e., vector with size 15, corresponding to the above attributes) into different environment types that are a representation of the most standard locations where accidents happen in Barcelona involving cyclists. To group accident environments together I test multiple clustering techniques: k-Nearest Neighbour (Cover et al., 1967), Hierarchical Clustering (Cecil C. Bridges, 1966), and Spectral Clustering (Shi and Malik, 2000). All produce similar results, thus I only focus on Spectral Clustering moving forward.

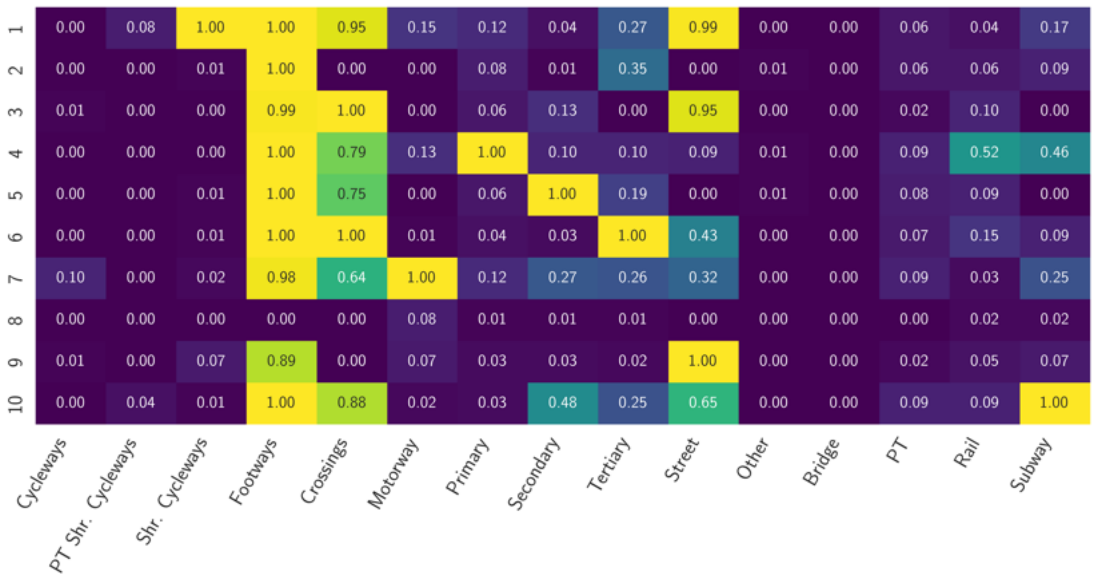
Spectral Clustering (SC) is an algorithm used for clustering data points into groups based on their similarity or proximity. It operates by transforming the data into a lower-dimensional space and then applying a clustering algorithm on the transformed data. Overall, it starts by constructing a similarity graph between points which represent pairwise relationships between these. Next, using the equivalent adjacency matrix from the similarity graph it computes the Laplacian matrix, capturing structural information on the representation similarity graph using a radial basis function kernel. Next, the Laplacian matrix eigenvectors and eigenvalues are computed, which represent embeddings and structure connectivity in a lower dimensional space. Finally, a clustering is applied using the eigenvectors and eigenvalues as the new data representations. Further details can be found in Shi and Malik (2000). SC has several advantages. It can handle non-linearly separable data, detect clusters of various shapes and sizes, and is relatively insensitive to initialization.

4.3 Results

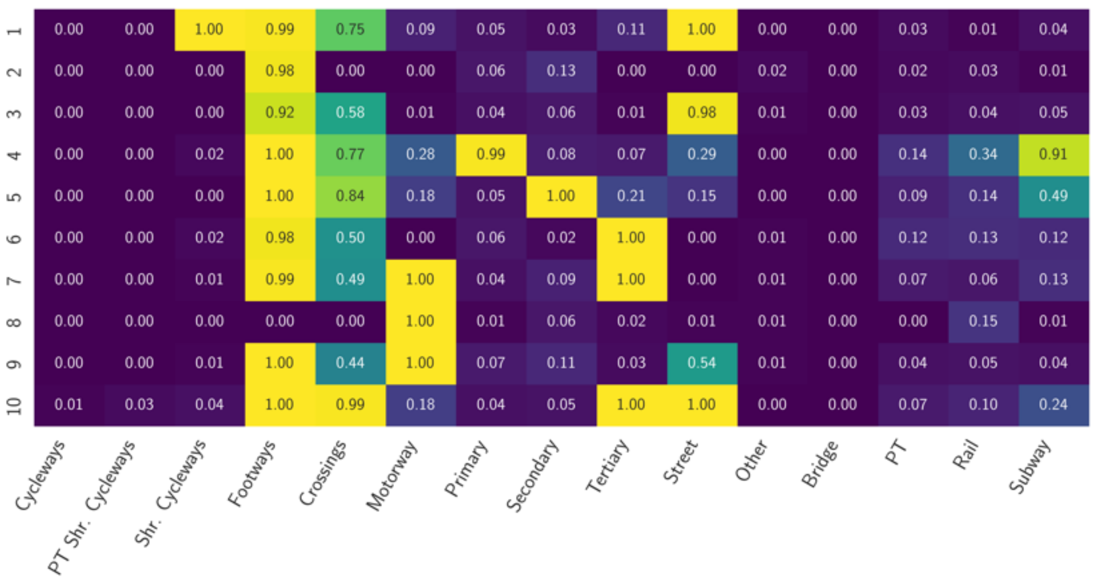
I used SC to uncover ten distinct Accident Environment Type (AET) in Barcelona pertaining to typical enviornments where cycling accidents have happened. Figure 4.2.a illustrates the ten AET found. Each row constitutes a type of environment, while columns indicate what types of infrastructures are present in each. The more yellow the cell is, the higher the association between that row's AET and infrastructure type. For example, AET 2 only large non-zero entries in the Footways and Tertiary roads columns, indicating that AET 2 is heavily constituted of Footways and contains Tertiary roads to some degree. AET 3 contains Footways, Crossings, and Streets, indicating an environment closer to an intersection between road and pedestrian networks. Finally, I note the special case of AET 8 which shown no key presence of any type of infrastructure, which represent accident locations that are far from any type of included infrastructure (i.e., corresponds to the centroid of a urban block, or in the middle of a park) and thus no infrastructure was captured.

Figure 4.3 shows the different AET across Barcelona. Here, one can look at the geographical distribution of AET and their dispersion across the different neighboorhoods. For instance, AET 7 can be seen more heavily around El Clot, whereas AET 10 is more prevalent around the Gothic Quarter. Further north-west, in L'Eixample, caracterized by its grid-style design, AET 3 and 5 are the most common AETs.

Similar to accident locations, I used the same procedure in locations in the whole city of Barcelona, aimed at comparing whether environment types throughout the city are identical to those of accident sites. To accomplish this, I randomly sampled 15.000 points (∼150 points/km^2) throughout Barcelona and applied the same methodological approach. Figure 4.2.b shows Barcelona's City Environment Type (CET) and their composition. Comparing the results for AET and CET, one can highlights several aspects:



(a)



(b)

Figure 4.2: Accident Environment Types (a) and City Environment Types (b) cluster representations.

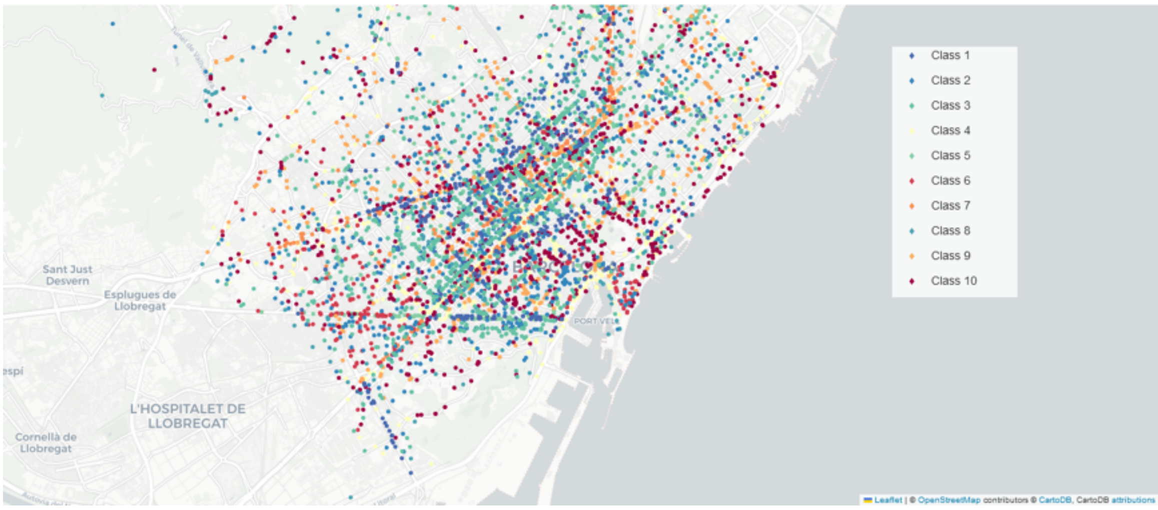


Figure 4.3: Accident Environment Types in Barcelona's accident locations.

- First, some environments are similar and appear in bot AET and CET, such as AET and CET 1, consisting of Shared Cycleways, Footings and Crossings, and Residential Streets. This entails that these environments are predominant in Barcelona and that there is a natural occurrence of accident on these sites;
- Second, and more importantly, some AET do not appear in the city-wide analysis, such as AET 7 through 9. This suggests that accidents happenning in these locations do not correspond to common environments in Barcelona, which, in turn, can mean that these built environment typologies are more prominent for the occurrence of cycling accidents.
- Next, looking at the cluster compositions, one can notice that sidewalks (Footways) and zebra crossings (Crossings) are the most common infrastructures. This makes sense since almost all streets and roads in Barcelona are present in both road sides. On the opposite spectrum, dedicated cyclelanes (Cycleways) and those shared with public transportation (PT Shared Cycleways), bridges, and dedicated public transportation infrastructure are very rare, both where accidents happen and throughout the city.
- Unsurprisingly, most accidents are also linked with residential streets, more than when looking at a city-wide scale. Similarly, motorways are much more significant in the whole Barcelona than where cycling accidents occur. This makes sense since cyclists are much less prone to cycle in major arterial highways or avenues where speeds tend to be higher and prefer much quieter, slower roads to cycle in (Buehler and Dill, 2016; Van Cauwenberg et al., 2018).
- Finally, it is worth noting that the majority of environments comprise numerous infrastructure components. Moreover, within AETs, we can observe that some consist of intersections, such as AET 6 or 10, which frequently encompass various road hierarchies, including residential streets as well as tertiary or secondary roads.

4.4 Summary and conclusions

In this chapter, I explored how data can be complemented to enrich existing cycling accident data. From cycling accident locations, I suggest a procedure to complement accident datasets with readily available geographical data and how it can be used to analyze typical infrastructures associated with cycling accidents.

Results highlight differences between cycling accident locations and common city environments, providing insights into how the built environment might influence cycling safety. Such findings show the value of augmenting existing cycling accident datasets using open data not found in the original dataset. Plus, the methodology here presented not only applies to the city of Barcelona but can be used to understand how different environment types might influence different cities and even find similarities between them.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/mncosta/aet_cet. Code is available for Python3. I present the code under Jupyter notebooks, which provide step-by-step instructions on how to reproduce the results here presented. The code is available under MIT license (https://opensource.org/licenses/MIT).

Chapter 5

Capturing Spatial Heterogeneity in Cycling Accident Severity Modeling

This chapter is partially under review as a journal article: "Costa, M., Lima Azevedo, C., Wilhelm Siebert, F., Marques, M., Moura, F. (N/A). Unraveling the Relation between Cycling Accidents and Built Environment Typologies: Capturing Spatial Heterogeneity through a Latent Class Discrete Outcome Model. [Manuscript under review in Accident Analysis & Prevention]."

5.1 Introduction

Cycling numbers have increased recently in many cities (Pucher and Buehler, 2017). Concurrent with this has been a growth in the display of stressful situations cyclists face. Despite a decrease in the number of fatalities from accidents in Europe in the past decade, fatalities resulting from cycling accidents have increased, representing about 10% of all accident fatalities in the European Union in 2020 (European Commission, 2022). The numerous dangers cyclists face, and their perceptions remain a major deterrent to cycling (Félix et al., 2019). Thus, strategies seeking to increase cycling numbers must provide safer conditions for those who cycle, whether through protected cycling infrastructure or education programs.

Research has tried to pinpoint and analyze what factors impact accidents to increase cyclists' safety. Ill-fated circumstances arise from interactions with other road users, pedestrians, or poorly designed infrastructure. A particular interest has been placed on the influence of the built environment since it can help planners design current and future safer cycling infrastructures and avoid severe accidents or all accidents, desirably. The impact of intersections, building densities, mixed land use, dedicated cycling lanes, and road hierarchies all affect cycling accidents (Zahabi et al., 2011; Chen and Shen, 2016a; Hu et al., 2018; Branion-Calles et al., 2020; Labetski and Chum, 2020; Bi et al., 2023). Understanding the impact of such urban features and their correlation to accident causes or contributing factors is vital to proposing adequate countermeasures to improve safety.

Yet, conducting such studies is not easy. Data on the built environment is often missing or not captured in accident records (Costa et al., 2022), albeit being essential for such analysis. To acquire this data, manual inspection of accident sites is usually employed, but this process constantly proves labor, time, and money-consuming. This data is particularly important to injury severity analysis to quantify danger and analyze how particular factors increase accident severities. More, while classic past research uses discrete outcome models (Kaplan et al., 2014; Chen and Shen, 2016a; Behnood and Mannering, 2017; Chen et al., 2017), generalized linear models (Chen and Shen, 2016a; Pedroso et al., 2016), or spatial models (Chen et al., 2017; Osama and Sayed, 2017), newer approaches started to explore machine learning models due to their usual higher predicting power, albeit lower explainable power (for models typically seen as black boxes). Yet, to the best of my knowledge, little research on cycling safety has tried combining machine learning and econometric approaches, exploiting the good predictive power of the former with the conventional explainability of discrete outcome models.

With this in mind, this chapter's main objectives are threefold:

- Apply a new two-part framework to analyze cycling accidents using Latent Class Discrete Outcome Model (LCDOM), a joint machine learning and econometric methodological tool.
- Use authoritative accident records augmented with VGI to understand the impact of built environment typologies and accident contributing factors on cycling accident severity outcomes.
- Understand how risk factors can be directly indexed to distinct built environment typologies and accidents simulated at a broader geographical scale.

My approach combines machine learning and econometric techniques to jointly estimate i) latent classes using a Gaussian-Bernoulli mixture and ii) a discrete outcome model directly applied to each estimated class, leveraging the power of unsupervised clustering to find classes of built environment types and the explainability of logit models conditional to such classes. I postulate that the comprehensive and holistic nature of the built environment may exert an impact on accident severity that individual components may not independently possess. Hence, this approach uses built environment classes to allow for more complex representations to capture heterogeneity in urban scenarios and better estimate interactions between built environment typologies and accidents' contributing factors, something unexplored in the literature, so far with such detail. With such a combination, one can extract vital insights from evermore larger and more complex datasets, retrieve essential understanding from cycling accidents, and align with McFadden's vision of a true discrete outcome model (Sfeir et al., 2021). I utilize this framework using authoritative accident records and VGI. I construct latent classes using a GBM, allowing binary and continuous variables to be used. Combining such data allows for more context-specific elements to be included in this analysis. This also steps away from traditional LCDOM research, where classes are typically used to cluster individuals based on their socioeconomic attributes. In contrast, here, I look to capture heterogeneity by latently classifying urban environments. Ultimately, this approach contrasts with other common methodologies, where impacts are assessed as a whole (as if all built environments were equal). With LCDOM, accident characteristics, and contributing factors can be found significant in one environment type but have no impact on others, highlighting the value of discovering and analyzing such relations.

Following this introductory section, I provide some specific background to this chapter and highlight related work in Section 5.2. Next, I explain the methodology and data used in Section 5.3, followed by the results in Section 5.4. In Section 5.5, I use the estimated model to simulate cycling accident outcomes and demonstrate how it can be used to understand and hypothesize how urban features and accident characteristics impact cycling safety in a whole neighborhood. I discuss the findings and results in Section 5.6, and finalize the chapter with conclusions and possible future research in Section 5.7.

5.2 Background

Cycling safety research investigates what factors may impact cycling accidents, their characteristics, and outcomes aiming at making cycling safer for everyone. Accidents are often complex events usually resulting from a combination and interaction of up to five different factors: human factors (e.g., driver, cyclist, or pedestrian behavior), traffic conditions (e.g., traffic density or velocity), infrastructure factors (e.g., roadway design, signalization), vehicle-related factors (e.g., characterization of the vehicle and its shape), and environment conditions (e.g., weather or lighting conditions) (Miaou et al., 2003). To increase cyclists' safety, researchers have tried to pinpoint and analyze what critical factors are more likely to increase accident severities. Street elements (Chen, 2015), road network (Marshall and Garrick, 2011), land use (Kaplan and Prato, 2015), cycling volumes and safety-in-numbers phenomenons (Elvik and Bjørnskau, 2017), and personal characteristics (Cripton et al., 2015) have been investigated and found to have an impact on cycling risk. Understanding how such factors impact cycling accidents is of the utmost importance, as it can guide planners and decision-makers to devise urban changes that lead to safer environments.

Within these factors, a particular interest has been put on how the built environment (i.e., infrastructure) and different behaviors (both cyclists' and drivers') may increase or decrease accident severity outcomes (Salmon et al., 2022). For one, planners can learn and plan how future infrastructures may help prevent or minimize accident outcomes, or education programs can be taught to promote less risky behaviors. Several elements have been studied, such as intersections (Zahabi et al., 2011; Hu et al., 2018), urban and building density (Chen and Shen, 2016a; Branion-Calles et al., 2020), bus and metro stops (Bi et al., 2023), road types and hierarchies (Bi et al., 2023), roadside elements (Wang et al., 2021), existence and types of bike lanes (Morrison et al., 2019), to name a few. However, studies typically select one type of infrastructure layout, urban characteristic, or contributing factor and analyze how it correlates to cycling accidents, to the detriment of investigating multiple hazards at once as is typically done in risk analysis (Yang et al., 2021). Understanding relations between different contributing factors is critical in any research attempting to understand cycling accident causation (Salmon et al., 2022).

Yet, such endeavors result because of data availability in accident observations. Those who study the topic often face many challenges, including under-reporting (Winters and Branion-Calles, 2017), fragmented records spanning multiple files and indexing, differing specifications, and unfeasible characteristics (Costa et al., 2022). These hurdles have hampered the comparison and transferability of models and findings between locations. To circumvent these problems, many have tried to perform and apply multiple data mining techniques to gather a complete set of characteristics on how and where accidents have occurred. This need for data mining techniques arises from the complex data on cyclist accidents (Scarano et al., 2023). Seeking to untangle such large and complicated datasets, results have shown that these data-mining methods may be preferred to more traditional econometric models by requiring relatively short data preparation time and providing good accuracy (Mannering et al., 2020; Rella Riccardi et al., 2022).

As such, recently, we have witnessed a rise in the use of machine learning models in cycling safety research. Researchers resort to methods such as deep neural networks (e.g., fully connected networks, convolutional neural networks, or generative adversarial networks) (Jeong et al., 2018; Zhao et al., 2019; Janstrup et al., 2022; De Bock and Verstockt, 2022) or other traditional models (e.g., random forest, logistic regression, nearest neighbor) (Cara and de Gelder, 2015; Jeong et al., 2018; Goldhammer et al., 2020; Fischer et al., 2022; Eriksson et al., 2022).Uniquely, some of these approaches combine conventional hospital and police accident records with other data sources to complement such records, enabling more contextual information about the accident to be examined. This steps away from traditional research approaches, where discrete (both ordered and non-ordered) outcome models (Kaplan et al., 2014; Chen and Shen, 2016a; Behnood and Mannering, 2017; Chen et al., 2017), generalized linear models (Chen and Shen, 2016a; Pedroso et al., 2016), or spatial models (Chen et al., 2017; Osama and Sayed, 2017) have been employed. Other approaches have used latent classes (subgrouping accident types, individuals, or infrastructure characteristics) to analyze and identify common risk factors that impact similar cycling accidents (Heydari et al., 2017; Prati et al., 2017; Myhrmann et al., 2021; Sekiguchi et al., 2022), or to perform spatial clustering on urban factors at different levels (Labetski and Chum, 2020). In particular, latent class discrete outcome models have sought to perform such type of subgroup clustering at population-level (Myhrmann et al., 2021), together with different accident characteristics, to model cycling accident severities. Latent class discrete outcome models are finite mixture approaches where mixtures arise from distinct subgroups with consistent features within each group. It differs from other random mixture approaches (e.g., mixed logits) as unobserved heterogeneity is not captured by a continuous mixture but rather by a discrete distribution that is represented by a specified number of classes. In turn, this frees the analyst from distributional assumptions on distribution parameters (Eluru et al., 2012). Comparisons between random parameters and finite mixtures have been conducted (Greene and Hensher, 2003; Shen, 2009), with results varying from case to case. Hybrid models to account for group and observation heterogeneity have been proposed (e.g., Greene and Hensher (2013); Xiong and Mannering (2013)), but, again, these require assumptions on random parameter distributions and can be structurally complex to model (Xiong and Mannering, 2013).

5.3 Methodology

This section describes the methodological framework applied to analyze cycling injury severity. First, in Section 5.3.1, I use a Gaussian-Bernoulli Mixture Latent Class Discrete Outcome Model (GBM-LCDOM) to model cycling accident outcomes, first introduced by Sfeir et al. (2021) in the context of travel mode choice. Second, I overview the data used in Section 5.3.2, using part of CYCLANDS present in Chapter 3 and following a similar approach to the one used in Chapter 4.

5.3.1 Gaussian-Bernoulli Mixture Latent Class Discrete Outcome Model

This section describes the methodological framework applied to analyze cycling injury severity. I use a GBM-LCDOM to model cycling accident outcomes, first introduced by Sfeir et al. (2021). LCDOM are random utility outcome models that expand the traditional multinomial discrete outcome model by employing the concept of the latent class formulation. LCDOM are divided into two sub-modules: the class membership model, responsible for categorizing observations into classes, and the class-specific component, responsible for explaining outcomes for each class. Using latent classes, LCDOM captures heterogeneity in the severity outcome process by allocating groups of observations to a set of defined classes distinct from each other. Observations are implicitly categorized into a set of K classes, with the analyst unaware of which observation belongs to which class (Greene and Hensher, 2003; El Zarwi, 2017). In my case, I assume that accidents are modeled by discrete types of built environments, which are latent (unobserved). In turn, these latent typologies are characterized by impacting accident outcomes differently and depending on accident characteristics.

While different extensions have been proposed to expand and loosen constraints on how classes are defined (Bujosa et al. (2010); Greene and Hensher (2013); Train (2016), to name a few), in this chapter I use a Gaussian-Bernoulli Mixture Latent Class Outcome Model (Sfeir et al., 2021). In contrast to previous approaches, GBM-LCDOM uses a mixture of distributions approach to model latent classes and improve their flexibility while retaining the interpretability trait of LCDOM. This way, the membership class component is a Gaussian-Bernoulli Mixture, a probabilistic machine-learning approach for unsupervised clustering. GBM can handle different size clusters, allows for incorporating continuous and binary variables, and can be used to estimate the probability of an observation belonging to a given class, proving a useful tool to estimate built environment classes for this problem.

Figure 5.1 presents an outline of GBM-LCDOM. First, as aforementioned, I hypothesize that different built environment typologies affect how cycling accidents occur. I assume these typologies are latent classes representing different subgroups of built environments that show similar outward characteristics, which I draw from street view images, mapping points of interest, and urban metrics. By estimating these subgroups jointly with the accident outcome model, the inferred subgroups are directly relevant to safety. I use the GBM class membership model to estimate these latent classes. Next, a traditional multinomial logit model specifically modeled each latent class, where utility functions are drawn using accident characteristics. Ultimately, I used these to model cycling accident outcomes.

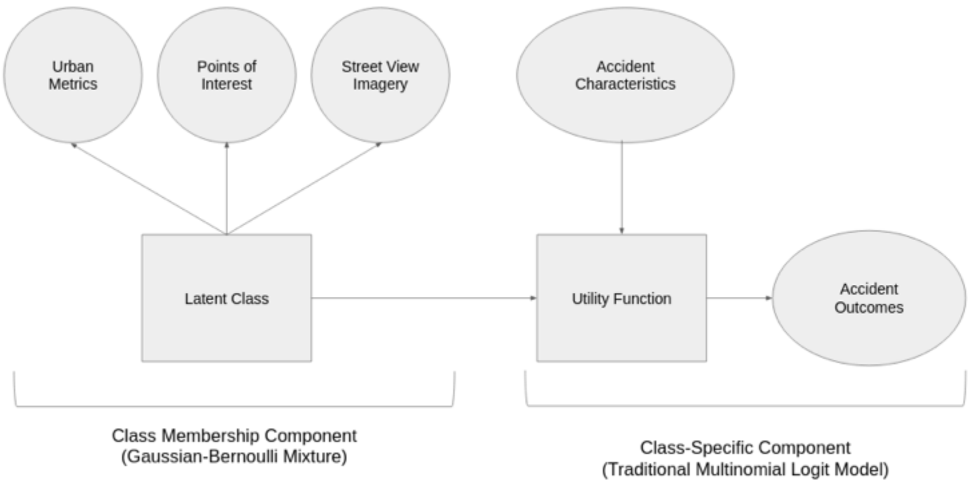


Figure 5.1: Gaussian-Bernoulli mixture latent class choice model for cycling accident outcome estimation.

I now present each sub-model of the GBM-LCDOM formulation and its estimation procedure using an Expectation-Maximization algorithm.

Class Specific

Cycling accidents result from a combination of different characteristics. Following past research (Mannering and Bhat, 2014; Savolainen et al., 2011), I model the outcome of cycling accidents as a function of observed exogenous attributes using an unordered framework, a multinomial logit (MNL). Multinomial logit models are traditional discrete outcome models that consider the accident outcome severity j as a linear function U defined as:

$$U_{njt} = \beta X_{njt} + \epsilon_{njt} \tag{5.1}$$

where β correspond to unknown parameters for a set of observed attributes X_{njt}, for accident observation n during time instance t, and ϵ_{njt} is a random error component that is expected to be independent and identically Extreme Value Type I distributed. The probability of an accident with outcome j among J possible outcomes can be expressed as:

$$P(y_{njt}|X_{njt},\beta) = \frac{e^{\beta X_{njt}}}{\sum_{j=1}^{J} e^{\beta X_{njt}}} \tag{5.2}$$

As aforementioned, I plan to determine the outcome of cycling accidents dependent on where these accidents occurred. Specifically to my case, I employ a multinomial logit to model accident outcomes (fatality, serious injury, or light injury) based on accident characteristics or contributing factors (e.g., crossing an intersection, turning, slippery road surface, darkness). This means that for different k built environment typologies (classes of built environments), I estimate a separate MNL model. This implies that the set of unknown parameters β is expanded to depend on class k. Similarly, without loss of definition, I expand the notation to specify that accidents occur on built environment n and different outcome situation t, with outcome situations responsible for capturing heterogeneity for equal environments (e.g., accidents occurring in the same location, on different time instances or situations).

Class Membership

The GBM is modeled by a Gaussian Mixture Model (GMM) combined with a Bernoulli Mixture Model (BMM), with continuous variables being introduced by the former and binary variables by the latter. I split the built environment features into two sub-vectors, B_{cn} and B_{dn}. B_{cn} corresponds to continuous features from built environment n (e.g., urban metrics such as closeness, betweenness, and objects extracted from street-view images) and B_{dn} to binary characteristics from built environment n (e.g., urban points of interest such as land-use, presence of cycleway, sidewalks, traffic lights). First, GMM stems from a combination of K Gaussian densities, $\mathcal{N}(B_{cn}|\mu_{ck},\Sigma_{ck})$. If, for a given component k and built environment n belongs to class q_{nk}, it is defined by:

$$P(B_{cn}|q_{nk}=1,\mu_{ck},\Sigma_{ck}) = \mathcal{N}(B_{cn}|\mu_{ck},\Sigma_{ck}), \tag{5.3}$$

with μ_{ck} and Σ_{ck} its mean and covariance, respectively. Second, the BMM is a combination of K mixture components, with each component k being a product of independent Bernoulli probability functions, which is defined as:

$$P(B_{dn}|q_{nk}=1,\mu_{dk}) = \prod_{i}^{D} \mu_{dki}^{B_{dni}}(1-\mu_{dki})^{B_{dni}}, \tag{5.4}$$

with B_{dni} being the binary built environment characteristic i out of D binary characteristics and μ_{dki} the Bernoulli component mean for component k.

Latent Class Discrete Outcome Model

The joint probability of B_{cn}, B_{dn}, q_{nk}, and accident outcomes y_n can be defined as:

$$\begin{aligned} &P(B_{cn},B_{dn},y_n,q_{nk}=1|X_n,\beta_k,\pi_k,\mu_{ck},\Sigma_{ck},\mu_{dk}) = \\ &\qquad P(q_{nk}=1|\pi_k)P(B_{cn}|q_{nk}=1,\mu_{ck},\Sigma_{ck})P(B_{dn}|q_{nk}=1,\mu_{dk})P(y_n|X_n,q_{nk},\beta_k) \end{aligned} \tag{5.5}$$

where $P(q_{nk}=1|\pi_k)=\pi_k$ and $\sum_k^K \pi_k = 1$ with π_k being a mixing coefficient representing the overall probability that an observation comes from component k (Bishop and Nasrabadi, 2006). The joint probability of B_{cn}, B_{dn}, y_n can be found by marginalizing (5.5) over all components K.

Finally, one can formulate the likelihood function of the GBM-LCDOM model as:

$$\begin{aligned} P(B_c, B_d, y) &= \prod_{n=1}^{N} P(B_c, B_d, y, |X_n, \beta_k, \pi, \mu_c, \Sigma_c, \mu_d) \\ &= \prod_{n=1}^{N} \sum_{k=1}^{K} \pi_k \mathcal{N}(B_{cn}|\mu_{ck}, \Sigma_{ck}) \prod_{i}^{D} \mu_{dki}^{B_{dni}} (1-\mu_{dki})^{B_{dni}} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J} e^{\beta_k X_{njt}}} \right]^{y_{njt}} \end{aligned} \tag{5.6}$$

Estimating GBM-LCDOM is a hard task because of the summation over k in (5.6) (Sfeir et al., 2021), setting its derivatives to zero will not lead to a closed-form solution (Bishop and Nasrabadi, 2006) as parameters $\pi_k, \mu_{ck}, \Sigma_{ck}, \mu_{dk}, \beta_k$ and classes q_{nk} cannot be simultaneously estimated, normal likelihood maximization becomes more time- and computationally-expensive as the number of parameters increases, and inverting the hessian matrix may become numerically challenging as empirical singularity issues may arise (Train, 2008). Thus, estimating GBM-LCDOM can be hard to estimate using normal likelihood maximization like other traditional discrete outcome models. However, if q_{nk} is known, then the remaining unknown parameters can be found using (log-)likelihood maximization. To circumvent this problem, I use an Expectation-Maximization (EM) algorithm. First, writing the joint likelihood for observed clusters (latent classes q_{nk}), yields:

$$\begin{aligned} &P(B_c, B_d, y, q) = \\ &\prod_{n=1}^{N} \prod_{k=1}^{K} \left[\pi_k \mathcal{N}(B_{cn}|\mu_{ck}, \Sigma_{ck}) \prod_{i}^{D} \mu_{dki}^{B_{dni}} (1-\mu_{dki})^{B_{dni}} \right]^{q_{nk}} \prod_{n=1}^{N} \prod_{k=1}^{K} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J} e^{\beta_k X_{njt}}} \right]^{y_{njt} q_{nk}}, \end{aligned} \tag{5.7}$$

and its corresponding log-likelihood:

$$\begin{aligned} &log(P(B_c, B_d, y, q)) = \\ &\sum_{n=1}^{N} \sum_{k=1}^{K} q_{nk} \cdot \log \left(\pi_k \mathcal{N}(B_{cn}|\mu_{ck}, \Sigma_{ck}) \prod_{i}^{D} \mu_{dki}^{B_{dni}} (1-\mu_{dki})^{B_{dni}} \right) + \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{t=1}^{T} \sum_{j=1}^{J} y_{njt} q_{nk} \cdot \log \left(\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J} e^{\beta_k X_{njt}}} \right) \end{aligned} \tag{5.8}$$

Now, the unknown parameters $\pi_k, \mu_{ck}, \Sigma_{ck}, \mu_{dk}, \beta_k$ can be found by using the derivatives of 5.8 if q_{nk} is known. To find q_{nk}, one can find its expectation (E-step) using Bayes' theorem:

$$\begin{aligned} &E[q_{nk}] = \gamma_{nk} = \\ &\frac{\pi_k \mathcal{N}(B_{cn}|\mu_{ck}, \Sigma_{ck}) \prod_{i}^{D} \mu_{dki}^{B_{dni}} (1-\mu_{dki})^{B_{dni}} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J} e^{\beta_k X_{njt}}} \right]^{y_{njt}}}{\sum_{k=1}^{K} \left[\pi_k \mathcal{N}(B_{cn}|\mu_{ck}, \Sigma_{ck}) \prod_{i}^{D} \mu_{dki}^{B_{dni}} (1-\mu_{dki})^{B_{dni}} \right]^{q_{nk}} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J} e^{\beta_k X_{njt}}} \right]^{y_{njt}}} \end{aligned} \tag{5.9}$$

Next, by maximizing the likelihood, one can find the unknown parameters. Again, since (5.9) cannot be maximized directly, one can compute the expected value of the log-likelihood, where one can use the q_{nk} expectation:

$$E[Log - likelihood] =$$
$$\sum_{n=1}^{N}\sum_{k=1}^{K}\gamma_{nk}\cdot\log\left(\pi_k\mathcal{N}(B_{cn}|\mu_{ck},\Sigma_{ck})\prod_{i}^{D}\mu_{dki}^{B_{dni}}(1-\mu_{dki})^{B_{dni}}\right)+\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{j=1}^{J}y_{njt}\gamma_{nk}\cdot\log\left(\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J}e^{\beta_k X_{njt}}}\right) \tag{5.10}$$

Setting the derivatives of (5.10) with respect to the unknown parameters to zero, one can obtain the values of $\pi_k, \mu_{ck}, \Sigma_{ck}, \mu_{dk}, \beta_k$ as:

$$\begin{aligned}
\pi_k &= \frac{N_k}{N} \\
\mu_{ck} &= \frac{1}{N_k}\sum_{n=1}^{N}\gamma_{nk}S_{cn} \\
\Sigma_{ck} &= \frac{1}{N_k}\sum_{n=1}^{N}\gamma_{nk}(S_{cn}-\mu_{ck})(S_{cn}-\mu_{ck})' \\
\mu_{dk} &= \frac{1}{N_k}\sum_{n=1}^{N}\gamma_{nk}S_{dn} \\
\beta_k &= \arg\max_{\beta_k}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J}y_{njt}\gamma_{nk}\cdot\log\left(\frac{e^{\beta_k X_{njt}}}{\sum_{j=1}^{J}e^{\beta_k X_{njt}}}\right)
\end{aligned} \tag{5.11}$$

with $N_k = \sum_{n=1}^{N}\gamma_{nk}$. All parameters, except β_k can be found in a closed-form solution. As for β_k, one can resort to a gradient descend numerical method. All in all, EM is an iterative process split into two parts: first, the expected values of the latent classes q_{nk} are estimated (Expectation (E)-step), and then, the unknown parameters $\pi_k, \mu_{ck}, \Sigma_{ck}, \mu_{dk}, \beta_k$ are updated (Maximization (M)-step). After this, the log-likelihood is evaluated and checked for convergence (i.e., the log-likelihood has not improved by a given margin, or a given number of maximum iterations has been performed). If convergence has not been achieved, E-step and M-step is repeated. Algorithm 5.1 presents the pseudocode for this procedure.

Algorithm 5.1 EM algorithm to estimate the GBM-LCDOM

1: Initialize $\mu_{ck}, \Sigma_{ck}, \pi_k, \mu_{dk}, \beta_k$
2: **E-Step**: Estimate the expected values of q_{nk} using (5.9)
3: **M-Step**:
4: Using the posterior probabilities of q_{nk} from the E-Step compute the expected value of the log-likelihood function using (5.10).
5: Set its derivative and update the values of $\mu_{ck}, \Sigma_{ck}, \pi_k, \mu_{dk}$ via closed-formed solution and β_k using gradient-based optimization.
6: Evaluate the log-likelihood of current parameter estimates and check if convergence criteria were met. If not, return to step 2.
7: After converging, estimate the marginal probability with respect to accident locations, built environment characteristics, accident characteristics, and accident outcomes can be computed for out-of-sample prediction.

5.3.2 Data

This section describes the data used in this analysis. Cycling accidents and their characteristics are presented, as well as summary statistics, including how I perform data augmentation with built environment details using volunteered geographical information through mapping and imagery data.

Accident Data

In this work, I explore how GBM-LCDOM can be used to understand and analyze cycling accidents in Berlin, Germany. I start by filtering the data corresponding to the city of Berlin from the CYCLANDS cycling accident collection presented in Chapter 3 and Costa et al. (2022).

Accidents include vehicular traffic accidents based on police reports where personal injury has occurred (property damage-only accidents are not included). Observations are registered by the police and undergo a multi-stage check process. This analysis focuses on cycling accidents between 2018-2019, totaling 7516 cycling accidents. Details include location, date, road surface conditions, light conditions, accident type, collision type, and accident severity outcome. Table 5.1 presents descriptive statistics of the observations in the data.

Accident outcomes are split between 3 levels depending on the accident's outcome: i) fatalities (if an individual has passed away within 30 days as a result of the accident), ii) serious injuries (if an individual is immediately taken to the hospital for treatment for at least 24 hours), and iii) light injuries (which include any other form of injuries). Police officers recorded accident characteristics at the accident location, together with road surface circumstances, type of accident, and collision. Accident location (geographic coordinates) is also noted and verified *a posteriori* to ensure correct positioning using a plausibility algorithm (Statistische Ämter des Bundes und der Länder, 2021).

Given the importance of analyzing and understanding the built environment's impacts on cycling accidents and similarly to the previous chapter, I augment cycling accident characteristics with available open data. Consequently, I add built environment data to each cycling accident using mapping data (through OpenStreet Map) and street-view imagery data (using Mapillary[1]).

Data Augmentation: Mapping Information

Adding to the cycling accident data, I extract data from volunteered geographic data sources, similarly to Chapter 4. First, I pull data from OSM[2]. OSM data contains geographic information about the world contributed by users who voluntarily add to its creation, edition, and expansion. Data elements represent physical characteristics (e.g., roads, trees, buildings, or traffic signals) and their location. Elements are often categorized into specific groups (e.g., primary roads, lamp posts, fences) and may include many details (e.g., type of road, number of lanes, type of traffic signal).

In this section, I use accident locations (geographic coordinates) as a starting point to extract information about the built environment where accidents happened. I build a private server of Overpass[3] and load an instance of OSM data from December 31st, 2020, which I use query OSM data. Since

[1] https://www.mapillary.com/
[2] https://www.openstreetmap.org
[3] https://overpass-turbo.eu/

Table 5.1: Descriptive statistics of cycling accidents in Berlin, Germany for the period 2018-2019.

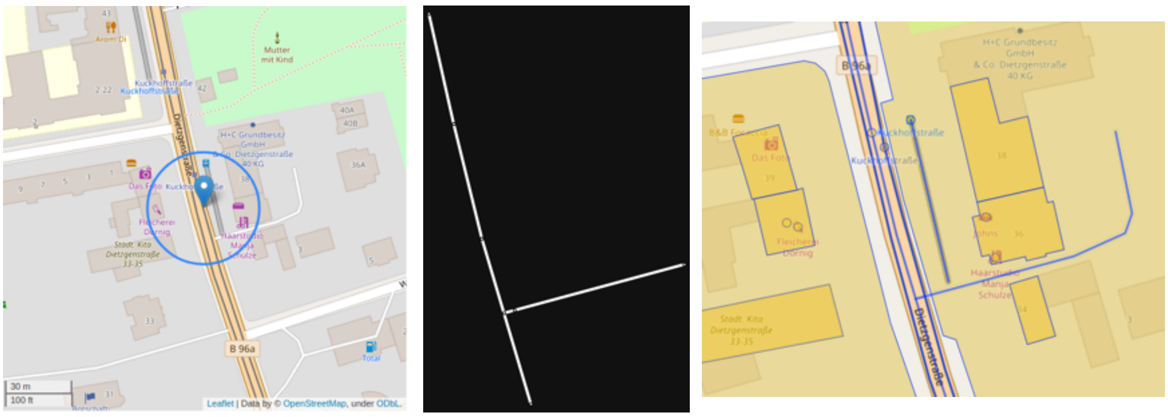
Accident Characteristics	n	%	Accident Characteristics	n	%
Accident Outcome			**Vehicles**		
Fatality	13	0.2	Bicycle	7516	100.0
Serious Injury	1034	13.8	Car	5772	77.0
Light Injury	6469	86.0	Motorcycle	143	1.9
Date			Goods Vehicle	201	2.7
Year			Other	737	9.8
2018	3830	51.0	**Light Conditions**		
2019	3686	49.0	Daylight	6008	79.9
Month			Twilight	424	5.6
January	340	4.5	Darkness	1084	14.5
February	335	4.5	**Accident Type**		
March	383	5.1	Moving vehicle	401	5.3
April	659	8.8	Turning off the road	2852	37.9
May	882	11.7	Turning into the road	2231	29.7
June	966	12.9	Crossing the road	323	4.3
July	754	10.0	Stationary vehicle	567	7.5
August	843	11.2	Moving along in the carriageway	696	9.2
September	782	10.4	Other	446	5.9
October	651	8.7	**Collision Type**		
November	519	6.9	Collision with stopped vehicle	529	7.0
December	402	5.3	Collision with moving vehicle ahead	446	5.9
Hour			Collision with vehicle moving laterally in the same direction	409	5.4
00:00 - 04:00	123	1.6	Collision with oncoming vehicle	87	1.1
04:00 - 08:00	771	10.3	Collision with other vehicle crossing the road	4598	61.2
08:00 - 12:00	1883	25.1	Collision with pedestrian	409	5.4
12:00 - 16:00	2005	26.7	Collision with obstacle	7	0.1
16:00 - 20:00	2163	28.8	Leaving carriageway to the right	13	0.2
20:00 - 00:00	571	7.5	Leaving carriageway to the left	3	0.0
Road Surface Conditions			Other	1015	13.5
Dry	6332	84.2			
Wet	1156	15.4			
Slippery in Winter	28	0.4			

I am interested in the immediate surroundings of cycling accidents, I extract all available information within 25-meter radius of accident locations (similar to the approach employed by Moosavi et al. (2019); Golze, J and Feuerhake, U and Sester, M (2022) approach). This value was chosen to be big enough to capture available information in the immediate surroundings of accident locations (including both sides of the road and any buildings next to it) yet small enough to disregard any data from objects/buildings not directly on line-of-sight of accident locations (e.g., structures and objects behind buildings next to the road where the accident occurred) and potentially introduce noise.

First, the data extracted from each location contains 729 different elements. To reduce the number of variables, I ontologize OSM elements given their urban function. For example, I aggregate *football fields*, *basketball courts*, and other sports locations into a single *sport* category, or *benches* and *post boxes* into a single *street furniture* category. In short, I summarize OSM data into 68 categories (hereafter named OpenStreetMap Points of Interest (OSM POIs)), such as sports, shops, building types (e.g., residential, commercial, civic), land use (e.g., residential, commercial, industrial), or circulation spaces (e.g., roads, highways, streets, cycleways, footways). I use these urban features as specific built environment elements to understand whether particular components impact cycling accidents.

Second, from the same OSM data, I compute urban metrics. I use the walkable, cyclable, and drivable networks to add urban morphology metrics and characteristics using `osmnx` (Boeing, 2017) around accident locations. In short, I include information about street length, existence and type of intersections (e.g., 3-way, 4-way), betweenness, closeness, and degree centrality (Boeing, 2017). I use OpenStreetMap metrics (OSM Metrics) data to understand whether urban morphology plays a role in cycling accidents, contributing to typical built environments where cycling accidents happen.

Figure 5.2 shows how data is extracted from OSM given an accident location, such as the network from which urban metrics are computed and other points of interest, including buildings, land use, and the presence of a bus stop.



(a) (b) (c)

Figure 5.2: Cycling accident location and area around accident location where data is extracted from OpenStreetMap (a) such as urban metrics from the available network (b) and urban elements as buildings, land use, or bus stops (c).

Data Augmentation: Street-View Imagery Information

Finally, I add SVI data to each cycling accident observation. Following recent trends using images to evaluate urban features and perceptions (Najafizadeh and Froehlich, 2018b; Song et al., 2020; Ito and

Biljecki, 2021; Ye et al., 2021; Ding et al., 2021; Gong et al., 2019), I use SVI from accident locations as another way to add contextual built environment data to this analysis. For this, I use images from Mapillary, which consists of street-level images contributed collaboratively by users.

As before, I use accident locations' (geographic coordinates) to fetch up to 5 images within 10 meters to minimize the effect of dynamic events captured in each photo while ensuring that each image reflects the built environment where accidents occurred. Since users voluntarely contribute images, imagery coverage varies from location to location. This means that I retrieve only one image for some observations, while for others I retrieve five images (4.74 images retrieved by accident location on average).

Following this step, I automatically extract information from each retrieved image using semantic segmentation. Semantic segmentation is the process of labeling each image's pixel to a given class given what is being represented, i.e., a traffic sign in an image would have its corresponding pixels labeled as *traffic sign*. In this work, to automatically extract information about the represented objects (classes) in each image, I use OCRNet (Yuan et al., 2020) with the HRNetV2p-W18 backbone and trained on Cityscapes, which has achieved high accuracy in processing SVI. I feed-forward the retrieved images from Mapillary and, for each image, extract 1) the presence of each class, i.e., if the class appeared on the image, and 2) the ratio of pixels categorized as one class over the total number of pixels in the image, i.e., the area occupied per class in the image. Figure 5.3 shows an example of an original image from an accident location before and after I perform semantic segmentation. In total, 19 classes are extracted: *road*, *sidewalk*, *building*, *wall*, *fence*, *pole*, *traffic light*, *traffic sign*, *vegetation*, *terrain*, *sky*, *person*, *rider*, *car*, *truck*, *bus*, *train*, *motorcycle*, and *bicycle*.

(a) (b)

Figure 5.3: Example of a Mapillary image corresponding to an accident location (a) and its semantical segmentation information using Yuan et al. (2020) (b). Different objects are encoded using different colors and information from images regarding the presence of different objects are extracted.

5.4 Results

This section details the results of modeling cycling accidents using GBM-LCDOM, including the results for both the class membership and the class-specific components. I describe each built environment class and how different accident characteristics are impactful in some environments but not others. I identify the value of the data augmentation process and joint model estimation, which can provide insights into cycling accidents and the locations where these happen.

Implementation Details

As aforementioned, I estimate the GBM-LCDOM using an EM algorithm for maximizing the joint likelihood function for the class membership and class-specific components. EM's convergence was assumed when a change in the log-likelihood function was smaller than 0.0001, or a maximum of 1000 iterations had been performed. The model always converged before the limit of 1000 iterations. Although the EM algorithm is a powerful method for estimating models containing latent variables, it is sensitive to starting values and might not guarantee convergence to the global maximum (Bishop and Nasrabadi, 2006). Different approaches have been proposed to overcome this limitation, including random initialization. I randomly initialize all parameters and estimate the model 10 times. Finally, I check whether all runs converge to the same solution, which I find true.

As described before, GBM-LCDOM comprises two sub-models: class membership and class-specific components. First, I used the mapping and imagery data to create built environment classes (class membership) and then used accident details to estimate the probability of accident severity outcome (class-specific) for each estimated class. I split the mapping and imagery data variables into continuous and binary variables. The former were used in the GMM, whereas the latter was used in the BMM component of the class membership sub-model. The number of estimated classes K needs to be specified *a priori*. I used the Akaike Information Criterion (AIC) (Akaike, 1974) to determine the optimal number of classes. For the class-specific component, I used the accident characteristics for the linear function U. To statistically improve the model, I iteratively removed coefficients that were not statistically significant at the 10% level, beginning with the least significant one. I repeated this process until only significant variables at the 10% level were left, or the AIC did not improve further.

In sum, modeling each accident outcome was a lengthy process of carefully and thoughtfully evaluating the available data and model results, trying different specifications and variable interactions. Accident outcomes may result from various factors as each accident most certainly results from different characteristics, both in terms of accident contributing factors and built environment features. The results below show the model with the best results, harvesting the best relation between model results and interpretability of why cycling accidents resulted in such outcomes. Next, I present the results of the class membership and class-specific sub-models, followed by the overall GBM-LCDOM goodness of fit indicators.

Class Membership

Table 5.2 summarizes the class membership sub-model results for six built environment classes ($K = 6$), as per the details above, from which I draw the key difference between the built environment classes. The complete results can be found in Appendix C. I show both the results for the BMM containing the binary context variables and the continuous context variables, i.e., the GMM component of the class membership. For each class, I present the existence or absence of a given attribute in that specific class. Because input data is standardized, higher values indicate the attribute is more present than average, and lower values mean a lower presence of the displayed attribute in that environment.

With this in mind, one can analyze and understand what these built environment classes represent. For instance, Class 1 includes more residential buildings and land use levels, with fewer industrial and commercial areas. Cycleways are present, as access to the subway. Conversely, there is less parking and access to buildings. Poles, traffic lights, signs, bars, cafes, and restaurants are abundant to serve residential buildings. Figure 5.4 shows examples of street view images for each class. Doing the same analysis for the remaining classes, one can semantically and more generally characterize each built environment as a whole:

- **Class 1 - Residential with Cycling Infrastructure:** Residential area with cycling infrastructure and connections to public transport, bars, cafes, and restaurants. Street furniture is present with fewer amounts of vegetation.
- **Class 2 - Wide Intersections:** Large intersection with high presence of cycleway, sidewalks, and pedestrian crossings. Not many buildings are present, yet trees, plants, and flowers exist. Public transportation networks for buses, trams, or subways exist, with some on-street parking.
- **Class 3 - Central Residential:** Residential area with some vegetation, bars, cafes, and restaurants, little parking, and no heavy vehicles or primary road infrastructure.
- **Class 4 - High Traffic Intersection:** Main road intersections, where heavy vehicles are typically seen, together with buses and trains. There are many traffic signs and walls/fences and lower amounts of vegetation.
- **Class 5 - Distribution Centers:** Commercial and predominant industrial area, highly accessible by main roads, where usually there is little infrastructure for pedestrians and cyclists. There are more vegetation and on-street parking than average and little traffic signage.
- **Class 6 - Car-oriented:** Car-driven infrastructure with many commercial buildings, focused on signalized primary roads and parking spaces, with fewer opportunities for cycling.

Figure 5.5 shows the classified built environments for all accidents, and I highlight two particular cases: Bergmannstraβe and Straβe des 17. Juni. For the former, one can see an overall trend where cycling accidents happen on this street, as most occur at intersections, thus being classified as Class 4. Nevertheless, in one particular case, the accident location was classified as Class 5. The same trend can be seen in the latter example. These events highlight one key aspect of LCDOM and how it can be actually used. The rationale behind the Class Membership component of LCDOM is a sort of spatial clustering submodule, grouping environments that are closely linked in terms of urban context (one would expect that observations spatially closer together contain similar characteristics). However, it outlines that these particular locations are distinct in terms of their attributes and built environments. Thus, they are classified into different clusters. In practice, using this approach, one can highlight areas that are slightly different from their immediate surroundings. In turn, this may indicate that further analysis ought to be performed on these particular observations to understand the impact of that built environment on accidents and hypothesize how urban changes to that particular location (i.e., transforming it by including features from safer environments) may improve safety.

Table 5.2: Summary of key class membership coefficients for the GBM.

μ_k=-1 μ_k=1

		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Image Objects	Building	0.2019	-0.1155	-0.1815	0.1820	-0.1389	0.2052
	Wall	-0.1406	-0.1449	-0.0384	0.7926	-0.0570	-0.2205
	Fence	-0.1098	-0.1111	0.0239	0.4120	0.0796	-0.2264
	Pole	0.1405	-0.0746	-0.0722	0.1531	-0.1715	0.0838
	Traffic Light	0.1639	-0.0483	-0.1288	0.0434	-0.2471	0.3142
	Traffic Sign	0.1390	-0.1272	-0.0612	0.3203	-0.1155	-0.0856
	Vegetation	-0.2713	0.1919	0.2496	-0.3249	0.2315	-0.3052
	Truck	0.3736	-0.2597	-0.2843	0.5162	0.0732	-0.1835
	Bus	-0.1870	-0.1925	-0.1608	0.3393	-0.1957	0.7023
	Train	-0.1488	-0.1529	-0.1548	1.1116	-0.1547	-0.1535
	Bicycle	0.4969	-0.3194	-0.3678	0.0015	-0.3467	0.7998
Urban Metrics	Drive: Count of Intersections	0.0307	0.6807	-0.1042	0.2187	-0.6522	-0.1383
	Drive: Degree Centrality	-0.0961	-0.7446	0.0523	-0.1360	0.8785	0.0901
	Bike: Count of Intersections	-0.2239	0.9188	-0.3299	0.2889	-0.3884	0.0341
	Bike: Degree Centrality	0.1602	-0.7595	0.3368	-0.1565	0.2529	-0.1244
	Walk: Count of Intersections	0.0138	0.6875	-0.2516	0.2261	-0.4496	-0.0518
	Walk: Degree Centrality	0.0926	-0.6442	0.3203	-0.1689	0.2289	-0.0980
Points of Interest	Bar/Cafe/Restaurant	0.1409	-0.1319	0.0817	-0.0424	-0.0853	-0.0705
	Building: Residential	0.0915	-0.2371	0.1108	-0.0546	0.0343	-0.0539
	Land-use: Residential	0.0939	-0.1749	0.1361	-0.0120	-0.0977	-0.0790
	Land-use: Industrial	-0.0666	-0.0276	-0.0559	-0.0024	0.1942	0.0302
	Land-use: Commercial	-0.1083	0.0526	-0.1520	-0.0149	0.2354	0.1520
	Land-use: Greenery	0.0227	0.3060	-0.0311	0.0090	-0.2436	-0.0774
	Cycleways	0.1554	0.0715	0.0262	0.0497	-0.2737	-0.1019
	Sidewalk	0.0051	0.3600	-0.1636	0.1457	-0.2459	0.0257
	Sidewalk crossing	0.0813	0.4590	-0.0103	0.0778	-0.5738	-0.0896
	Motorway	-0.6184	0.3572	-0.6042	0.1482	0.9298	0.5031
	Primary Road	-0.0554	0.4043	-0.1534	0.0818	-0.2736	0.1231
	Residential Street	0.1093	-0.2105	0.1715	-0.0502	-0.1181	-0.0721
	Rail	0.0047	0.1273	-0.0318	0.0184	-0.1216	0.0201
	Rail subway	0.0875	0.1867	-0.0117	-0.0337	-0.2500	-0.0187
	Barrier	-0.0035	0.1671	-0.1286	0.0041	-0.0051	0.0666
	Barrier Access	-0.1676	-0.0698	-0.1601	0.0538	0.4186	0.1352

Street Furniture	0.1205	-0.0447	0.0185	-0.0101	-0.0931	-0.0402
PT Stop	0.0284	0.0677	-0.0020	0.0322	-0.1252	-0.0101
Parking	-0.1353	0.1019	-0.2032	0.0848	0.2516	0.1248
Notes: π_k	0.1085	0.1648	0.1952	0.1605	0.1161	0.2550

Values correspond to the GMM μ_c parameters for Image Objects and Urban Metrics and the BMM μ_d parameters for Points of Interest.
For the entire results, we refer the reader to Appendix C.

Class 1 Class 2 Class 3

Class 4 Class 5 Class 6

Figure 5.4: SVI from each built environment class.

(a)

(b)

(c)

Figure 5.5: Classes of accident location according to its built environment (a) and the particular case of Bergmannstraβe (b) and Straβe des 17. Juni (c).

With the ability to distinguish and interpret urban environment classes, and since GBM is a probabilistic model, one can individually look at the probability of a given accident location being classified into one of the six existing classes. This fundamental concept of the class membership component allows for further analysis into whether a location is well defined within its built environment class or whether a specific location is a liminal environment between 2 or more types. Looking at the probabilities of all observations' environments, I found that 99% of accidents are distributed across the six classes with probabilities higher than 70%, suggesting the classes found have highlighted the typical cycling accident environments well.

Next, I compute the cosine similarity between each class to identify how similar or disparate environment classes are. Cosine similarity is a measure that captures the similarity between two nonzero vectors and can be computed using

$$\text{Cosine Similarity} = \frac{\mathbf{Q_i} \cdot \mathbf{Q_j}}{\|\mathbf{Q_i}\| \|\mathbf{Q_j}\|} \tag{5.12}$$

with $\mathbf{Q_i}$ being the vector characterizing Class i (i.e., the result from the mixture model means for each class) and $\|\mathbf{Q_i}\|$ its magnitude and it can vary between -1 (classes are the complete opposites) and 1 (classes are equal). Figure 5.6 shows the cosine similarities between all six classes. As one can see, Class 2 and 5 and Class 3 and 6 are very different from one another, whereas Class 1 and 6 show some signs of sharing similar attributes. The classes found are mostly different from one another, emphasizing that the built environments found capture the variety of urban contexts in the city of Berlin. In practical terms, it can also serve as a surrogate measure for the cost of transforming environments from one to the other. For example, if one understand that a given urban setting is riskier for cyclists, ideally, one would transform these spaces by including some safety features from safer ones. By analyzing urban settings' inherent and accident characteristics dependency, planners and decision-makers can hypothesize the cost of such transition.

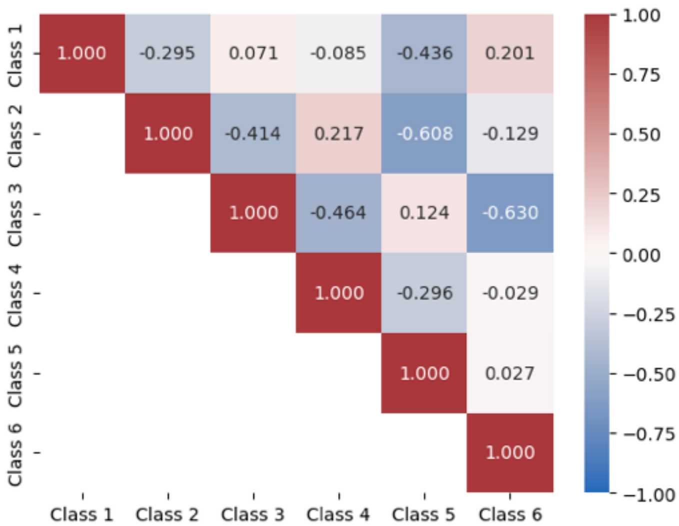


Figure 5.6: Cosine similarity between all environment classes.

Class Specific

Together with the class membership, I jointly estimate the class-specific component, which maps the impact of different accident characteristics on accident outcomes. Again, a multinomial logit is estimated for each urban environment class found. Table 5.3 shows these results for each class and further details on the joint GBM-LCDOM model estimation.

Looking at the estimated parameters, one can notice a few key differences between the different classes. Notably, not all accident characteristics are significant in all urban environments. In fact, due to the nature of LCDOM, I can accurately identify statistically significant characteristics in some environments while remaining redundant in others (e.g., collision with a vehicle ahead). On the other hand, some features (e.g., being dark or involving a heavy vehicle) appear significant (in differing degrees) in almost all classes.

Looking into more detail at the results, I also identify several other key aspects, from which I highlight a few. First, I notice different Alternative Specific Constant (ASC) throughout the classes. This entails that the average effect of each severity outcome is slightly different for each environment. Namely, Classes 2 and 5 show an ASC closer to the reference value than the remaining classes, indicating that the pre-defined/uncaptured risk is slightly higher in these environments. Unnacounting for the remaining accident contributing factors, this means that for accidents that happen in locations of classes 2 and 5 (Wide Intersections and Distribution Centers), there is a higher probability of accidents resulting in fatalities. Next, accidents occurring in locations of Classes 1 and 6 (Residential with Cycling Infrastructure and Car-oriented locations) exhibit a higher chance of resulting in Serious Injuries (with average probabilities of 19% and 22%, respectively) than the remaining environment classes. As aforementioned, if the goal is to transform locations to include features from safer environments, planners and decision-makers should look into environments from Class 3 - Central Residential, as accident outcome probabilities from these environments showcase the lower odds of resulting in Fatal or Serious Injuries.

Table 5.3: Class-specific component results: outcome model for each built environment class.

	Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**
ASC (SI)	4.89 (15.00)***	4.41 (14.80)***	4.72 (20.18)***	4.89 (14.18)***	4.29 (10.90)***	4.88 (22.46)***
ASC (LI)	6.32 (19.42)***	5.95 (20.07)***	6.48 (27.77)***	6.49 (18.90)***	5.93 (15.11)***	6.14 (28.21)***
Collision w/ car (SI)						
Collision w/ car (LI)						0.47 (2.23)**
Collision w/ heavy vehicle (SI)	-3.60 (-5.37)***	-2.45 (-4.93)***	-2.80 (-7.24)***	-3.37 (-6.11)***	-2.20 (-3.95)***	-2.37 (-6.47)***
Collision w/ heavy vehicle (LI)	-4.14 (-6.55)***	-3.13 (-6.29)***	-3.15 (-8.48)***	-3.95 (-7.63)***	-3.00 (-5.54)***	-2.92 (-8.08)***
Collision w/ other vehicle (SI)	-0.80 (-1.79)*	-0.60 (-1.68)*	-1.02 (-2.68)***	-1.10 (-2.10)**	-0.60	-0.57 (-1.94)**
Collision w/ other vehicle (LI)						
Wet/Slipery road (SI)						
Wet/Slipery road (LI)	0.47 (1.58)*		0.50 (2.16)**			
Darkness (SI)	-0.81 (-2.16)**	-0.47 (-2.09)**	-1.14 (-5.12)***	-0.40 (-1.63)**		-1.03 (-4.79)***
Darkness (LI)	-0.84 (-2.25)**	-0.64 (-2.82)***	-1.24 (-5.60)***	-0.61 (-2.51)***	-0.54 (-1.80)*	-0.83 (-3.89)***
Moving vehicle (SI)	1.11 (2.24)**	0.96 (2.53)***	0.77 (2.49)***	1.76 (4.02)***	1.19 (2.47)**	0.97 (3.06)***
Moving vehicle (LI)				1.08 (2.48)***		0.53 (1.67)*
Turning into road (SI)	0.72 (3.02)***	0.58 (2.93)***	0.29 (1.63)*	0.43 (1.91)**		0.24 (1.53)*
Turning into road (LI)						

Crossing the road (SI)					0.63 (1.36)**
Crossing the road (LI)					
Stationary vehicle (SI)		0.78 (2.32)**			
Stationary vehicle (LI)		0.64 (1.91)**	0.92 (2.35)***		
Moving in carriageway (SI)	0.96 (2.26)**		0.61 (2.08)**		1.12 (2.00)**
Moving in carriageway (LI)	1.03 (2.45)***		0.56 (1.90)**	0.72 (1.63)*	1.09 (1.97)**
Collision w/ vehicle ahead (LI)					-1.89 (-4.37)***
Collision w/ vehicle ahead (SI)					-2.46 (-3.62)***
# of Observations	7516				
AIC	15181.22				
BIC	45713				
Joint Final Log-Likelihood	-219505.1				
Joint-ρ^2	0.33				

Notes: Values showcase the model parameters β_k, with t-test values in parenthesis.
Fatal outcome was set as the reference category for all variables. SI: Serious Injury, LI: Light Injury.
***, **, *: Significance at 1%, 5%, 15% level. Parameters beyond a 15% significance level were omitted.

Next, I analyze the impact of accidents involving heavy vehicles. Accidents involving these vehicles significantly increase the odds ratio of resulting in a *Fatal* accident. The same can be seen when accidents happen in the dark, although with lower odds ratio than those involving heavy vehicles.

Another set of takeaways can be drawn by analyzing the accident characteristics' results throughout the different classes. First, an accident where there was a collision with a vehicle in front is only statistically significant for Class 5. This makes sense since Class 5 environments show the highest decrease in the presence of cycleways, making cyclists ride on the road. This points to accidents involving bikes hitting a vehicle in front or being run over from behind due to the lack of dedicated cycling lanes in these locations for cyclists to ride on much more significant.

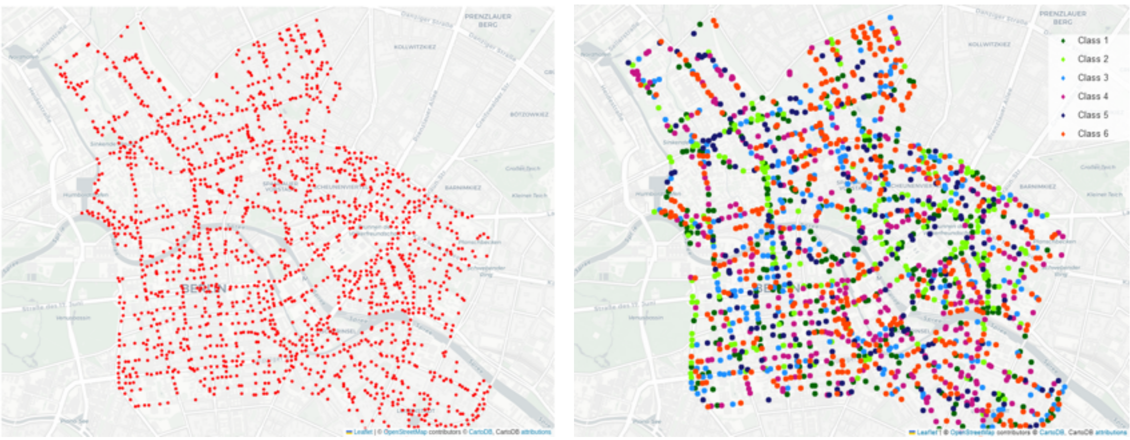
Interestingly, having an accident with a moving car (*While Driving*) and while turning (*Turning into road*) is mainly significant for accidents resulting in *Serious Injuries*. Although it is vital to find that these maneuvers increase the odd ratio of only serious injuries and do not result in increased odd ratios of *Fatal* accidents, it is necessary to find out why this happens. A possible reason for this is lower speeds while cars turn, resulting in non-fatal accidents. However, lowering the impact of such accidents on cyclists is paramount, so additional analysis needs to take place to understand how these infrastructures can be changed to minimize these accidents (or constraining accidents to result in lower severities).

5.5 Accident Simulation and Mapping

Predicting and mapping cycling accident risk can be helpful for urban planners, road safety researchers, decision-makers, and cycling advocates. Such a tool can be used to understand and analyze the network as a whole, identifying key areas where infrastructure changes are needed or better information should be given to road users to make cycling safer. To illustrate how this model can be used to analyze cycling risk further, I exemplify how accident prediction and mapping can be performed using GBM-LCDOM. Next, I describe the data used in this illustration, its results, and its analysis.

Data

To demonstrate GBM-LCDOM's potential as a planning tool, I simulate the outcomes of cycling accidents throughout a neighborhood in my case study city: Mitte, Berlin's central district. First, I uniformly sample points throughout Mitte's road network every 25m, providing comprehensive and complete coverage of the entire neighborhood. Following the approach described in Section 5.3, I use the geographical coordinates of these points to extract actual data from OSM and Mapillary, collecting context data about the urban and built environment in and around each location. Again, data regarding urban metrics, urban images, and points of interest are collected to characterize each point's type of environment. I disregard places where a complete set of urban metrics, OSM POIs, and images is unavailable. Figure 5.7.a shows the 1688 sampled points in Mitte, which I then use to simulate cycling accident risk.



(a) (b)

Figure 5.7: Distribution of simulated accident locations in Berlin's Mitte (a), and their associated built environment types (b).

Accident Simulation

After generating fictitious accident locations and collecting the associated data, I use the estimated GBM-LCDOM to compute the probability of different cycling accident outcomes with different accident characteristics. In other words, I simulate the impact of varying accident contributing factors per environment class utilizing each location's data. First, using the GBM, I compute the probability of a given location belonging to any of the six urban environment classes found above. Figure 5.7.b shows the estimated environment class for each site. After assigning the location to the class with the highest probability, I simulate the impact of different accident characteristics on the accident outcome using Equation 5.2.

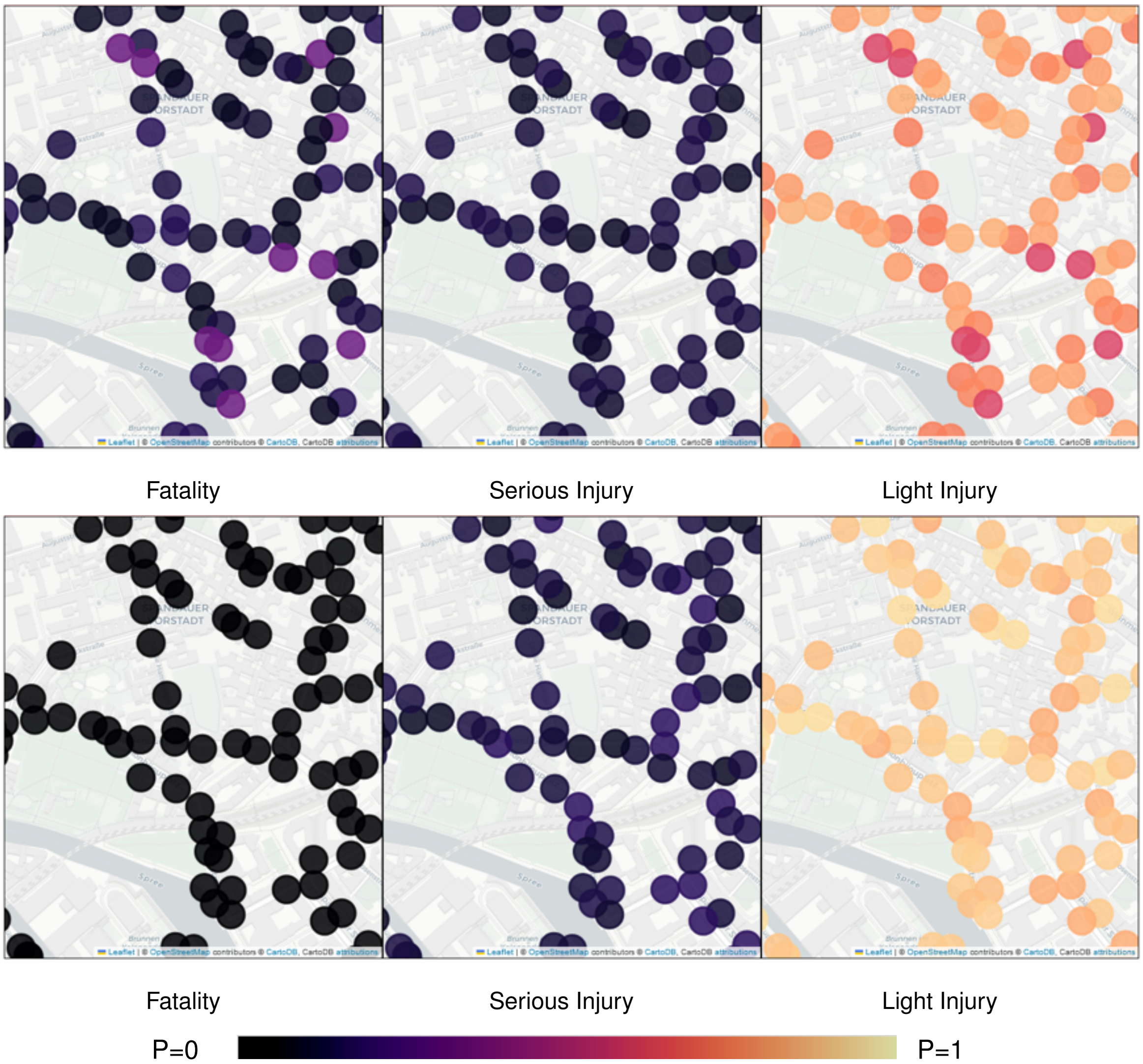


Figure 5.8: Predicting accident outcome probabilities for different scenarios. Top: cycling accident involving heavy vehicles colliding with cyclists in darkness; Bottom: involving other stationary vehicles and a wet/slippery surface.

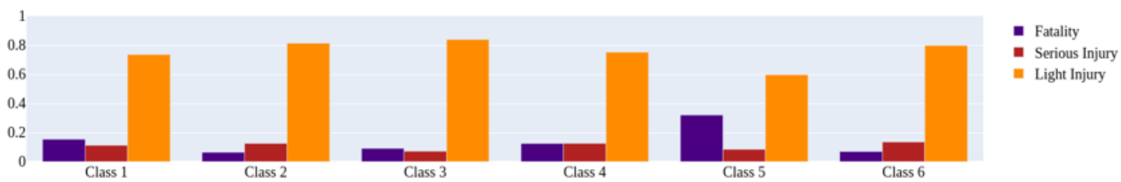


Figure 5.9: Accident outcome probabilities across the six classes for Simulation B.

Figure 5.8 shows the predicted outcome probability distribution (light injury, serious injury, and fatality) for different simulated accident characteristics, assuming a cycling accident happened in the sampled locations. To exemplify, I simulate two types of accidents and illustrate how the probability of different outcomes varies according to the area where the simulated accidents happen. I simulate A) accidents involving heavy vehicles colliding with cyclists in darkness (top) and B) involving other stationary vehicles and a wet/slippery surface (bottom).

As one can see, different accident characteristics impact the probabilities of the accident outcome differently. Also, depending on the built environment context where accidents happen, these characteristics directly impact accident outcome probabilities. For instance, in Simulation A (which recreates accidents with the characteristics that increase the odds ratios of fatal outcomes the most), I identify locations with a higher probability of resulting in fatalities for areas of Class 5, 1, 6, and 4. Figure 5.9 highlights the varying outcome probabilities according to which environment class the accident belonged to, despite the same accident characteristics. As shown, Class 5 exhibits the highest fatality probability of 32%, followed by Class 1 (15.4%), Class 6 (13.4%), Class 4 (12.3%), and lower for Classes 2 and 3 (probabilities lower than 9%). Simulation B shows the impact of collisions between cyclists and other stationary vehicles while the road is wet/slippery. As shown, accident severities also differ according to where accidents happen, with very low odds of fatalities and barely any difference between locations, but varying probabilities for *serious injuries* for different sites.

Despite being possible to simulate other examples of accident types in different combinations of contributing factors, the two examples above highlight the applicability of GBM-LCDOM. On the one hand, one can use this framework to understand what environments and accident characteristics pose more danger to cyclists. On the other hand, it highlights the connection between the two, allowing researchers to see this interaction and account for built environment heterogeneity, something often overlooked in the literature.

5.6 Discussion of findings

To improve cycling safety, research has analyzed the impacts of human, traffic, infrastructure, vehicle-related, and environmental factors (Miaou et al., 2003). In this chapter, I combined machine learning and discrete outcome models to analyze the influence of the built environment and contributing factors to cycling accident outcomes. This combination allows for more complex representations to capture heterogeneity in urban environments and, consequently, better estimation of the existing interactions between urban factors and accidents' contributing factors. This diverges from previous methods, which have explored cycling safety either by using machine learning or econometrical methods. The former, often employed in data mining studies to identify typical groups sharing identical behaviors or characteristics, typically outperforms the latter in terms of accuracy (Cantarella and de Luca, 2005; Lee et al., 2018) and yet, discrete outcome modelers do not trust such methods due to the missing connection with economic theory (Brathwaite et al., 2017) and its unclear econometrical interpretation (Wang et al., 2020). By combining the two approaches, GBM-LCDOM aims at embedding unsupervised clustering techniques in an econometric framework that is aligned with McFadden's vision of a genuine choice model (Sfeir et al., 2021), keeping its interpretability while also considering some of the machine learning advantages, such as the need to be able to extract vital insights from evermore larger and complex datasets and expound critical understanding from accidents and why these happen.

GBM-LCDOM uses a membership component to cluster and classify built environments based on urban physical characteristics and a specific component to quantify the impact of different accident-contributing factors. Using this modeling framework, one can concomitantly analyze the effect of various factors and their relation to different built environment typologies in a two-step process: first, looking at types of built environments where cycling accidents occur; and second, understanding how different contributing factors impact accident outcomes (severities) on those locations.

With the first (membership) component, I classified urban environments into six different classes. These classes use high-dimensional VGI to classify urban contexts in a probabilistic approach. However, using VGI has its challenges. On the one hand, it allows to draw knowledge from multiple sources and, therefore, use much more data than typically allowed and available; on the other, every single urban characteristic is not fully verified. Data completeness has been improving, with efforts from users and private and public organizations, with estimates for transportation infrastructure being complete for Germany (Barrington-Leigh and Millard-Ball, 2017) and other critical infrastructures characteristics being continuously updated (Nirandjan et al., 2022). Even so, the lack of complete information is not confined to VGI as it is known in accident reporting and understood to be a common problem in accident reports (Rolison et al., 2018). Notwithstanding, a clustering component can overcome dependence on a single variable as the classification of different classes does not entirely rely on a single feature but instead on a combination of multiple urban characteristics. One can use the resulting clusters to identify urban context classes and spot their differences with ease and, ultimately, capture urban heterogeneity. This differs from other approaches, which seek to quantify the impact of various characteristics directly and individually, whereas with this approach, one creates classes of environment typologies. Ultimately, this also implies that these classes can be used to understand how the context of where cycling accidents happen can impact its outcomes. In turn, practitioners can use this analysis to understand what city areas have an inherently higher chance of increasing cycling accident severities and take measures to decrease such risk. Accidents usually do not result from a single factor but rather a combination of different factors (Mannering et al., 2016). By analyzing the location's context altogether, devising measures to transform the built environment as a whole might help increase cycling safety. More importantly, it enables the capture of a collective effect of these elements and, in essence, showcasing that the built environment has a holistic influence on the severity of accidents, as opposed to impacts from individual elements.

Next, conditional on said classes, the second (specific) component offers quantifiable insights into accident outcomes. Here, I used a multinomial conditional logit for each built environment class to analyze the impact of each accident characteristic and its impact on accident severities. The results show what factors permeate all urban environments and those specific to particular built environment typologies. This approach brings forth a pivotal difference to traditional discrete outcome modeling as contributing factors can be directly linked to being significant in some cities' areas or whether contributing factors are impactful regardless of where the accident has happened. In practice, such understanding can help planners prioritize and target a specific set of dangerous elements in a group of known locations or tackle another impactful factor regardless of location.

GBM-LCDOM features a finite mixture strategy, which contrasts with random parameter approaches as one captures subgroups of built environments with distinct attributes. Yet, both aim to capture heterogeneity among observations. As such, I have tried to compare this approach to a random parameter one (i.e., mixed logit), which has been used before in cycling safety research (e.g., Chen et al. (2017)). To do so, I have used the available data, both accident contributing factors and built environment characteristics, as independent variables, tried multiple mixing distributions, and "utility" formulations to predict accident outcomes. This proved unsuccessful, as a valid model with satisfactory and statistically significant results could not be estimated as I kept running into non-invertible Hessian matrices, which I believe is linked to the dimension and complexity of this problem and data. This follows past research that compared finite to random mixture models and outlined that results vary from one case study to the other and is hard to analyze which approach is statistically better (Shen, 2009; Greene and Hensher, 2013). Yet, as found and supported by the results, using such a finite mixture approach is of great value as it captures a more holistic nature of how the built environment may exert an impact on accident severity, rather than individual components of the built environment.

Compared to typical latent class discrete outcome models, this mixture model offers more flexibility than the traditional linear-in-parameters utility specification of the latent classes, allowing it to capture complex heterogeneity better. Plus, it circumvents the usual problem of manually specifying and selecting what explanatory variables might influence latent classes, which can only be performed by experts or following previous studies. Another takeaway of GBM-LCDOM relates to its estimation procedure. Classical latent class discrete outcome models focus on estimating the class membership and class-specific components separately. While such an approach often yields meaningful results, estimating both sub-models jointly has shown to provide better out-of-sample prediction and to better represent heterogeneity without weakening the interpretability of the model (Sfeir et al., 2021). This implies that planners' and researchers' analyses using such a procedure find the best possible fit between urban contexts and accident characteristics, meaning better information can be used to devise strategies to minimize cycling accident consequences. Alternative to the estimation procedure used (EM), other estimation methods, such as Bayesian estimation, have shown to have some advantages over EM (Depaoli, Sarah, 2013), which should be explored in the future. Moreover, for practical purposes, GBM-LCDOM can group observations closely linked to the urban context and highlight certain observations that are slightly different from their surroundings. This may indicate that further analysis ought to be performed on these particular observations to understand the impact of that built environment on accidents and hypothesize how urban changes to that particular location (i.e., transforming it by including features from safer environments) may improve safety.

Finally, I draw from the estimated model to illustrate how such knowledge can be used to predict and analyze an entire neighborhood or city. The example shown directly applies the estimated model to analyze and hypothesize how the city “behaves” concerning cycling safety. In this context, urban environments can be examined, and accident characteristics can be simulated to help visualize, predict, and eventually understand the impact on cyclists. Predicting hypothetical accident outcomes is not new but has been gaining popularity in recent years with the advent of evermore available data and more detailed models (see, for example, (Vandenbulcke et al., 2014; Collins and Graham, 2019; Moosavi et al., 2019; Xie et al., 2021)). Even though cycling accident risk is far from being negligible in locations where no reported cycling accidents happened, such mapping tools serve as an approach that can aid in drawing measures and locating places with a higher potential for more harmful or costly accidents.

5.7 Summary and conclusions

This chapter explored how a GBM-LCDOM can be used to model and analyze cycling safety. This approach combines machine learning techniques with traditional discrete outcome modeling, leveraging the former’s flexibility and power of dealing with complex interactions and the latter’s conventional explainability capabilities. Additionally, while traditional latent class discrete outcome models are typically used to capture behavioral heterogeneity, in this work, I was able to capture heterogeneity within built environment contexts where cycling accidents happen.

LCDOM consists of two components: class membership and class-specific sub-models. First, by using GBM-LCDOM, I clustered environments into classes that share specific urban features related to either road networks or physical traits, such as cycleways, bars, cafes, or restaurants. Secondly, given each context class, I characterized accident outcomes given their characteristics or contributing factors. By combining this approach within a single estimation procedure, this methodology best approximates what key accident characteristics are impactful in specific urban environments (and not in others) and vice-versa. The joint estimation procedure helps to determine better how physical urban characteristics are related to cyclists’ accidents, potentially helping urban planners and decision-makers mitigate problems specific to either component.

I applied GBM-LCDOM to accidents in Berlin, drawing typical environments where cycling accidents occurred and understand what types of accidents have more consequences than others and where. I draw from this knowledge to illustrate how this methodology can be used to analyze a whole neighborhood or city. Such a tool quantifies potential cycling accident outcomes and can help road safety researchers and decision-makers develop strategies to reduce the risk cyclist face.

Supporting materials

Supporting materials, namely the code used, for this section are available at `https://github.com/mncosta/lcdom`. Code is available for Python3. The code is available under MIT license (`https://opensource.org/licenses/MIT`).

Part A: Summary of Key Findings

In Part A, I focused on cycling accidents and their link to the built environment. The following items emerged as essential points from the carried research.

Cycling accident data needs to be better standardized and detailed

Cycling accident data is becoming more easily attainable as more cities publish road accident data. However, it is often fragmented, and details differ for different publishing authorities, hindering knowledge transfer and comparison from one location to another. CYCLANDS, the proposed collection, takes a step towards this undertaking, compiling and homogenizing characteristics of cycling accidents. Looking ahead, more effort needs to be put forward to better standardize cycling accident data to expedite research in cycling safety.

Combining authoritative cycling accident data with volunteered geographical data

Despite being more available than before, cycling accident records still fail to account for many critical factors about the involved individuals, the surrounding built environment, or other accident characteristics. To overcome this, I have proposed a new data augmentation process by combining both authoritative and volunteered geographical data (mapping and imagery data). Such an approach proved helpful, driving insights from accidents and their connection to typical urban settings where these have happened. Further research should look at expanding these endeavours with other available open data, such as weather data, or traffic counts.

Integrating machine learning and discrete outcome models to analyze cycling accidents

I have explored how machine learning techniques (known for their flexibility and power to deal with complex interactions) can be combined with traditional discrete outcome modeling (characterized by its explainability capabilities). This approach captured heterogeneity within built environment contexts where cycling accidents happen, discovering what key accident characteristics are impactful in specific urban environments (and not in others) and vice-versa. This can help planners better understand how physical urban characteristics relate to cyclists' accidents in an era where data is becoming larger and more complex.

Tool for continuously simulate the impact of physical factors on cycling safety

As demonstrated, GBM-LCDOM can be used to understand cycling safety at a neighborhood-wide scale (or larger) and how different cycling environments relate to various accident factors. Predicting hypothetical accident outcomes has been gaining popularity in recent years. As such, mapping tools are a necessary approach that can aid in drawing measures and locating places with a higher potential for more harmful or costly accidents. In the future, more simulation scenarios ought to be tested and verified such that a more global testbed can be setup to uncover dangerous circumstances to cyclists.

Understanding cycling safety at a larger scale

The work developed here was framed to easily and automatically help researchers and decision-makers analyze large areas of interest. However, it has mainly focused on presenting and analyzing its impact on a single city. As such, surveying how it would be used in other cities is vital to understand whether similar built environments (classes) arise from those found in Berlin. Such a study may lead to further insights into cycling safety and how cyclists can, more generally, be protected.

Some accident factors permeate all urban environments, whereas others are specific to particular built environment typologies

Through Chapters 4 and 5, I postulate that there are a number of different built environment typologies that influence cycling safety differently. Results have confirmed this, with different classes inherently having different levels of risk (with different probabilities of accident severities), and having different relations to accident contributing factors. These results expound that accident circumstances are affected differently by the location where they have happened, highlighting the fact that, depending on any cities goals, different strategies need to be taken. In essence, there is no “one solution fits all”, with different plans of action needing to be devised, both in terms of changes to the built environment as to accident contributing factors, to increase cycling safety.

Holistic nature of how the built environment may exert an impact on accident severity

The approach used captures spatial heterogeneity through a finite mixture approach, which contrasts to more traditional random parameter model strategies employed in the past where individual elements of the urban context are analysed. Although the latter was tested, no statistically valid model could be estimated. Yet, as found and supported by the results found, using such a finite mixture approach is of great value as it captures a more holistic nature of how the built environment may exert an impact on accident severity, rather than individual components of the built environment, suggesting that such methodology is of great value when dealing with such intricate relations between accident severities, accident contributing factors, and built environment.

Part B

Subjective Cycling Safety

What have we learned so far

So far, we have looked at cycling safety from an objective standpoint, analyzing the relation between the built environment, accident circumstances, and accident severities. While such understanding helps reduce the occurrence and severity of accidents, it does not encompass individuals' perceptions about accident risk, which are often regarded as a major barrier for people to cycle. This subjective side of cycling safety is typically approached via *in loco* surveys or post-riding interviews, often revealing themselves as slow and not easily scalable. Again, faster and scalable approaches need to be developed so swift urban changes can take place to improve the sense of safety felt by cyclists.

What we will explore next

Seeking to develop a more scalable approach to continuously and ubiquitously evaluate individuals' perceptions of cycling risk, we will explore a new strategy to score urban environments based on their perceived levels of cycling safety. As we will discover, this new methodological approach using multiple machine learning tools to learn and understand individuals' perceptions can help planners and decision-makers design environments where cyclists feel safer. We will also explore how such an approach can be used to analyze and map subjective safety at a city-wide scale, allowing one to analyze how different areas in a city are felt by cyclists.

Research Questions

2. What urban factors impact the perception of cycling safety?

2.1. *Can we capture cycling safety perception through street-view images?*

2.2. *Can we understand cycling perception of safety in a scalable and continuous manner?*

2.3. *How do different urban elements influence the perception of risk?*

Subjective cycling safety research aims to comprehensively analyze fears and perceptions that individuals have about accident risk when cycling. Perception of cycling risk is heavily associated with the decision to cycle and, as such, if cities' goals are to increase cycling numbers, they must provide cyclists with environments they feel safe to cycle in. This part presents my contribution to studying cycling safety perceptions through a new approach to assess the impact of built environment on individuals' safety perceptions, highlighted in Figure B

Chapter 6 lays out the foundations for the remainder sections in this chapter. Here, I present the deployed survey which used a novel approach to studying subjective cycling safety through pairwise image comparisons. In this survey, I repeatedly presented respondents with two road environment pictures and asked them to select the one they perceived as safer for cycling, while also collecting data on respondents' cycling profiles. Unlike traditional surveys, this methodology is often more straightforward, well suited for non-experts participants, and generally leads to lower measurement error than direct ratings (Perez-Ortiz and Mantiuk, 2017).

Chapter 7 demonstrates how one can transform paired comparison observations into perceived safety scores. I reviewed and compared current literature paired comparison models, demonstrating how they can objectively classify cycling environments based on individuals' perceptions. In essence, these models rank items with an easily understood score. Lastly, I exemplified how such scores can be used to model perceived safe or unsafe environments.

Chapter 8 presents a deep learning approach to predict the outcome of paired image comparisons. All in all, the introduced model predicts which image would be perceived as safer when shown two cycling environments, seeking to simulate human perception of cycling safety. While improving accuracy over traditional paired models explored in Chapter 7, the proposed model extends current literature by including ties (when there is no perceived safety difference between two images), which are often discarded in the literature. In the end, I believe this approach leads to much better subjective safety score estimates and can be used to analyze subjective cycling safety at a city-wide scale, as I demonstrated for Berlin.

Chapter 9 explores what urban factors impact perceived cycling safety. For that, I employed an Explainable Boosting Machine to quantify the impact of different factors on the previously estimated subjective safety scores. These factors included both imagery and mapping data, including built environment elements, road users, and urban morphology. This approach accounted for both non-linear effects and pairwise interaction between factors, enabling more in-depth constructs to be formulated on individuals' perceptions. Ultimately, I showed that while some factors can be analyzed linearly, others' effect on subjective safety is non-linear, and careful considerations ought to be made when designing policies or recommendations for urban changes to make cyclists feel safer.

Finally, I close this part, providing a summary of findings within these chapters and contributions. Overall limitations are addressed and I layout possible research directions on perception of cycling safety.

Part B: Subjective Cycling Safety
(Chapters 6, 7, 8, and 9)

Pairwise Image Comparison Survey
(Chapter 6)

⇒ New approach to study perception of safety using pairwise image comparisons;

⇒ Survey deployed online to capture individuals' cycling profiles and safety perceptions.

Pairwise Comparion Modeling
(Chapter 7)

⇒ Scoring environments from pairwise comparisons on their perceived cycling safety levels;

⇒ Comparison of different pairwise models;

⇒ Classification of which environments are perceived safe and unsafe.

Learning Perceived Scores from Images
(Chapter 8)

⇒ PCS-Net: a siamese-convolutional neural network capable of estimating an image's perceived cycling safety which allows ties to be included;

⇒ Perceived safety scores are learned directly from images;

⇒ A simulation tool to understand cities perceived cycling safety levels.

Non-linear Effects of Urban Elements
(Chapter 9)

⇒ Interpreting perceived safety scores based on automatically extracted information from images and their surroudings;

⇒ Simultaneous large-scale analysis of urban elements impact on perceived safety;

⇒ Interpreting non-linear and pairwise interactions effects of urban factors.

Figure B: Summary of research for Part B: Subjective Cycling Safety. Part B is divided in four chapters and main research highlights are listed for each chapter.

Chapter **6**

Pairwise Image Comparison Survey

This chapter details the survey I used to capture individuals' perception of cycling safety. A new approach was used by using pairwise image comparisons, which steps away from traditional methods of using Likert-scale based questionnaires to enquire people's perceptions. An online survey was designed to collect data on individuals' perceptions of cycling safety. It was designed to be simple and take approximately 10 minutes to complete. It was reviewed and approved by Instituto Superior Técnico's Ethics Committee. I will now detail its structure in Section 6.1 and overview the data collection process and sample in Section 6.2.

6.1 Survey Structure & Questions

Users taking the survey were informed of the data being gathered, its aim, how it would be used, and its risks, which, in this case, were next to none, as no identifiable information was being gathered. When starting the survey, users had to agree to the terms of consent (a copy is available in Appendix D), at which point they could start the survey. If refused, the survey would immediately terminate at no cost or penalty to the user.

The survey was divided into two parts. First, a small questionnaire aimed to classify the respondent according to their cycling profile, following a categorization popularized by (Geller, 2006). Second, respondents would be repeatedly presented with two road environment pictures and asked to select the one they perceive as safer. I will now explain both survey parts in detail.

6.1.1 Survey Part I: Cycling Profiles

Seeking to categorize users into distinct profiles according to their cycling proficiency, the first part of the survey asked individuals a series of simple and direct questions. Appendix E shows a copy of this survey part. A modified version of Dill and McNeil (2016) survey was used to accomplish this. This part of the survey was subdivided into three sections:

1. First, some questions seeked to contextualize individuals' cycling background and bicycle use:
   - *Do you agree of disagree with the following statement: "I like to use a bicycle?"*
     If respondents disagreed, they would be forwarded to the next section after answering the following questions:
     - *What is the main reason for you not to cycle?*
     - *Would you consider cycling if you could?*
   - *How often do you cycle?*
   - *How long have you been cycling for (more regularly)?*
   - *When do you cycle?*
   - *What is the main purpose of your cycling trips?*
2. Next, a series of written descriptions asked respondents about their comfort levels cycling in different situations in the original survey. To approximate this survey from the second part (where images of cycling environments are shown), I replaced these written descriptions of cycling situations with virtual photos generated using Unity (Unity Technologies, 2023) depicting the descriptions provided. Figure 6.1 shows the queried images. For each image, respondents were asked how comfortable they would be riding a bike in such a situation (using a 7-point Likert scale).
3. Finally, some questions collected socio-demographic data:
   - *What is your age?*
   - *How would you describe your gender?*
   - *What city are you based in?*

I aimed at classifying users into four possible classes, popularized by (Geller, 2006): *No Way, No How*; *Interested, but Concerned*; *Enthused and Confident*; and *Strong and Fearless*. For this, I employed Dill and McNeil (2016)'s approach using the above questions. Appendix F shows a flow chart with the classification process for each profile class.

(a) Segregated cycle lane.

(b) Residential street with no traffic.

(c) Residential street with high levels of traffic.

(d) Main street with cycling lane.

(e) Main street.

Figure 6.1: Virtual environments used during Part I of the survey to assess respondents' cycling profiles.

6.1.2 Survey Part II: Pairwise Image Comparisons

The second part of the survey consisted of pairwise image comparisons, a robust methodology that sought to explore and quantify individual preferences. In essence, I repeatedly presented respondents with two real-world images of cycling environments and asked them to select the one they considered safer for cycling. Equally sized images were shown side-by-side, and users could choose the image they thought was safer for cycling between the left image and right image, or, if they thought there was no apparent difference between the two, they could choose a "tie" option. Figure 6.2 depicts an example of the setup used.

Images showcasing different cycling environments were extracted from five different European Cities: Barcelona (Spain), Berlin (Germany), London (United Kingdom), Munich (Germany), and Paris (France). These captured a wide range of infrastructure layouts, urban features, lighting conditions, traffic conditions, etc. For later (in Part C) to perform a comparative analysis between objective and subjective cycling safety, images from cyclable environments were extracted from Mapillary from locations where

Figure 6.2: Pairwise image comparison survey. Example of cycling environments being assessed. Users are shown two images and asked to choose between the left and right images and a tie option, depending on which appears safer for cycling.

cycling accidents occurred in the past. Thus, using the CYCLANDS collection presented in Chapter 3, I downloaded SVI from cycling accident locations in the five cities above.

Next, given the wide range of cycling environments captured, I performed a fractional factorial design to choose which pairs of images were shown to users. Here, I pre-processed each image (cycling environment) to extract context data around each location, similar to the process described in Section 5.3.2:

- **Semantic data:** semantically segmenting each image and extracting built environment data using the OCRNET (Yuan et al., 2020), a deep learning model to perform semantic segmentation. For each image, I extracted object areas from the image, i.e., how much of the image corresponds to vegetation, people, cars, etc., and
- **Street-level data:** extracting built environment data in a 20m radius around each location from OSM, capturing road hierarchies, land use, the presence of cycling lanes, urban furniture, etc.

Next, I used semantic and street-level data to create possible pairs by defining a subset of matching information between images (e.g., the same level of cars, vegetation, and cycling lanes) while allowing the remaining variables to vary freely. This fractional approach to factorial design ensured that maximum information could be gained by choosing pairs of images to be shown while, at the same time, using a fraction of the full factorial design in terms of experimental runs, which would be impossible to cover given the problem's dimension.

Lastly, given all pairs of possible images to be shown, I prioritized images shown fewer times in the past, ensuring that, as the number of comparisons grows to infinity, all images were shown the same amount of times. All in all, a pair of images was shown to the user to maximize the information gained by each comparison. Figure 6.3 shows some examples of images presented in the survey.

Figure 6.3: Examples of cycling environment SVI used in the survey from Berlin.

6.2 Data Collection & Sample

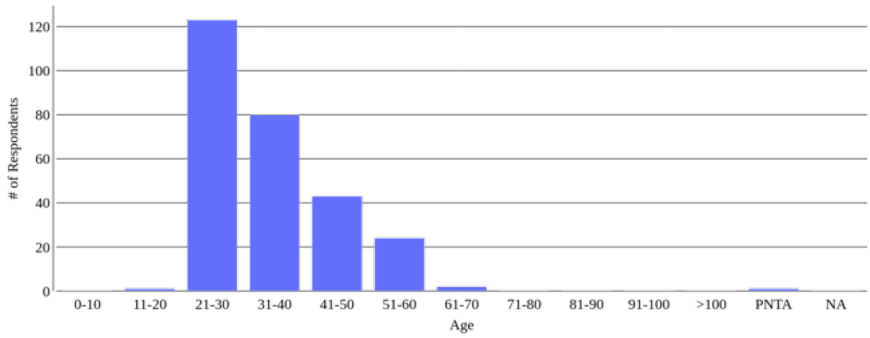
The survey was deployed in August of 2022 following a convenience sample approach. The survey was distributed on social media, the press, and mailing lists. Under an online-only format, the survey seeked to collect answers from a diverse backdrop of respondents with different cycling contexts and backgrounds.

As of March 2023, data was collected from 275 respondents. Descriptive statistics from Part I of the survey are shown in Table 6.1 and Figure 6.4 from those who answered the survey. As aforementioned, cyclists were classified using Dill and McNeil (2016)'s approach as: *No Way, No How* (6.2%); *Interested, but Concerned* (52.5%); *Enthused and Confident* (37.3%); and *Strong and Fearless* (4.0%). This distribution differs slightly from the regional household survey by Dill and McNeil (2016), especially for the *No Way, No How* class. However, this is to be expected since those who cycle or will potentially cycle are more willing to answer the conducted survey and potentially be rewarded with environments that feel safer.

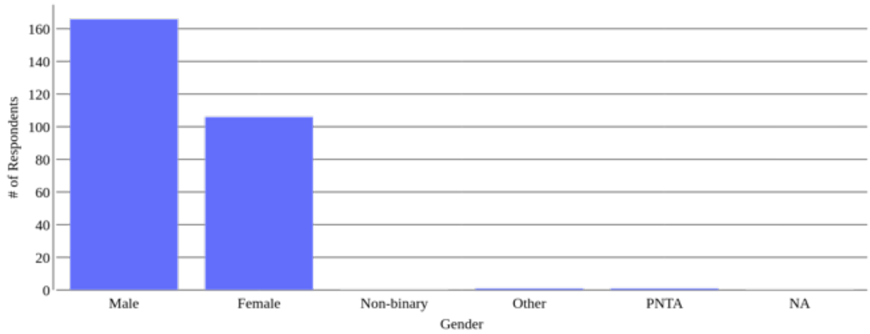
Table 6.1: Descriptive statistics of the survey respondents.

	Total		No Way, No How (n=16)		Interested but Concerned (n=145)		Enthused & Confident (n=103)		Strong & Fearless (n=11)	
	n	%	n	%	n	%	n	%	n	%
Age										
0-10	0	0.0	0	0.00	0	0.00	0	0.00	0	0.00
11-20	1	0.4	0	0.00	1	0.69	0	0.00	0	0.00
21-30	123	44.7	4	23.53	73	50.34	44	43.14	2	18.18
31-40	80	29.1	8	47.06	39	26.90	29	28.43	4	36.36
41-50	43	15.6	4	23.53	22	15.17	14	13.73	3	27.27
51-60	24	8.7	1	5.88	9	6.21	13	12.75	1	9.09
61-70	2	0.7	0	0.00	1	0.69	0	0.00	1	9.09
71-80	0	0.0	0	0.00	0	0.00	0	0.00	0	0.00
81-90	0	0.0	0	0.00	0	0.00	0	0.00	0	0.00
>100	0	0.0	0	0.00	0	0.00	0	0.00	0	0.00
Prefer not to answer	1	0.4	0	0.00	0	0.00	1	0.98	0	0.00
No answer	1	0.4	0	0.00	0	0.00	1	0.98	0	0.00
Gender										
Male	166	60.4	10	58.82	84	57.93	65	63.73	7	63.64
Female	106	38.5	7	41.18	60	41.38	35	34.31	4	36.36
Non-binary	0	0.0	0	0.00	0	0.00	0	0.00	0	0.00
Other	1	0.4	0	0.00	1	0.69	0	0.00	0	0.00
Prefer not to answer	1	0.4	0	0.00	0	0.00	1	0.98	0	0.00
No answer	1	0.4	0	0.00	0	0.00	1	0.98	0	0.00
Cycling Frequency										
Never	22	8.0	16	94.12	6	4.14	0	0.00	0	0.00
Rarely (a few times a year)	47	17.1	0	0.00	28	19.31	18	17.65	1	9.09
Ocasionally (a few times a month)	58	21.1	0	0.00	38	26.21	19	18.63	1	9.09
Frequently (a few times a week)	65	23.6	0	0.00	33	22.76	31	30.39	1	9.09
Daily (every day or almost every day)	82	29.8	1	5.88	40	27.59	33	32.35	8	72.73
No answer	1	0.4	0	0.00	0	0.00	1	0.98	0	0.00
Cycling Experience										
Less than 6 months	24	8.7	0	0.00	16	11.03	8	7.84	0	0.00
Between 6 months & 1 year	148	53.8	1	5.88	78	53.79	59	57.84	10	90.91
Between 1 year & 5 years	65	23.6	0	0.00	37	25.52	27	26.47	1	9.09
Greater than 5 years	15	5.5	0	0.00	8	5.52	7	6.86	0	0.00
No answer	23	8.4	16	94.12	6	4.14	1	0.98	0	0.00
Cycling during the week										
Only on weekdays	41	16.3	0	0.00	24	16.55	16	15.69	1	9.09
Only on weekends	65	25.8	0	0.00	40	27.59	23	22.55	2	18.18
Both on weekdays and weekends	146	57.9	1	5.88	75	51.72	62	60.78	8	72.73
No answer	23	9.1	16	94.12	6	4.14	1	0.98	0	0.00
Trip purpose										
Commuting	144	52.4	1	5.88	76	52.41	60	58.82	7	63.64
Work-related	13	4.7	0	0.00	7	4.83	4	3.92	2	18.18
Utilitarian	123	44.7	1	5.88	69	47.59	47	46.08	6	54.55
Leisure/Social	172	62.5	1	5.88	95	65.52	70	68.63	6	54.55
Sports/Exercise	107	38.9	1	5.88	57	39.31	57	55.88	5	45.45
Taking kids to school	18	6.5	0	0.00	11	7.59	11	10.78	2	18.18

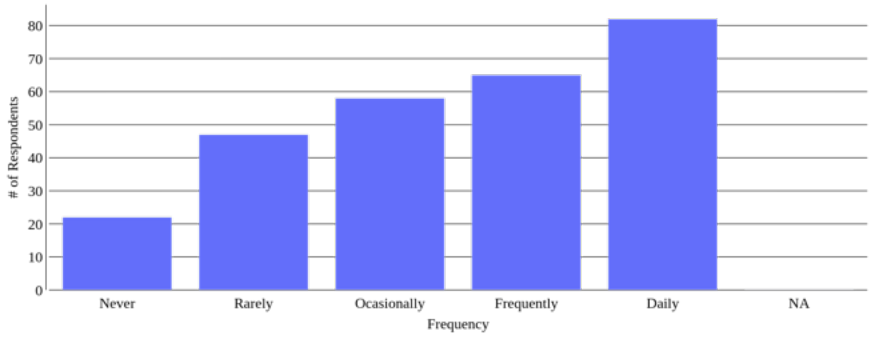
Cyclist Profile		
No Way, No How	17	6.2
Interested but Concerned	145	52.5
Enthused & Confident	103	37.3
Strong & Fearless	11	4.0



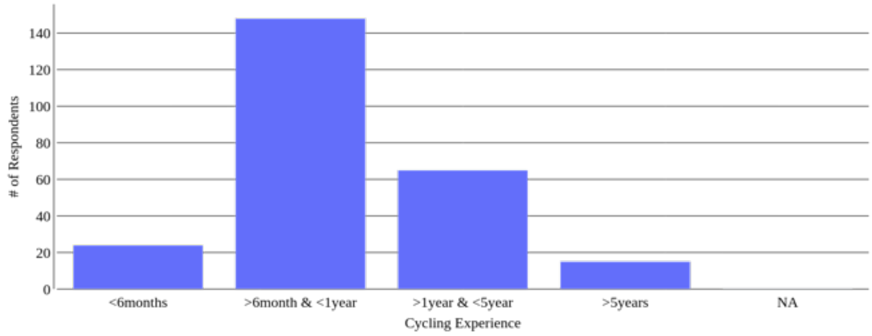
(a) Age



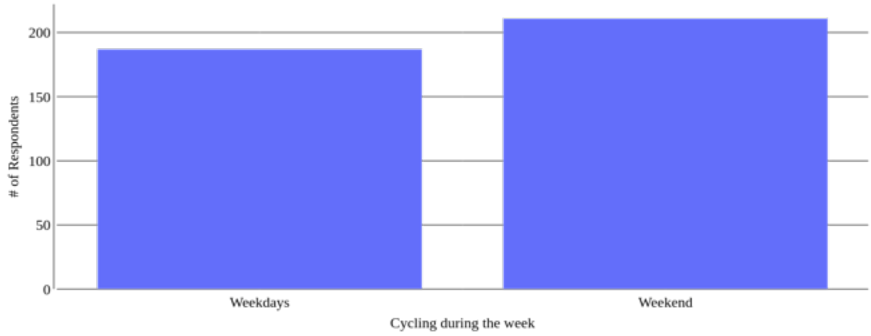
(b) Gender



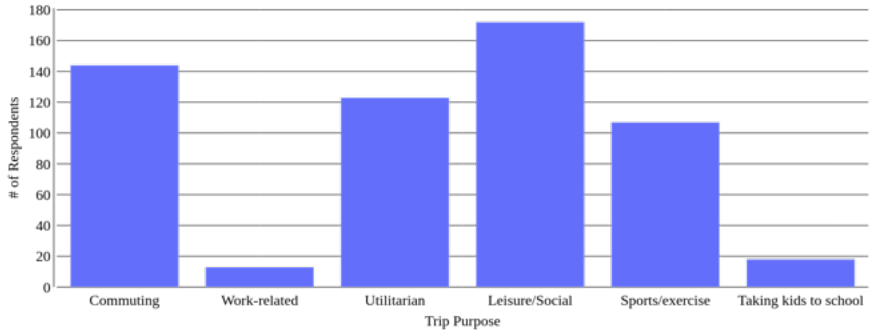
(c) Cycling frequency.



(d) Cycling experience.



(e) Cycling during the week.



(f) Trip purpose.

Figure 6.4: perception of cycling survey sample details.

For Part II of the survey, a total of 10647 pairwise comparisons were performed by respondents for the different cities: Berlin – 7281 (68.4%); Barcelona – 1158 (10.9%); London – 1124 (10.6%); Paris – 554 (5.2%); and Munich – 530 (4.9%). Given the vast majority of votes (i.e., comparisons) were made for the city of Berlin, I have focused the remaining work of this part on this dataset. Again, respondents had to decide (left image, right image, or tie) which image appeared safer for cycling. Choices were somewhat evenly distributed between the left (39.9%) and right (41.3%) images, with only about 18.8% consisting of ties.

Chapter 7

Scoring Cycling Environment Perceived Safety

This chapter was partially presented and is available as: "Costa, M., Marques, M., Siebert, F. W., Azevedo, C. L., Moura, F. (2023). Scoring Cycling Environments Perceived Safety using Pairwise Image Comparisons. IEEE Intelligent Transportation Systems Conference. Bilbao, Spain." and "Costa, M., Siebert, F. W., Azevedo, C. L., Marques, M., Moura, F. (2023). Understanding Perception of Cycling Safety through Pairwise Image Comparisons. International Cycling Safety Conference 2023. The Hague, The Netherlands."

7.1 Introduction

The main deterrent to cycling relates to safety concerns Aldred and Crosweller (2015); Lawson et al. (2013); Félix et al. (2019). If cyclists feel unsafe or are afraid to cycle, they will prefer other means of transportation. Thus, for cities aiming to boost cycling numbers and the effectiveness of such strategies, it is increasingly important to understand what affects individuals' perceptions. Current research shows that infrastructure layout, fear of traffic, and distracted cycling are some aspects that influence this perception Heinen et al. (2010); Sanders (2015); Wang and Akar (2018). Most research focuses on surveys and in-loco and post-riding interviews to compare factors influencing perceptions Sanders (2015). Even though these approaches are vital to understanding cycling perception of safety, they need to be more scalable over space or time due to their high cost (human resources, time, and money).

Studying such perceptions has traditionally been carried out using direct rating methods (users assign a score to each event or situation). This procedure requires a well-defined scale, user training and is particularly difficult to conduct when events or conditions substantially differ from one another Perez-Ortiz and Mantiuk (2017), which is often the case when analyzing real-world environments. In contrast, using pairwise comparisons (users compare two situations and choose one of the two) is often simpler and faster to set up, well-suited for non-expert participants Perez-Ortiz and Mantiuk (2017), and presents lower measurement error compared to direct ratings Shah et al. (2015). With this in mind, I employ pairwise comparisons to analyze cycling safety perceptions. Moreover, I draw current practice and knowledge from other research areas (e.g., sports outcome prediction and preference learning) about pairwise comparisons and how algorithms can be used to study cycling safety perceptions, something unexplored in cycling safety research. This paves the way to scale safety perception studies and ubiquitously understand how individuals perceive cycling risk.

This novel approach uses a survey showcasing images of two road environments and asking users which one they find safer, if any. With the respondents' answers, I compare different methodologies, previously applied to sports prediction and preference learning (Maystre et al., 2019; Xu et al., 2016), and show how these can be directly applied to our main goal: understanding cycling perception of safety. Lastly, I draw from these results to objectively classify cycling environments based on urban characteristics and cycling environments.

Next, I overview specific related work to this chapter's contributions in Section 7.2. Section 7.3 presents the methodology, overviewing all algorithms and the environment classification procedure. Section 7.4 presents the results and highlights what environments are perceived as safer or riskier. Finally, Section 7.5 concludes the section and draws possible paths forward.

7.2 Background on Pairwise Comparison Models

Pairwise Comparison Models (also known as Paired Comparison Models, or simply Paired Models) aim to predict the outcome of comparing two items, i.e., when items A and B are compared, would a user prefer item A, item B, or would they be perceived equally (tie)? These models were first proposed in psychophysics and marketing research and have typically followed the seminal works of Thurstone (Thurstone, 1927) and Bradley–Terry (Bradley, Ralph Allan and Terry, Milton E, 1952). In the past decades, paired comparison models have been explored and applied to many domains, including sports skill ranking and game prediction (Maystre et al., 2019; Chau et al., 2023), image quality analysis (Xu et al., 2016), and city perceptions (Naik et al., 2014a; Costa, 2019).

Typical models assume that there is a latent score s_i for each item i and the outcome probability on a comparison between items i and j is a function of the difference between their scores, e.g., $\theta(s_i - s_j)$. Models' usual underlying goal is to estimate the latent scores s_i from the data to obtain an interpretable and comparable score for each item. If $s_i > s_j$, a user would have a greater probability of picking item i. The function θ can have many forms but usually follows a Gaussian or logistic distribution initially proposed by Thurstone (Thurstone, 1927) and Bradley–Terry (Bradley, Ralph Allan and Terry, Milton E, 1952), respectively.

Several methodologies have been proposed to extend comparison models, including iterative algorithms, Bayesian-based models, and covariate-based or covariate-free models. Covariate-based models often allow for new items to be added to the comparison set seamlessly without any prior comparison involving new items. Yet, these methods require having said covariates and do not rely entirely on the outputs of paired comparisons. For this work, we focus on covariate-free models requiring only results from pairwise comparisons. For iterative algorithms, probably the most well-known case is the Elo rating (Elo, 1978), which has been used to rank chess players by FIDE[1], by FIFA to rank women's national football teams[2], or by FiveThirtyEight to rank NFL teams[3]. Elo uses a simple online stochastic update rule based on an item's scores and the expected outcome of one item winning over the other. Despite its simplicity, Elo has remained one of the most used procedures since it is tractable and can easily adjust to diverse situations and scenarios. For Bayesian models, both Glicko (Glickman, 1999) and TrueSkill (Herbrich et al., 2006) have been put forward as probabilistic methods that measure not only the latent scores s_i but also the uncertainty associated with each score, which is often valuable.

More recently, other approaches have been suggested using alternative methodologies. These include spectral ranking that (usually) involves computing the pairwise comparison matrix leading eigenvalues and eigenvectors (Chau et al., 2023), convex problem formulation that usually penalizes wrongly or contradictory answers (Xu et al., 2016; Costa, 2019), or Gaussian processes to model different data dynamics (Maystre et al., 2019; Chu and Ghahramani, 2005).

In this chapter, I study paired comparison models to analyze cycling perception of safety. To the best of my knowledge, this has not been explored before and can potentially help researchers analyze the impact of the cycling environments on individuals' perceptions, enabling faster and continuous evaluations of such effects.

7.3 Methodology

I now detail how pairwise comparison observations can be modelled to compute an individual perceived safety score to each cycling environment using the pairwise comparison data detailed in Chapter 6. Section 7.3.1 overviews five different paired comparison models and Section 7.3.2 describes how one can use binary classification tools to classify environments as being perceived safe or unsafe.

7.3.1 Computing Safety Scores

Using the pairwise image comparison survey data, I now explore and compare covariate-free methodologies to compute subjective safety scores. In essence, this score allows non-experts and decision-

[1] https://ratings.fide.com/calc.phtml?page=change
[2] https://www.fifa.com/fifa-world-ranking/procedure-women
[3] https://fivethirtyeight.com/methodology/how-our-nfl-predictions-work/

makers to understand and compare cycling environments easily. I now provide an overview of each method.

Elo (Elo, 1978)

In Elo, we start by setting an initial score s_0 for each image. Next, after each comparison, one computes the expected result for item A for a comparison between items A and B:

$$E_A = \frac{1}{1 + 10^{(s_B - s_A)/\delta}}, \tag{7.1}$$

with δ modulating the scores difference. The new score for item A, s'_A, can be updated using:

$$s'_A = s_A + k(\gamma - E_A), \tag{7.2}$$

with k modulating the impact of the outcome on the new score and γ being 1 for the winning item and 0 for the losing one, or 0.5 for ties for both items.

TrueSkill (TS) (Herbrich et al., 2006)

This Bayesian framework assumes that each image's score is modeled by a $\mathcal{N}(\mu, \sigma^2)$ random variable, which is updated after each comparison. Update rules follow that, for image A winning over image B:

$$\begin{aligned} \mu'_A &= \mu_A + \frac{\sigma_A^2}{c} \cdot f(\frac{\mu_A - \mu_B}{c}, \frac{\varepsilon}{c}) \\ \mu'_B &= \mu_B + \frac{\sigma_B^2}{c} \cdot f(\frac{\mu_A - \mu_B}{c}, \frac{\varepsilon}{c}) \\ \sigma_A^{2'} &= \sigma_A^2(1 - \frac{\sigma_A^2}{c} \cdot g(\frac{\mu_A - \mu_B}{c}, \frac{\varepsilon}{c})) \\ \sigma_B^{2'} &= \sigma_B^2(1 - \frac{\sigma_B^2}{c} \cdot g(\frac{\mu_A - \mu_B}{c}, \frac{\varepsilon}{c})) \\ c^2 &= 2\beta^2 + \sigma_A^2 + \sigma_B^2 \end{aligned}, \tag{7.3}$$

with β being a per-game variance parameter, ε an empirical probability of a comparison resulting in a tie, functions $f(\theta) = \mathcal{N}(\theta)/\Phi(\theta)$ and $g(\theta) = f(\theta) \cdot (f(\theta) + \theta)$ defined as the Gaussian density function $\mathcal{N}(\theta)$ and Gaussian cumulative density function $\Phi(\theta)$.

Convex Optimization (CO)

To model paired comparisons, I solve a convex optimization program following (Costa, 2019):

$$\begin{aligned} \underset{s,t}{\text{minimize}} \quad & 1^T t + \lambda_{ties} 1^T |B^T s| \\ \text{subject to} \quad & 1^T s = 0 \\ & \epsilon - b_n^T s \leq t_n \\ & 0 \leq t_n, n = 1, ..., N \end{aligned}, \tag{7.4}$$

with $s \in \mathbb{R}^M$ being the score vector for M images, N the total number of comparisons, b_n a vector containing information for comparing pairs (b_n is a vector of zeros, with 1 in the m-th position of the winning image, and -1 in the m-th position of the losing one), and ϵ an error margin to tolerate offending comparisons. This cost function penalizes scores that violate the error margin greater than ϵ. The optimal scores s will be the one that violates the least paired comparisons and, if so, the ones where image scores are closer.

Gaussian Process (GP)

Maystre et al. (2019) proposed an approximate Bayesian inference over pairwise comparisons using gaussian processes. Here, scores are approximated by a Gaussian process (GP) ($s(n) \sim \mathcal{GP}(0, k(n, n'))$) defined by the joint distribution of N pairwise comparisons of scores s, with $s \sim \mathcal{N}(0, K)$, with K being the covariance matrix $K = [k(n_i, n_j)]$, defined by a covariance function that models the dynamics of scores over comparisons. A logit observation model is chosen and the likelihood is set accordingly. For further detail on the approximate posterior probabilities and inference through Expectation-Propagation, I refer the reader to (Maystre et al., 2019).

Luce Spectral Ranking (LSR) (Maystre and Grossglauser, 2015)

By constructing pairwise comparisons as a graph, where edges represent comparisons and their results, this algorithm works as a scoring function of such graph representation. The graph's structure defines probabilities as the stationary probability of a natural random walk over nodes (images) or a stationary distribution of a Markov chain. Essentially, this measures the likelihood of moving from item A to item B, which depends on how many comparisons item A won versus item B. As such, it captures an item's preference globally over all other items.

7.3.2 Binary Classification of Cycling Environments: Perceived Safe *vs.* Perceived Unsafe

Finally, after scoring each cycling environment, I aim to predict if environments are perceived as safe or unsafe based on image characteristics. This classification can help urban planners and designers to understand what urban features impact individuals' cycling perception of accident risk.

As such, I perform binary classification to classify environments as perceived *safe* or *unsafe*. To get a representation of the image, I run images through the widely popular deep neural network InceptionV3 (Szegedy et al., 2016) pre-trained on ImageNet, from which I remove the final softmax classification layer. Other architectures were tested, with InceptionV3 providing the best results for this task. From this, I extract a latent representation of the urban environment for each image to be used as the predictor in this classification problem.

Table 7.1: Hyperparameters used in the paired comparison and classification models.

Model	Hyperparameters
Elo	$\gamma = 400, k = 32, s_0 = 1500$
TrueSkill	$s_0 = 25, \sigma_0 = 8.33, \beta = 4.17, \varepsilon = 0.1$
Convex Optimization	$\epsilon = 0.1$
Gaussian Process	Tie margin $= 2$
XGBoost	Max depth $= 2$, N Estimators $= 105$, Learning Rate $= 0.01$, Subsample $= 0.5$, Feature sample by tree $= 0.5$

Next, I label environments as *safe* or *unsafe* by setting a threshold on the predicted rating using one of the algorithms from Section 7.3.1. I set s_H and s_L, where images with a score above s_H are perceived as *safe*, and below s_L are perceived as unsafe. These thresholds are defined as $s_H = \bar{s} + \alpha\sigma_s$ and $s_L = \bar{s} - \alpha\sigma_s$, with $\bar{s}$ and σ_s being the average and standard deviation of the scores on the test set, respectively, and α a varying parameter set to control how distant perceived safer environments are from unsafe ones. Particularly, if $\alpha = 0$, then $s_H = s_L = \bar{s}$, meaning that their environments are either perceived as safe or unsafe. Finally, I use eXtreme Gradient Boosting Tree (XGBoost) (Chen and Guestrin, 2016) to perform binary classification due to being a powerful approach to this classification task.

7.4 Results

This section details the results of modeling pairwise comparisons using the methodologies above. I begin by presenting implementation details. Next, I present the results for each paired comparison model and the information about predicting environment perception scores based on environment characteristics.

7.4.1 Implementation Details

I begin by splitting the available pairwise comparisons into train and test sets (85-15% split). I run a grid search for each model over tunable hyperparameters and present results for the best model. Table 7.1 shows the best hyperparameters. To evaluate each method, I compute the negative average logarithmic loss (L):

$$L = -\frac{1}{N}\sum_{n=1}^{N} log(p(y^*)), \tag{7.5}$$

for pairwise comparison output y^*, and average accuracy. Note that a random predictor's accuracy would be 50%. Log loss provides a good gauge of model calibration, heavily penalizing models for outcomes it considers improbable. I report evaluation metrics on the test set, averaged over five different seeds. All models were implemented in Python.

Table 7.2: Evaluation metrics for each pairwise model.

Model	Log loss ↓	Accuracy ↑
Elo	0.658	0.658
TrueSkill	**0.630**	0.667
Convex Optimization	0.774	0.599
Gaussian Process	0.839	**0.671**
Luce Spectral Ranking	0.952	0.464

7.4.2 Cycling environment ratings

Table 7.2 shows each model's log loss and accuracy. As one can see, the spectral ranking model exhibits a lower accuracy than the remaining models, closer to a random predictor. This means that, with this number of available comparisons, it cannot learn cycling safety perceptions from these observations. TrueSkill (TS) reveals the lowest log loss but with values close to those of the Elo rating model. In turn, GP showcases the highest accuracy but with a log loss much higher than that of TS, meaning that, while it is more accurate, its probability of choosing the winning environment is usually much lower than that of TS or Elo.

I depict the normalized predicted perceived safety scores in Figure 7.1 for all models, with higher values representing environments perceived as safer. All methods show similar perceived safety score trends, showcasing the lowest scores for the same environments and similar tendencies for the perceived safer ones. I highlight some characteristics by visually inspecting each environment and its predicted score. First, images with non-parked cars (Images 1 and 2) show the lowest score, indicating that the presence of these vehicles decreases the perception of safety. Image 5 has the highest perceived safety score showing a cycle lane and no cars in sight. Images 3 and 4 show average to high scores. While Image 3 shows a cycling lane, it also shows an intersection with other vehicles crossing it. In turn, Image 4 was not taken in an intersection, which was perceived as slightly safer. Additionally, lighting conditions and slight lens distortion play no role in individuals' perception, and only semantic and urban characteristics seem to influence perceptions score.

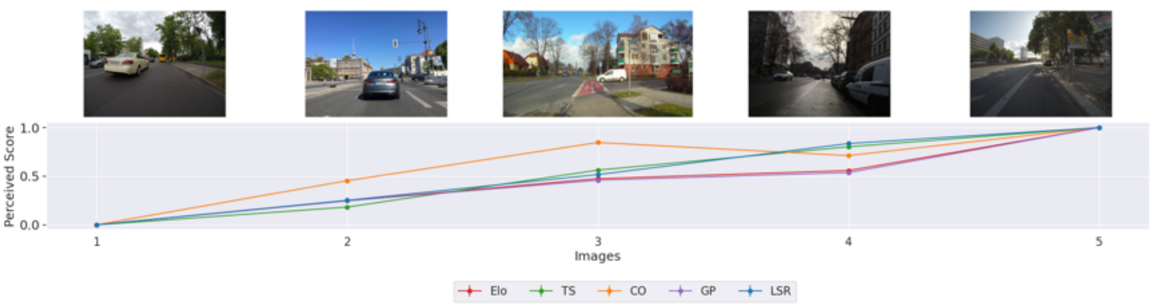


Figure 7.1: Normalized perceived cycling safety scores for all paired comparison models.

7.4.3 Binary classification

Lastly, I aim to understand if cycling environments can be predicted to be perceived as either safe or unsafe directly from image features. I use XGBoost to perform binary classification on cycling environments, tuning hyperparameters using grid search over a 5-fold cross-validation procedure. Optimal hyperparameters are shown in Table 7.1. Given its relatively high accuracy and low log loss, I perform classification using TS scores. To decrease the impact of pictures with few comparisons, I conduct classification only on images whose certainty has reduced past $1/6$ of the initial σ value. Images with scores within $[s_L, s_H]$ are considered neutral and removed from this analysis.

Classification accuracy is shown in Figure 7.2. When $\alpha = 0$, the model has 61.4% accuracy, reaching an accuracy of 89.5% when $\alpha = 1.5$. While increasing the value of α limits the grouping of environments being perceived as safe or unsafe, it also increases the distinction between the two classes, thus increasing the model's accuracy. For urban planners who seek to massively understand how their cities impact cyclists' perception of risk, this process can be widely adapted to analyze a city's urban form and infrastructure.

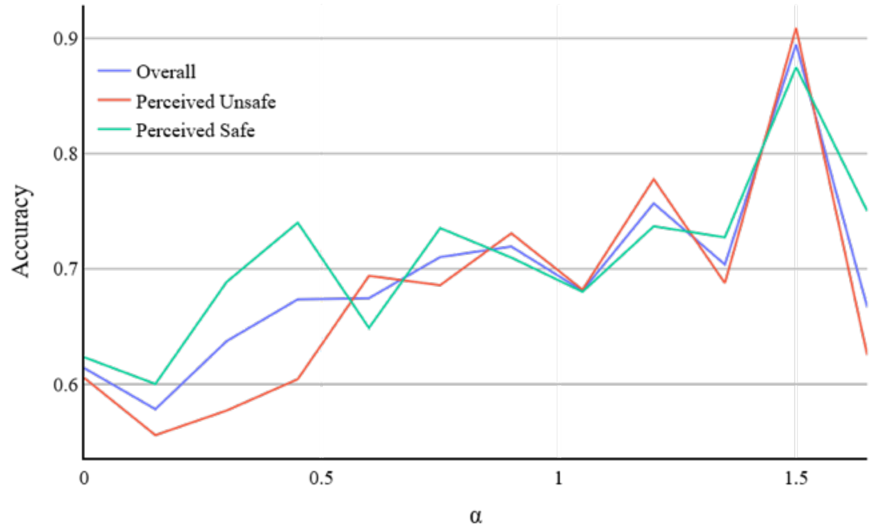


Figure 7.2: Classification accuracy of *perceived safe* and *perceived unsafe* cycling environments as a function of α.

7.5 Summary and conclusions

In this section, I have explored a novel methodology to analyze the perception of cycling safety using pairwise image comparisons. I explore and compare different popular covariate-free paired models to rate cycling environments according to individuals' perceptions, achieving good results for the available number of comparisons. In addition, I explore how binary classification can be used to classify environments as being perceived as safe or unsafe directly from image characteristics. The results show this methodology's potential for widely comparing cycling environments and understanding how these environments impact individuals' perceptions of risk. Moreover, even with few comparisons, the information extracted is very relevant. This knowledge is critical as perceptions of safety significantly impact cycling adoption, potentially hindering any city's strategy to increase cycling numbers if safety perceptions are not encompassed.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/mncosta/scoring_pairwise. Code is available for Python3. The code is available under MIT license (https://opensource.org/licenses/MIT).

Chapter 8

Learning Perceived Safety Scores from Images

This chapter is partially under review as a journal article: "Costa, M., Marques, M., Azevedo, C. L., Siebert, F. W., Moura, F. (N/A). Which cycling environment appears safer? Learning cycling safety perceptions from pairwise image comparisons. [Manuscript under review in IEEE Transactions on Intelligent Transportation Systems]."

8.1 Introduction

Safety concerns (fears of being involved in an accident) are often considered the main deterrent to cycling (Sanders, 2015; Félix et al., 2019). If individuals perceive cycling environments as unsafe, they will avoid cycling and most certainly prefer other modes of transportation, hindering any region's strategies for increasing cycling numbers. Thus, understanding what may cause or increase these concerns is vital. Previous research has identified cycle helmets and clothing (Lawson et al., 2013; Aldred and Woodcock, 2015), perceptions and expectations on other road users' behavior (Chaurand and Delhomme, 2013), urban roads usage and road rules compliance (Lawson et al., 2013), or road infrastructure and cycling facilities (Møller and Hels, 2008; Wang and Akar, 2018; Chataway et al., 2014; Jensen et al., 2007) as relevant factors for the assessment of risk by cyclists. Subjective safety research has been carried out using *in situ* surveys or post-riding interviews and traditional choice modeling tools. However, these are often not scalable due to their inherent high cost, only provide a snapshot of the current cycling panorama, and cannot be easily redeployed over time or space.

To circumvent this, new approaches have been proposed. These explore new ways of acquiring data, such as physiological data to identify negatively arousing hotspots (Zeile et al., 2016), street-view imagery (SVI) about intersections (Doorley et al., 2015), cyclist perspective video clips (Parkin et al., 2007), mental maps with geographical data (Manton et al., 2016) or using virtual reality (Nazemi et al., 2019), to name a few. However, while these approaches seek more and new types of data on individuals' perceptions, most methods still require considerable manual labor to analyze and understand whether environments are perceived as safe or unsafe.

This chapter presents a novel methodological approach to efficiently assess the perception of cycling safety and is based on individuals' perceptions of what categorizes one environment as safer than another. Effectively, I want to answer the following question: "*Given two cycling environments, which is perceived as safer for cycling?*" For this, I propose PCS-Net, a neural network that predicts which environment is perceived as safer for cycling when comparing two images. Moreover, PCS-Net is able to predict and learn from ties (when there is no perceived difference between the two images), which are often discarded in past research. In effect, PCS-Net learns the perception of cycling safety directly from two real-world images and users' choices. Ultimately, this model can be used to score perceived safety for different cycling environments, effectively allowing one to map perceived safety geographically, which I showcase for Berlin, Germany.

Next, Section 8.2 presents a background to the approach employed throughout the chapter. Then, Section 8.3 explains the proposed approach. Then, I detail the experimental results in Section 8.4 and apply the proposed model to analyze the perception of safety on a city-wide scale in Section 8.5. Section 8.6 discusses the results and this study's limitations. Finally, Section 8.7 finalizes the section.

8.2 Background

All in all, most subjective cycling safety research aims to measure the impact of different elements on individuals' perceptions. Ultimately, such understanding can be indexed to objectively characterize urban environments, leading to the creation of indicators and metrics that can help urban planners and designers easily compare and analyze cycling environments. To this end, the Bicycle Stress Level (Sorton, Alex and Walsh, Thomas, 1994) and the Level of Traffic Stress (Mekuria, Maaza C and Furth, Peter G and Nixon, Hilary, 2012; Furth, 2017) remain the most well-known indices that attempt to measure bikeability and perceived risk. Yet, to compute such metrics, manual labor is usually employed, requiring individuals to annotate environment elements manually. Ito and Biljecki (2021) approach fills this gap, deriving a bikeability index from computer vision-extracted features from SVI, facilitating an automatic and scalable methodology to score environments effortlessly, which can eventually replace more traditional techniques. Nevertheless, this index covers five bikeability aspects, of which perceptions are one, which can be inadvertently mischaracterized if appropriate supervision is not employed. In this chapter, I am interested in a similar approach that covers the perception of cycling risk only, is based on individuals' perceptions of what categorizes one environment as safer than another, and is equally scalable. Such an approach can, in effect, simulate individuals' perceptions and thus reduce the time and cost of subjective cycling safety assessment compared to traditional methodologies.

Recently, a growing number of works have been exploring image processing and computer vision techniques to study urban environments and human perceptions. For example, these have explored openness and enclosure (Li et al., 2018), greenery (Toikka et al., 2020), house prices (Nouriani and Lemke, 2022), and different human perceptions (Naik et al., 2014b; Dubey et al., 2016; Verma et al., 2020; Ramírez et al., 2021).

Research has typically used traditional or deep learning-extracted features from SVI in classification or regression problems to evaluate the impact of such environment-related features. With the growing access to openly available street-view images, researchers can perform continuous and scalable assessments of urban environments more easily than in the past. In transportation, using SVI has been proven useful in, among others, studying accessibility (Najafizadeh and Froehlich, 2018a; Saha et al., 2019), walkability (Ramírez et al., 2021), bikeability (Ito and Biljecki, 2021), and objective road safety (Song et al., 2018).

With this in mind, the work presented in this chapter is greatly inspired by that of Dubey et al. (2016), which uses computer vision to predict how individuals sense urban environments across different perspectives: safe (crime-related), lively, beautiful, wealthy, boring, and depressing. The authors use a large database of image comparisons to train a model capable of "simulating" human choice. Such work has laid the foundations for many possible city-wide analyses, such as understanding how the built environment might affect behavior, travel choices, and even home location. Further, as the authors demonstrate and hypothesize, such an approach can be used to enlarge existing datasets and expand predictions across geographies. This endeavor can help to better allocate city resources and make data-driven decisions. Yet, their model disregards a vast number of observations as it cannot handle ties in image comparisons (equally perceived images). We consider that there is a lot of information to be gained here. Thus, I build up from Dubey et al. (2016)'s approach, proposing a methodology that draws from pairwise image comparisons, includes ties, and can be applied to analyze cycling perception of safety.

8.3 Methodology

The proposed model seeks to uncover the underlying patterns and principles that guide individuals' subjective safety judgments when comparing and selecting between different images. In practical terms, this means that I model individuals' choices directly from images. Let x_i be an image i, I seek to learn the image transformation function $f(x_i)$ to predict the individual's choice y. Naturally, this can be encoded as a classification problem, a ranking problem, or a combination of the two (i.e., finding a function $f(x_i, x_j)$). The models outlined here follow the SS-CNN and RSS-CNN networks by Dubey et al. (2016). However, I modify these networks to better suit the problem at hand and expand them to allow ties in comparisons as I believe these can often bring information gain. I will now detail the formulation for all approaches.

Classification Problem

I frame this approach to predict the individual's choice y under a classification scenario, where the model seeks to output $y \in \{-1, 0, +1\}$, i.e., the user chose the left image, a tie between images, or chose the right image. As such, I design the Classification-Perception of Cycling Safety Network (PCS-Net$_C$) for making such a prediction. Figure 8.1 shows the architecture of this network. This network is divided into two sections: i) a feature extractor sub-network (backbone) and ii) a fusion network. The former is a Siamese-style network (Chopra et al., 2005), where each identical branch with tied weights learns to map an input image to a latent representation of itself, acting as a feature extractor. Next, both branches are merged in the fusion sub-network (Dubey et al., 2016), which in turn learns a combination of filters, ending with a softmax loss used to train the network, L_C.

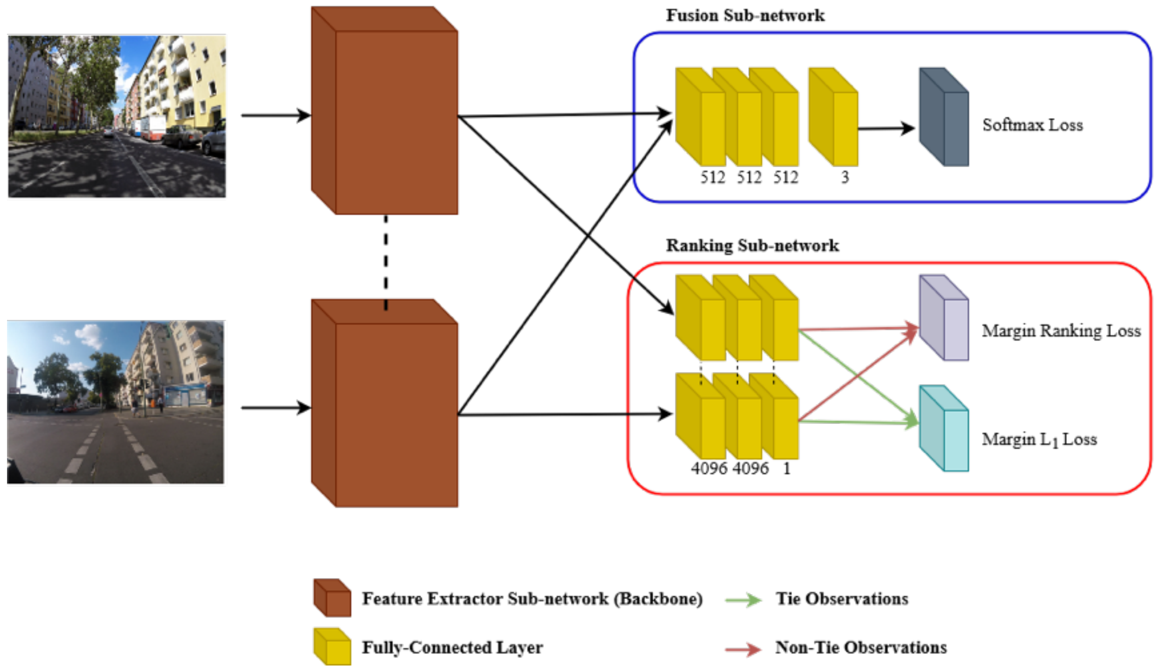


Figure 8.1: Architectures of the PCS-Net$_C$ (above) and PCS-Net$_R$ (below) networks, which make up the PCS-Net when combined.

Ranking Problem

This problem can be framed under a ranking formulation approach. In this case, the main goal is to find a ranking score for each image, such that it represents an ordinal ranking among all images in the dataset. To make a prediction, ranking scores are compared between the two input images, and a choice is made following the highest-ranked image, i.e., the one perceived as safer. To achieve this, a slightly different network is designed: Ranking-Perception of Cycling Safety Network (PCS-Net$_R$), as shown in Figure 8.1. This network is subdivided into two components: i) a feature extractor sub-network (equal to the classification formulation) and ii) a ranking sub-network (Dubey et al., 2016). In essence, this sub-network uses fully connected layers to reduce the features extracted from the backbone to a ranking score for an input image. As such, I seek to learn the function $f(x_i)$, such that when a choice y is made between x_i and x_j I want to satisfy

$$-y \cdot (f(x_i) - f(x_j)) > 0, \tag{8.1}$$

with $y \in \{-1, +1\}$, with $y = -1$ for when image x_i wins the comparison, and $+1$ if image x_j wins the comparison. In essence, I am learning a ranking function $f(x)$ that ranks images based on their features, with higher-ranked images denoting images perceived safer for cycling. This problem can be expanded to denote a ranking loss function of the form

$$L_{\hat{R}}(x_i, x_j) = \max(0, -y \cdot (f(x_i) - f(x_j)) + \gamma), \tag{8.2}$$

which also allows the introduction of a margin term γ. Using this loss function, I am essentially penalizing comparisons in which image ranking orders are opposite to the individual's choice while favoring comparisons where a choice was made for an image ranked higher (perceived safer). However, $L_{\hat{R}}$ does not account for possible ties in a decision maker's choice ($y = 0$). When a tie occurs, it means that their perceived cycling safety score should be similar, as the respondent could not distinguish which one was deemed safer between the two images. This entails that both image rankings should be closer, which can be translated using a different loss function for comparisons, resulting in a tie:

$$L_1(x_i, x_j) = \max(0, ||f(x_i) - f(x_j)||_1 - \gamma), \tag{8.3}$$

with $|\cdot|_1$ denoting the L1 norm. In essence, L_1 pushes images from tie comparisons together, similar to other approaches in skill ranking tasks (Doughty et al., 2018). Finally, to train the proposed model, one can combine both loss functions to be minimized:

$$L_R = \mathbb{1}_{y \in \{-1,+1\}} L_{\hat{R}} + \lambda_1 \cdot \mathbb{1}_{y \in \{0\}} L_1, \tag{8.4}$$

with $\mathbb{1}_{y \in \{-1,+1\}}$ being an indicator function for non-tie comparisons, $\mathbb{1}_{y \in \{0\}}$ an indicator function for tie comparisons, and λ_1 being a weight term to modulate the importance of ties.

Classification & Ranking Problem

Finally, I design an approach that combines both the classification and ranking tasks at the same time. This approach leverages both approaches, learning in an end-to-end framework how to predict which of the two input images is thought to be safer for cycling. This Perception of Cycling Safety Network (PCS-Net) joins all the above architectures: i) feature extractor sub-network, ii) fusion sub-network, and iii) ranking sub-network. Training is performed by minimizing the following multi-loss function, which combines the classification loss and ranking losses for ties and non-ties:

$$L = L_C + \lambda_{\hat{R}} \cdot \mathbb{1}_{y \in \{-1,+1\}} L_{\hat{R}} + \lambda_1 \cdot \mathbb{1}_{y \in \{0\}} L_1, \tag{8.5}$$

allowing for $\lambda_{\hat{R}}$ and λ_1 hyper-parameters to be specified to model loss component importance and maximize model accuracy. I experiment with different hyper-parameters in Section 8.4.

8.4 Results

8.4.1 Implementation details

I split the dataset in 70-10-20% for training, validation, and testing. Experiments were run using Python and PyTorch 2 (Paszke et al., 2019) using an NVIDIA GeForce 3080Ti GPU. Weights for the ranking and fusion sub-network were initialized from a uniform distribution relative to each layer's size. Learning rate was set to $1e-3$ decaying every 10k steps, ADAM (Kingma and Ba, 2014) as the optimization procedure, and a batch size of 128 and up to 20 maximum epochs, or until validation error stopped improving.

8.4.2 Evaluation

I compare the proposed approach to other paired models that do not include ties using accuracy. I compute a non-margin accuracy metric for non-tie observations as the ratio of the correctly predicted left (i.e., $f(x_i) > f(x_j)$) and right ($f(x_j) > f(x_i)$) comparisons to all comparisons.

8.4.3 Testing on semi-realistic data

I start by testing the proposed methodology using semi-realistic data. To this end, I use data adapted from von Stülpnagel and Binnig (2022), where users were asked to assess their perception of cycling safety on semi-realistic SVI from Berlin using a 4-point scale. Images represented typical cycling environments across Berlin with varying attributes. I refer the reader to von Stülpnagel and Binnig (2022) for further details. Data adaptation sought to transform judged images to pairwise comparisons following Dittrich et al. (2007)'s approach. If image A was judged higher than image B, I generated a paired comparison between A and B, such that A was chosen. If both images were scored equally, then I generated a tie. I repeated this process for all users, resulting in ~2 million pairwise image comparisons. As indicated above, I use these comparisons and semi-realistic images to train PCS-Net.

Figure 8.2 showcases examples of semi-realistic ranked images on their perception of safety, with increasing (left to right) perceived safety. The left-most image depicts the lowest perceived environment, where a cyclist shares a road with other traffic and tram rails are visible. On the opposite spectrum (right-most image), one can see a cyclist on a dedicated cycle lane as being perceived as very safe.

I compare the proposed model to other pairwise comparison methods: TrueSkill (Herbrich et al., 2006), Elo (Elo, 1978), Gaussian Process (Maystre et al., 2019), and Rank Centrality (Negahban

Figure 8.2: Examples of ranked semi-realistic (top) and real (bottom) images according to their perception of cycling safety score.

et al., 2012). Table 8.1 compares the PCS-Net's accuracy versus other models, achieving comparable performance.

Now, suppose I reduce the number of available average pairwise comparisons per image (effectively reducing the number of available comparisons). When constrained by the size of the training data, PCS-Net vastly outperforms the remaining pairwise models, as shown in Figure 8.3, reaching about 15% improved accuracy, which can be very beneficial when data acquired from surveys is limited.

Table 8.1: Comparison of PCS-Net versus other paired comparison models using the semi-realistic data.

Model	Accuracy ↑
Elo (Elo, 1978)	0.833
TrueSkill (Herbrich et al., 2006)	0.839
Gaussian Process (Maystre et al., 2019)	0.843
Rank Centrality (Negahban et al., 2012)	0.839
PCS-Net$_C$ [VGG] (Ours)	0.599
PCS-Net$_R$ [VGG] (Ours)	0.839
PCS-Net [VGG] (Ours)	0.839

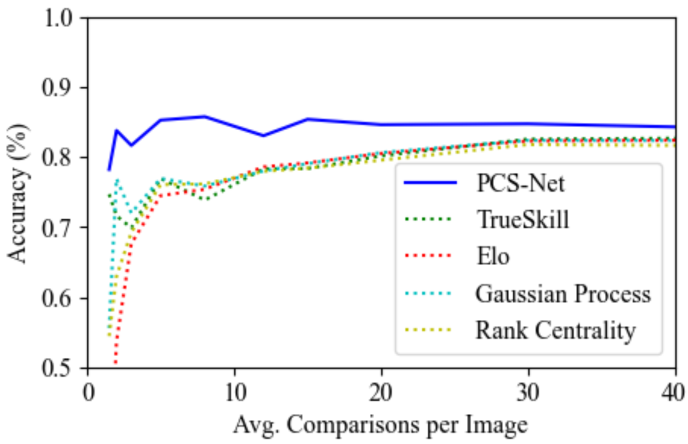


Figure 8.3: Model accuracy with varying number of average comparisons for different paired models.

Table 8.2: Comparison of PCS-Net versus other paired comparison models using real images from Berlin.

Model	Accuracy ↑
Elo (Elo, 1978)	0.591
TrueSkill (Herbrich et al., 2006)	0.624
Gaussian Process (Maystre et al., 2019)	0.632
Rank Centrality (Negahban et al., 2012)	0.611
PCS-Net$_C$ [VGG] (Ours)	0.849
PCS-Net$_R$ [VGG] (Ours)	0.855
PCS-Net [VGG] (Ours)	**0.867**

8.4.4 Testing on real data

Next, I move to this work's core results, which apply PCS-Net to real-world images and pairwise comparisons, previously detailed in Chapter 6. Data contains responses from 251 users on images from Berlin on 7281 comparisons (3.3 average comparisons per image), of which 18% consist of ties.

I begin by comparing this approach versus other pairwise models. Again, I test PCS-Net against TrueSkill (Herbrich et al., 2006), Elo (Elo, 1978), Gaussian Process (Maystre et al., 2019), and Rank Centrality (Negahban et al., 2012), shown in Table 8.2. As expected, given the low number of average pairwise comparisons per image available, PCS-Net outperforms competing approaches with a $\sim$17% improvement. This means that PCS-Net can effectively learn rankings directly from images, even when the number of available comparisons is limited.

Next, I experiment with different network backbones (feature extraction sub-network) and different model hyperparameters. Backbone networks (feature extractor sub-networks) were initialized using the pre-trained Imagenet weights available publicly: AlexNet (Krizhevsky et al., 2012), VGG (Simonyan and Zisserman, 2014), and ResNet50 (He et al., 2015). Table 8.3 shows the model's accuracy using different backbones. VGG achieves the highest accuracy, closely followed by ResNet and AlexNet. Additionally, I test whether augmenting the real image dataset by adding semi-realistic data improves model performance. For this, I train PCS-Net using each backbone and combine the real images dataset with a similar-sized set of random pictures taken from the semi-realistic image dataset aforementioned. Looking at the lower section of Table 8.3, one sees that results improve slightly, with the highest accuracy being achieved again with VGG. Thus, augmenting with semi-realistic image comparisons leads to slight better prediction accuracy.

Next, I test the impact of including ties and margin term γ. Figure 8.4 shows the model's accuracy over γ when PCS-Net is trained with and without ties. Additionally, I plot the default baseline when PCS-Net does not account for ties or margin effects (in blue). When one sets $\gamma > 0.4$, the model trained with ties achieves an average 3% lower accuracy than the non-tie trained model's accuracy.

So far, I have looked at model performance trained with and without ties and compared them to approaches that do not easily allow for the prediction of tie comparisons. Yet, including ties allows

Table 8.3: PCS-Net accuracy using different backbones, with and without data augmentation using semi-realistic data.

Augmented with Semi-realistic Data	Backbone	Accuracy ↑
No	AlexNet (Krizhevsky et al., 2012)	0.832
	VGG (Simonyan and Zisserman, 2014)	0.867
	ResNet (He et al., 2015)	0.846
Yes	AlexNet (Krizhevsky et al., 2012)	0.855
	VGG (Simonyan and Zisserman, 2014)	**0.874**
	ResNet (He et al., 2015)	0.846

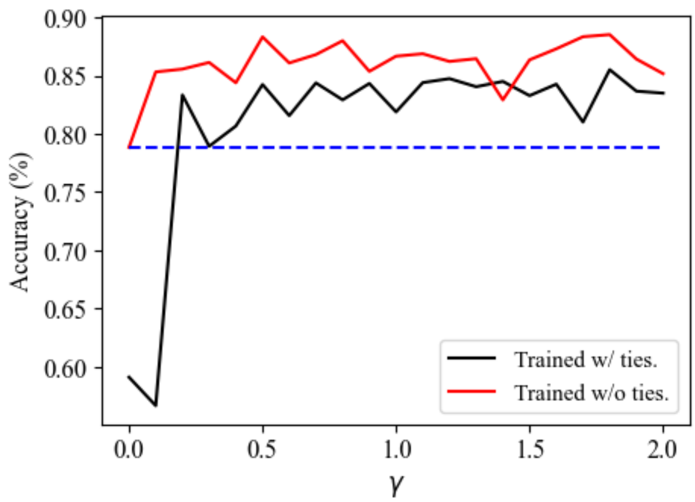


Figure 8.4: PCS-Net accuracy trained with and without ties, for varying γ. The dash blue line corresponds the accuracy of PCS-Net without ties and with $\gamma = 0$.

participants not to choose a preference when in fact there is none. More, knowing when there is no distinguishable difference between two images can be highly valuable in practice, informing planners and decision-makers which environments are perceived equally. To account for this aspect, I now compute a different accuracy metric to include *ties* as an output class and use γ to distinguish between ties and non-ties. This new metric is computed as the ratio of the correctly predicted left (i.e., $f(x_i) > f(x_j) + \gamma$), right ($f(x_j) > f(x_i) + \gamma$), and tie ($|f(x_i) - f(x_j)| < \gamma$) comparisons to all comparisons. It concedes an interval defined by γ when there is insufficient rank difference between images. When this happens, I consider there is no noticeable difference between the two images, and the comparison is expected to result in a tie.

Using this new, more general metric, one can rank images and simultaneously test whether a comparison is expected to result in a tie. I again test the models trained with and without ties and compute the new (3-class) accuracy and error rates for γ, achieving comparable results. However, analyzing the magnitude error of incorrectly classified observations (i.e., loss of misclassified observation) in Figure 8.5, one sees that the model trained with ties achieves an average absolute error much lower than that which did not include ties during training. Moreover, the absolute error on such wrongly classified images was relatively low (< 0.07) at its minimum ($\gamma = 0.7$), suggesting that even for misclassified comparisons, the inclusion of ties leads to a lower error.

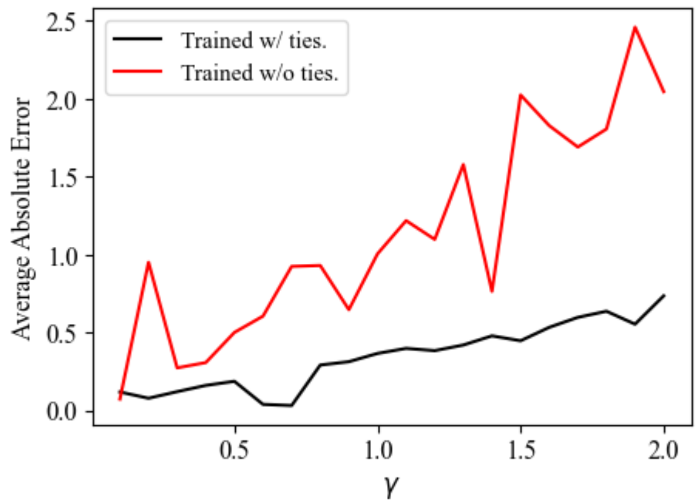


Figure 8.5: Average absolute error for misclassified observations between models trained with and without ties, for varying γ.

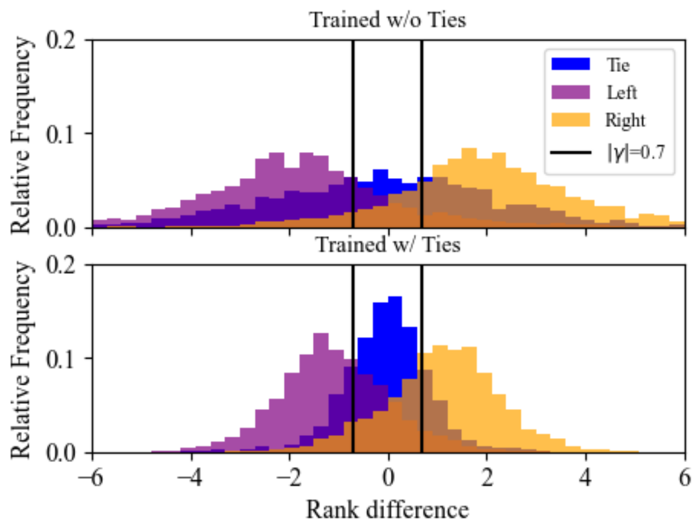


Figure 8.6: Comparisons rank difference distribution between tie and non-tie observations when PCS-Net is trained without (above) and with (below) ties, for $\gamma = 0.7$.

Using this γ, one can also analyze the distribution of image rank differences for tie and non-tie comparisons between a model trained with and without ties. Looking at Figure 8.6, the model incorporating ties (below) pushes tie observations below margin $|\gamma|$ and non-ties above $|\gamma|$. In the model trained without ties, tie observations are much less distinct and are dispersed among the left and right options. Additionally, Figure 8.7 showcases the average rank differences in comparisons for different margins. Notably, the average difference for ties lies below γ whereas above γ for non-ties. In all, this approach corroborates the idea of allowing participants to opt for ties to better reproduce their perceptions and therefore potentially improve their engagement in comparing images more carefully, as they are not forced to choose an option they are not completely sure.

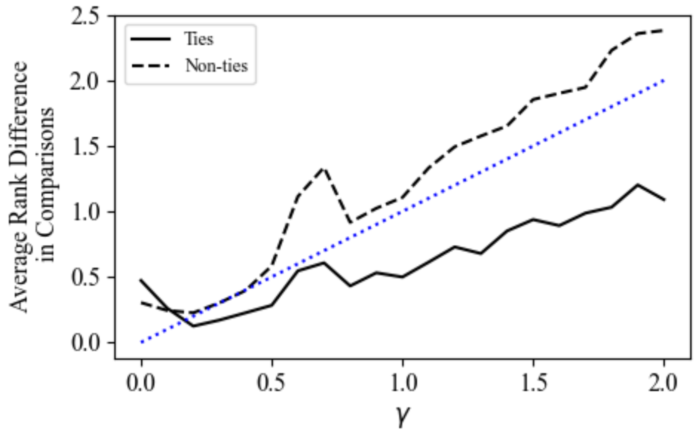


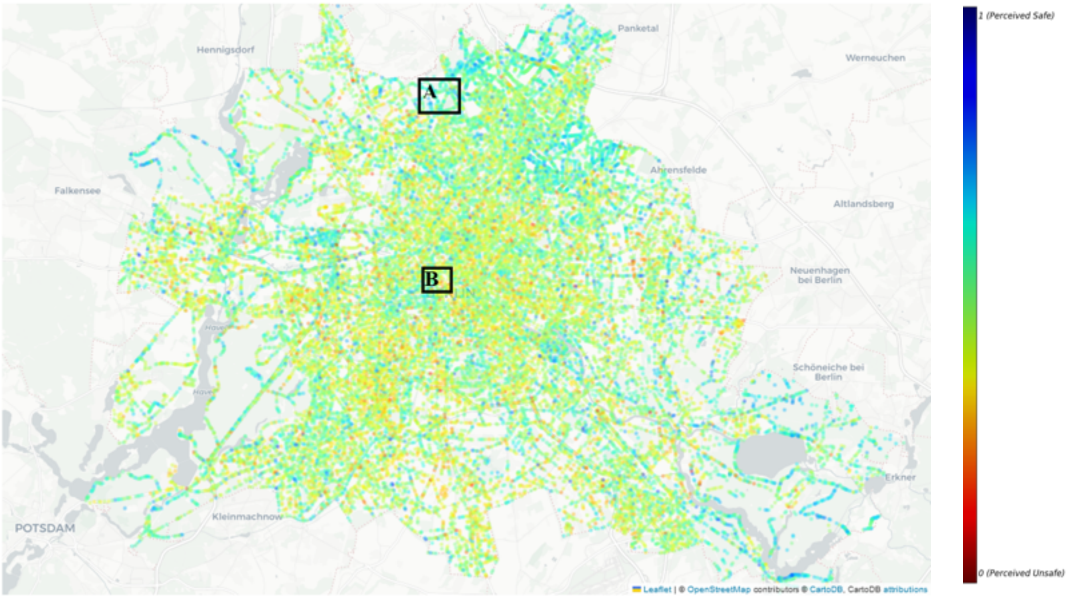
Figure 8.7: Average rank difference between images in comparisons for varying γ. I show the impact on the average rank difference between ties and non-ties observations.

8.5 City-wide Application

To demonstrate how PCS-Net can be used to analyze the perceived cycling safety of an entire city, I computed perceived safety scores for the entire city of Berlin. To cover all of Berlin, I geographically sampled points using a 100m by 100m grid and projected them to the nearest cyclable path or road. I then retrieved street view images from Mapillary for each point. I extracted 36,700 images, which I then ran through the most accurate PCS-Net model. This gave us a perceived cycling safety score for each image in Berlin, which, for readability, I scaled between [0, 1].

Figure 8.8 showcases the perceived safety scores for Berlin. As one would expect at the city-wide scale, scores are well distributed throughout the whole city. Taking a closer look (Figure 8.8.b), certain areas appear to be relatively perceived as safer (predominantly blue-ish, such as Berlin's north and southeast) and seem to be more continuous. Examining the corresponding images, one sees that these correspond to less urbanized areas where high levels of vegetation are visible in the images. In the center of the city (Figure 8.8.c), locations are not perceived as safe as before, with scores varying widely within a relatively small area, even on locations on the same road/street which exhibit changes in the levels of perception.

On the whole, I showcase that there are several key hotspots for environments that are perceived as safe and unsafe, while at the same time, some high-level continuous hierarchy of perceived safety score seems to exist. From this, aggregate and disaggregate metrics can help planners and decision-makers highlight and prioritize urban environment changes to make cyclists' trips more enjoyable, comfortable, and where cyclists feel safe to cycle in.



(a)

(b) (c)

Figure 8.8: Map of perceived cycling safety throughout Berlin (a). Scaled perceived safety scores, from safer (blue) to unsafer (red), are shown for sampled images in Berlin. Two areas are selected and shown in greater detail in (b) and (c).

8.6 Discussion

This work has focused on deriving cycling environments' perceived safety scores from pairwise comparisons. Pairwise image comparison surveys offer a systematic and quantitative approach to investigate visual preferences and individuals' perceptions, which can be used to quantify and categorize environments. Analyzing visual preferences from real-world images seeks to uncover the underlying patterns and principles that guide individuals' subjective perceptions. This is extremely valuable not only in research but also in practice for urban planners and decision-makers to adequately address cyclists' needs in terms of sense of safety and comfort.

Unlike most traditional paired models that ignore or avoid tied comparisons between two items, here I have included and underlined the importance of including ties. This follows the idea of the seminal work of Rao and Kupper (1967), where ties matter and should be included to model comparisons when there is not enough difference between two items for a user's sense of perception to note a difference. In addition, allowing participants to choose a tie potentially increases their engagement, resulting in more truthful choices and more accurate classification and ranking models. In this case, I propose the inclusion of margin γ to model this imperceptible difference. Yet, I used a fixed γ, which, in more general terms, may be different between individuals and cycling contexts. In this sense, estimating independent γ's for each user would allow for a better understanding of individual-level perceptions. Allowing for γ to vary, either through bootstrapping or other approaches, may be used to ably model heterogeneity at an individual level or for different individuals' cycling profiles. More, with reference to the Weber-Fechner laws of psychophysics (Fechner, 1860), which explore stimulus magnitudes and the ability to distinguish between two stimuli, it would be interesting to model which environmental factors influence users' perceptions of cycling safety in such a way that they can distinguish between environments that appear safer for cycling. This knowledge could provide researchers with even more approaches to understand different built environment impact on different cyclists.

All in all, much of the work here developed is based on the fact that ties should not be discarded when available. Results-wise, the inclusion of ties achieves comparable performance to non-ties-only trained models, meaning that I can include them without any major loss. Even with the limited number of average comparisons per image, I am able to derive good prediction power, meaning that I can learn directly from the presented images and survey responses to capture cycling safety perceptions. Further analysis with other, larger, and more complete datasets is necessary to understand if the model can capture the general sense of safety perception. Also, if it can be used for knowledge transfer between cities with different cycling cultures and urban design philosophies.

Another aspect that could be explored is the use of transformer-style networks (Dosovitskiy et al., 2020), as these have been recently gaining popularity in computer vision tasks (namely object detection, semantic segmentation, and other learning tasks) for their higher prediction accuracies. Yet, these are characterized by requiring more data and processing power than traditional convolutional-style networks. It would, however, be interesting to explore the power of transformers and other network configurations as more data on the perception of cycling safety together with street-view images becomes available or explore more robust training techniques when only smaller datasets are available (Liu et al., 2021).

8.7 Summary and conclusions

In this section, I have explored how cycling environment pictures can be ranked according to individuals' perceptions of safety. I base this work on pairwise comparisons, presenting participants with pairs of images and asking them to indicate their preferred choice of which environment appears safer for cycling. I then developed a siamese-style neural network that cannot only rank images based on choices (left or right image chosen), but also incorporate ties, often overlooked and ignored in the literature. The proposed methodology achieved good results, requiring fewer observations than current paired models, as knowledge can be directly driven from image features and individuals' decisions. I extensively tested this approach on real-world data and real-world enriched data using synthetic images. Finally, I tested a city-wide application of the proposed approach throughout Berlin and scored locations based on their perceived cycling safety.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/mncosta/learningpic. Code is available for Python3. The code is available under MIT license (https://opensource.org/licenses/MIT).

Chapter 9

Non-linear Effects of Urban Elements

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9.1 Introduction

All over the world, cities are investing in cycling infrastructure and network expansion, leading to an increase in cycling numbers (Pucher and Buehler, 2017). Yet, many factors deter people from cycling. From these, safety concerns (fears of being involved in an accident) are often considered a major deterrent to cycling (Parkin et al., 2007; Winters et al., 2012; Sanders, 2015; Aldred, 2016; Aziz et al., 2018; Félix et al., 2019). When people view cycling as risky or dangerous, they are likely to opt for alternative transportation modes instead of cycling. This poses a challenge to any city's efforts to boost cycling rates. As such, it is crucial to comprehend the factors that contribute to or exacerbate these safety concerns. Past research has found, among others, that road infrastructure and cycling facilities impact individuals' sense of safety (Chataway et al., 2014; Ng et al., 2017; Wang and Akar, 2018; Götschi et al., 2018; von Stülpnagel and Binnig, 2022; Ferreira et al., 2022). However, typical methods used frequently prove impractical due to their relatively high costs, require considerable manual labor to analyze and understand, and limited ability to capture non-linear effects of urban environment characteristics.

This chapters presents a new framework to uncover insights into the urban context's impact on individuals' perception of cycling safety. In essence, I am interested in answering "*What urban el-*

ements impact one's perception of cycling safety?". To answer this, I use an Explainable Boosting Machine (EBM) (Lou et al., 2013) as a way to predict perceived safety scores of street-view images from urban context factors, such as the presence of cycle lanes, vegetation, urban furniture, and presence of cars. As a result, one can learn the impact of each contextual element as it varies and its impact on either increasing or decreasing the sense of safety. EBM is a powerful, intelligible, and glassbox machine learning model that can account for both non-linear effects and pairwise interaction between factors, enabling more in-depth constructs to be formulated on individuals' perceptions of safety. Drawn from both image and mapping data, which include built environment elements (e.g., presence of cycle lanes, vegetation, bollards), dynamic road elements (e.g., presence of cars, other cyclists, pedestrians) and urban morphology (e.g., type of intersections, connectivity), we analyze the non-linear influence of different factors on subjective safety scores of urban cycling environments.

Next, I will outline related work in Section 9.2. Section 9.3 details the methodology used, including a description of the data and modeling tool. Then, I present the results in Section 9.4. Section 9.5 discusses this chapter's results and limitations. Finally, Section 9.6 concludes the chapter and draws lines of possible paths forward.

9.2 Background

Perceived or subjective cycling safety describes an individual's personal perception of the risk of cycling accidents. As the most significant barrier to urban cycling (Sanders, 2015; Félix et al., 2019), it is crucial to comprehend what factors impact this sense of risk. Understanding this is essential for creating environments where cyclists feel safe, which can, in turn, increase cycling uptake.

Data collection typically assumes the use of qualitative and quantitative surveys, *in situ* or post-riding interviews to collect data on individuals' perceptions to identify elements that negatively arouse individuals (Sanders, 2015; Aldred and Woodcock, 2015). Newer approaches, led by new technologies and the availability of open data in cities, have explored how to collect data on individuals' perceptions through wearable sensors (Zeile et al., 2016), cycling videos (Parkin et al., 2007), mental maps (Manton et al., 2016), virtual reality environments (von Stülpnagel and Krukar, 2018), semi-realistic street-view-style images (von Stülpnagel and Binnig, 2022), real-world street-view pictures (Costa et al., 2023), or gaze behavior via eye tracking devices (Schmidt and von Stülpnagel, 2018). However, despite the methodology used, most approaches usually require critical preparation and control over what stimuli are presented to individuals. This manual task of carefully calibrating what is shown and enquired to users often limits the scalability and complexity of environments explored. Ultimately, this hinders results' repeatability and transferability.

To uncover the effect of what elements impact cyclists' and non-cyclists' perceptions of safety, several strategies have been employed by researchers. These range from using qualitative methods (through interviews or focus groups) to quantitative methods (using principal component analysis or discrete choice modeling). In all, both approaches seek to uncover what factors impact one's perception of cycling risk, including the influence of urban elements or socio-demographic factors. Effects from traffic (Sanders, 2015), interactions with drivers and compliance with road rules (Lawson et al., 2013; Graystone et al., 2022), road and cycling infrastructure (Chataway et al., 2014; Ng et al., 2017) have been shown to impact the sense of safety of individuals. In this work, we are interested in analyzing the impact of different cycling context factors, mainly related to the built environment, the road, and its users. This has been explored before, such as the impact of intersection density (Wang and Akar, 2018), bicycle lanes (Ng et al., 2017; Wang and Akar, 2018), roads hierarchies and number of lanes (Chataway et al., 2014), lack of cycling network connectivity (Félix et al., 2019) and cycling facilities (Useche et al., 2019), presence of median refuge island (Wang and Akar, 2018), or roundabouts typologies (Møller and Hels, 2008). Yet, most studies look at factors independently, singling out one factor and understanding its effect on individuals' perceptions. While this reduces the chances for colinearity and allows researchers to focus on one single factor, urban environments are complex and heterogeneously composed of many elements altogether, and such factors cannot be singled out easily.

Other approaches focus less on a specific factor in the road environment, but use perceptional indicators and metrics to investigate types of different infrastructure layouts, aiding urban planners and designers in comparing and analyzing cycling conditions. Widely recognized indices like the Bicycle Stress Level (Sorton, Alex and Walsh, Thomas, 1994) and the Level of Traffic Stress (Mekuria, Maaza C and Furth, Peter G and Nixon, Hilary, 2012; Furth, 2017) attempt to assess bikeability and perceived risk. More recent approaches have expanded this strategy, deriving a bikeability index (Ito and Biljecki, 2021) and a perceived safety score (Costa et al., 2023) from street-view image-extracted features using computer vision techniques, offering an automated and scalable way to assess environments. Yet, not only are these indices usually created using linear effects of characteristics, but most other typical research methods (e.g., ordinal logit or factor analysis) often use linear-in-parameters approaches. While this is frequently a way to simplify and extract meaningful insights into safety perceptions, its effects may not be entirely linear, and thus, understanding a factor's effect may be over-simplified or not be entirely captured in its entirety.

All in all, understanding and analyzing the perception of cycling safety is critical to promoting cycling uptake. Research on the topic is typically based on surveys to quantify the impact of different factors on cyclists' perceptions. Planners and decision-makers can, in turn, use this knowledge to devise policies or urban changes to make cyclists feel safer while cycling through a city. However, this undertaking is often slow and requires considerable manual labor to prepare and analyze results. I consider that significant progress, both in terms of scalability and insight-attainability, can be made using a different approach to studying the perception of cycling safety.

9.3 Methodology

This section describes the data and methodology used in this chapter. I start by detailing the data used, including safety perception scores and available cycling environment data, already used and derived from previous chapters. Next, I explain the modeling approach using explainable boosting machine to uncover non-linear effects of urban elements on the perception of safety. Figure 9.1 presents an overall diagram of such approach.

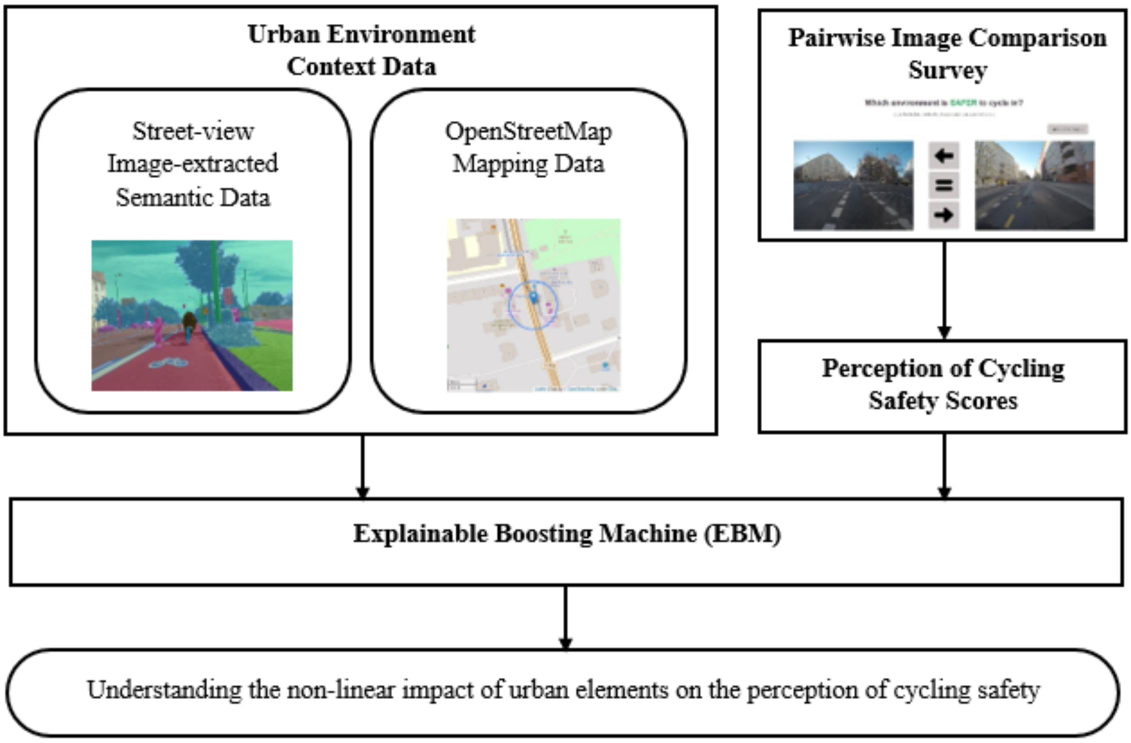

Figure 9.1: Methodological framework used in this chapter. I use urban environment context data to understand the perception of safety using an explainable boosting machine.

9.3.1 Data

In this chapter, I explore how we can extract insights into urban elements on individuals' perceptions of cycling safety. For this, I make use of available perception of safety scores (PSS) from 3850 SVI, where images portray real-world cycling environments from various locations across Berlin. Perceived scores for each image were previously obtained in Chapter 8. For ease of interpretability, all scores were normalized (scaled between 0-100), representing a comparative relative scale between all evaluated street-view images. Figure 9.2 shows some examples of image-computed PSS in ascending order, together with some extreme examples showcasing what images perceived as very unsafe and very safe. I use these image scores as the regressand in the employed modeling approach.

As we are interested in what urban elements impact the sense of safety, I retrieve urban element knowledge from the shown images and their surroundings. For this, I perform a two-step procedure

a) 21.68 b) 41.58 c) 61.36

Figure 9.2: Examples of cycling environment images and their respective standardized perceived safety scores and cases of images perceived as less safe (left) and more safe (right).

Figure 9.3: Example of a street-view image and its semantic segmentation map, where different classes are shown in various colors.

to form the urban environment context data: 1) I extract factors via image semantic segmentation (semantic data), and 2) I retrieve built environment information from available geographic data (mapping data) around each image's location to complement the segmentation data. Such similar scheme was already used in Chapters 4 and 5.

First, I begin by semantically segmenting images to extract relevant information about their composition. Again, a detailed description is presented in Section 5.3.2. However, a different semantic segmentation is used. Here, I process every image in the dataset using the publicly available Mask2Former (Cheng et al., 2022), trained using street-view images and able to detect 63 different urban elements. Figure 9.3 shows how semantic information is retrieved from images and Table 9.1 presents descriptive statistics on the object classes extracted from images. Similar to before, using the extracted segmentation map, I then obtained objects' areas on the image (e.g., what percentage of the image consists of cars, roads, pedestrians, and so forth for all available classes) and use this detailed information about urban environment composition as part of the regressors.

Second, to enrich the information we retrieved directly from images, I collect additional built environment context data from available mapping data. Again, details on this step can be reviewed in Section 5.3.2. As a reminder, Figure 9.4 shows how data is extracted from OSM given an image location, including points of interest and urban metrics computed from the associated street networks. In total, 192 urban characteristics are extracted for each environment (i.e., image location), which I also use as independent variables.

Table 9.1: Descriptive statistics on data from image segmentation.

Object (as image %)	N	Mean	(Std)	Object (as image %)	N	Mean	(Std)
Road	3825	0.22939	0.13061	Banner	1146	0.00059	0.0032
Vegetation	3827	0.19342	0.13097	Traffic sign (back)	1535	0.00055	0.00171
Sky	3826	0.17863	0.09993	Snow	39	0.00054	0.00788
Building	3783	0.12959	0.10714	Motorcycle	916	0.00045	0.00244
Sidewalk	3721	0.07124	0.1022	Street light	2885	0.0004	0.00065
Car	3746	0.04046	0.05084	Barrier	680	0.00038	0.00247
Bike Lane	1766	0.02888	0.06033	Catch basin	363	0.0003	0.0022
Lane marking (general)	3344	0.01886	0.02244	Bike rack	524	0.00027	0.00151
Curb	3749	0.01166	0.0115	Other vehicle	477	0.00021	0.00119
Pole	3782	0.01031	0.01044	Sand	48	0.00018	0.00351
Fence	3415	0.01003	0.01909	On rails	165	0.00017	0.00196
Terrain	2884	0.00955	0.02242	Bench	346	0.00015	0.0014
Crosswalk (plain)	886	0.00902	0.038	Wheeled slow	255	0.00012	0.00109
Billboard	3221	0.00569	0.01212	Traffic sign (frame)	201	0.00012	0.00134
Pedestrian area	422	0.00483	0.03979	Trailer	44	0.00011	0.00222
Rail track	346	0.00463	0.02704	Guard rail	242	0.00009	0.00124
Bridge	310	0.00447	0.02719	Caravan	43	0.00008	0.00226
Bicycle	1787	0.00378	0.01086	Phone booth	131	0.00008	0.00093
Wall	2390	0.00308	0.00984	Motorcyclist	220	0.00008	0.00127
Traffic sign (front)	3247	0.00307	0.00633	Water	45	0.00008	0.00178
Bicyclist	1352	0.00297	0.01099	Pothole	89	0.00004	0.00048
Parking	1494	0.00297	0.01116	Mailbox	57	0.00004	0.00098
Person	2557	0.00219	0.0054	Service lane	3	0.00002	0.00144
Truck	1340	0.0018	0.00883	Ground animal	53	0.00001	0.00008
Traffic light	1832	0.00162	0.00342	Other rider	51	0.00001	0.00032
Lane marking (crosswalk)	1109	0.00154	0.01699	Fire hydrant	89	0.00001	0.00008
Junction box	1208	0.00115	0.00605	Mountain	85	0.00001	0.00013
Curb cut	1736	0.00088	0.00309	CCTv camera	97	0.00001	0.00006
Bus	1320	0.00085	0.00346	Boat	16	0	0.00006
Utility pole	1170	0.00082	0.00305	Tunnel	5	0	0.0001
Manhole	800	0.00082	0.00376	Bird	37	0	0.00003
Trash can	1205	0.00064	0.00425				

Figure 9.4: Example of how data is extracted from OpenStreetMap using an image location in a 25m radius (left) and the corresponding extracted elements (right). *Source:* OpenStreetMap.org

9.3.2 Explainable Boosting Machine

Explainable Boosting Machine (Lou et al., 2013) is a glassbox machine learning algorithm that can be used for regression tasks. It belongs to the family of Generalized Additive Model (GAM) (Hastie and Tibshirani, 1987) of the form:

$$g(E[y]) = \beta_0 + \sum f_i(x_i) + \sum f_{i,j}(x_i, x_j) \tag{9.1}$$

where $g(\cdot)$ is a link function, y an image perceived safety score, $E[\cdot]$ its expected value, x_i a feature i, $f_i(\cdot)$ a feature function for feature i, and $f_{i,j}$ is a pairwise feature interaction function for features i and j. Feature functions and interaction functions are learned during model estimation through bagging and gradient boosting techniques. For further details on EBM, I refer the reader to Lou et al. (2013). EBM has been gaining popularity recently due to its comparable performance to state-of-the-art machine learning methods like Random Forest and Boosted Trees, while being highly intelligible and explainable, for which reason we use it in this analysis.

Because of its GAM form, EBM learns contributions from each feature and pairwise interactions between features in a modular format, allowing for easy assessment, understanding, and visualization of each feature's contribution to the predicted score. In this sense, they work as a multiple variable linear regression, yet each regressor is automatically transformed via a lookup table per feature, improving intelligibility and prediction power. In turn, this allows one to check for non-linear impacts of regressors on the perceived safety score, enabling a more in-depth and non-linear analysis of individuals' perceptions.

In our setting, I use EBM as a way to predict the perceived safety scores of each street-view image using the aforementioned regressors (i.e., built environment elements drawn from semantic and mapping data), such as the presence of cycle lanes, vegetation, urban furniture, and presence of cars. Again, I explicitly employ such approach to be able to uncover non-linear and pairwise effects from these contextual elements and how they moderate individuals' increased ou decreased sense of safety.

9.4 Results

This section details the results of modeling urban elements' impact on cycling perception of safety using EBM. I present the results of both the effects of data extracted directly from the images and the features retrieved from mapping data, highlighting their impacts and providing insights into cycling perception of safety.

Experimental setup: I estimated an EBM using Python to program and evaluate the model. For the results produced, EBM was trained using 15 maximum bins for each feature, a total of 256 possible pairwise interactions, 0.1 as our learning rate, 8000 maximum number of rounds, 1 minimum sample per leaf, 25 maximum leaves, 16 inner bags, 8 outer bags, and 40 rounds for early stopping. Lastly, as aforementioned, we use the urban context data used in the previous chapters, which includes semantic and mapping data comprising a total of 250 variables, to model our perception safety scores.

In the end, I achieved a model with $R^2 = 70.1\%$ ($RMSE = 4.04$), effectively learning what and how various urban elements impact the perception of cycling safety. As previously mentioned, two major benefits of using EBM are understanding the non-linear effects of different urban elements and being able to perform large-scale unified analysis using a vast number of cycling context features. However, covering and describing all the characteristics and variables' effects in this chapter is impossible as their number is too large. Hence, I highlight the main findings here, while the complete results can be found in Appendix G.

First, we take a look at the impact of semantic data. We notice that all variables exhibit a non-linear relation to our regressand, which is monotonic for some variables and non-monotonic for others. Figure 9.5 showcases how some factors influence variation in the perception of safety:

- *Sidewalks* are viewed as mostly positively increasing the sense of safety, except when they occupy a very low area on images (< 0.05). That effect increases until images contain about 28% of sidewalks. The increased perception effect stabilizes, and the sense of safety is no longer affected by an increase in the amount of sidewalks present in the image.
- *Roads* impact is more complex. When roads occupy less than 15% of the image, it increases the sense of safety, which is driven by the fact that the environment would show more cycling lanes, or sidewalks, environments often appearing safer for individuals. When roads occupy more than 15% of the image, they have a negative effect on safety perceptions, suggesting that the image showcases a road-heavy environment, usually viewed as unsafer for cyclists as they do not have dedicated infrastructure to cycle on.
- *Crosswalks* negatively impact the perception of safety, with that effect being almost constant regardless of the area occupied by it on images. Crosswalks represent points where possible interactions and conflicts with pedestrians might occur, so, as expected, it decreases the sense of safety felt by cyclists.
- *Cars* showcase a negative effect on the perception of safety, except when its occupancy area on images is very low (i.e., cars are very far from the image's viewpoint). The magnitude of this effect increases as the area occupied by cars increases (i.e., more cars are visible or these are closer to the image's viewpoint) until cars occupy about 13% of an image.
- *Cyclists* being present on images, on the other hand, positively increases the perception of safety, with that effect being nearly constant despite its occupancy area on images (i.e., more or less cyclists being shown, or being closer to the image's viewpoint).
- Finally, *Snow* also decreases the sense of cycling safety. This is expected, as adverse weather conditions may pose additional risks to cyclists as it may increase sliding events occurring with ice being present on roads or cycleways.

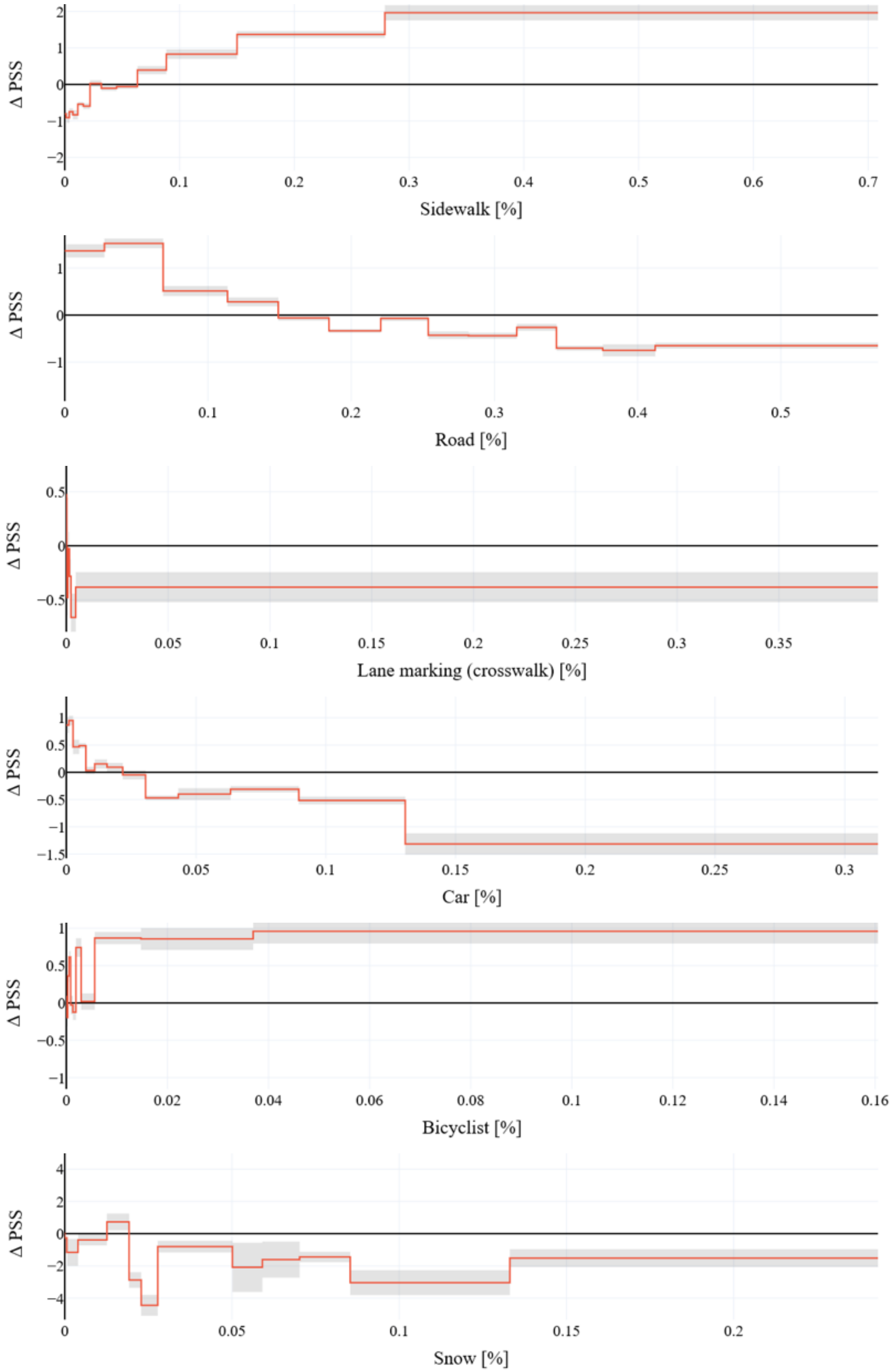

Figure 9.5: Impact of different elements from images' semantic segmentation on the perception of safety. Plots show the direct impact and variation on the perception of safety scores (ΔPSS) from different objects' areas (in %) pictured in the images and its associated error in grey (note the different y-axes scales).

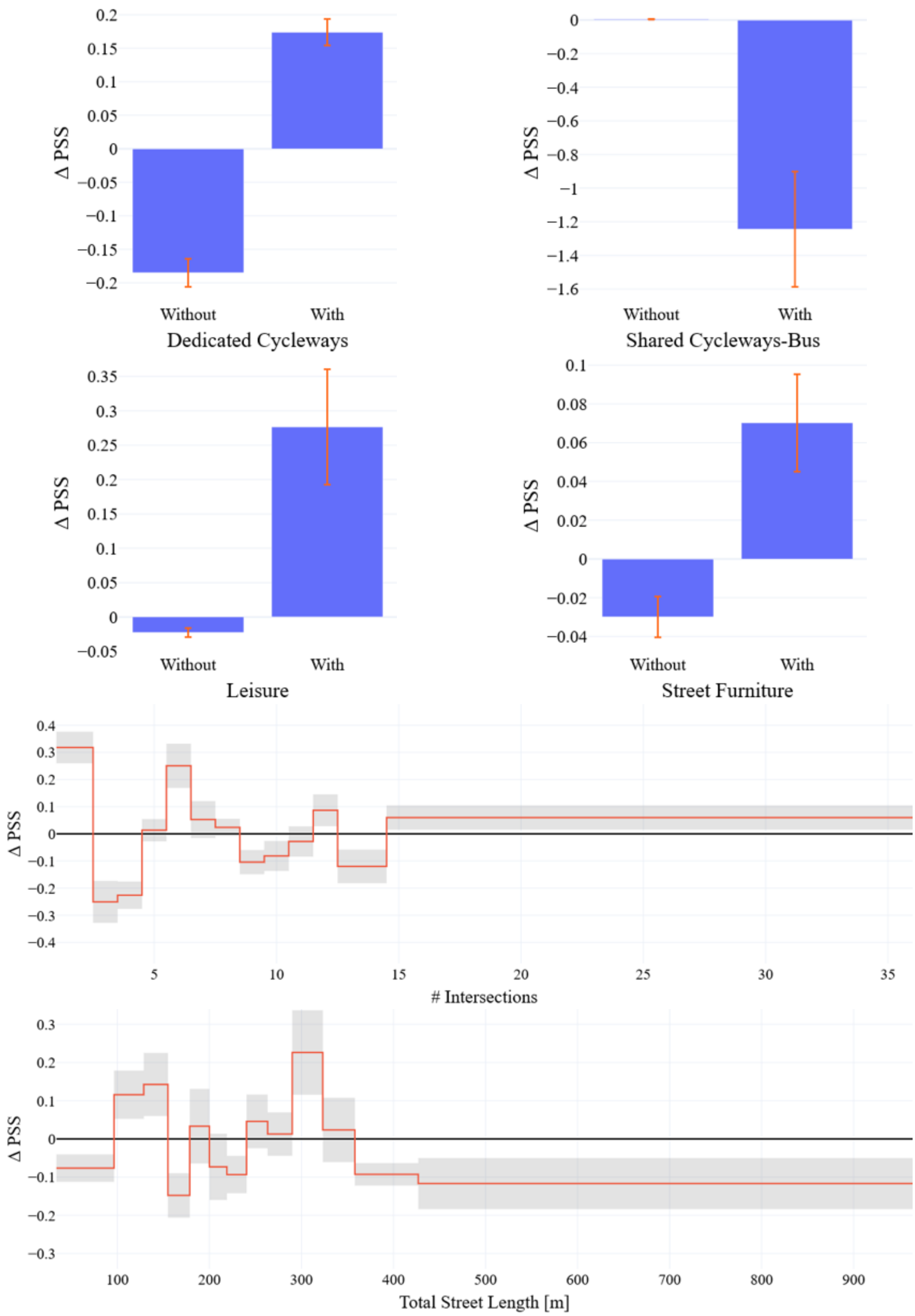

Figure 9.6: Impact of different mapping data variables on the perception of safety. Plots show the direct impact and variation on the perception of safety scores (ΔPSS) from different physical urban elements and network attributes and its associated error (note the different y-axes scales).

Second, we take a look at the effects of mapping data. As aforementioned, I have included regressors that seek to complement the information directly extracted from the street-view images and contain variables for urban physical elements and streets' network variables extracted around each image's location. For this, I highlight the results displayed in Figure 9.6:

- *Dedicated cycleways* clearly improve the sense of safety versus locations without any sort of dedicated cycle lanes.
- *Shared cycleways-bus* absence has no impact on perceived safety. However, when they are present, they heavily decrease the perception of safety. Sharing the space with heavy public transportation vehicles is not viewed as friendly or safe for those who cycle.
- *Leisure activity places* (e.g., restaurants, bars, shops, and others) near the images' viewpoints increase the sense of safety felt by cyclists.
- *Street furniture* improves the perception of safety for individuals versus environments where no street furniture elements are present. Street furniture might help delineate how urban space is used (such as to control overspill parking or block access to sidewalks or roads), improving the sense of safety in cities.
- *Number of intersections* impact on the perception of safety is not so clear. One would expect that with a growing number of intersections (and possible conflict points), a decrease in the sense of safety would occur. Yet, such behavior is not noticeable from the achieved results.
- *Street length* effect on the perception of safety also varies greatly as length increases, with perception increasing and decreasing as length increases. One would expect perception to decrease with longer streets, but that is not evident in the results achieved. It is also important to acknowledge that both the *number of intersections* and *street length* may not bt fully perceptible in the shown images, which may contribute to such behaviors.

Third, we take a look at pairwise interaction effects between variables, which can be retrieved directly to inspect how such interactions affect individuals' perceptions. Figure 9.7 showcases two of these interactions. The top plot shows the relation between *cars* and *roads* and their joint effect on individuals' perceptions. As shown, most of the interaction between the two exhibits no variation in the perception of safety. However, two key regions appear when the amount of *cars* increases in the images. When *cars* occupy an area above 15% and the amount of shown *road* are below 15%, we have a decrease in the sense of safety. On the opposite spectrum, when *cars* are above 15% and *road* is also above 42%, we see an increase in the sense of safety. This prompts two distinct image types: the former, which showcases an image greatly occupied by *cars* and not much road space is present, causing a decrease in the sense of safety; while on the latter, despite having a high amount of *cars*, there is more “free” *road* shown, causing an increase in the sense of safety. Additional analysis is required here to understand whether emptier roads are being perceived as less

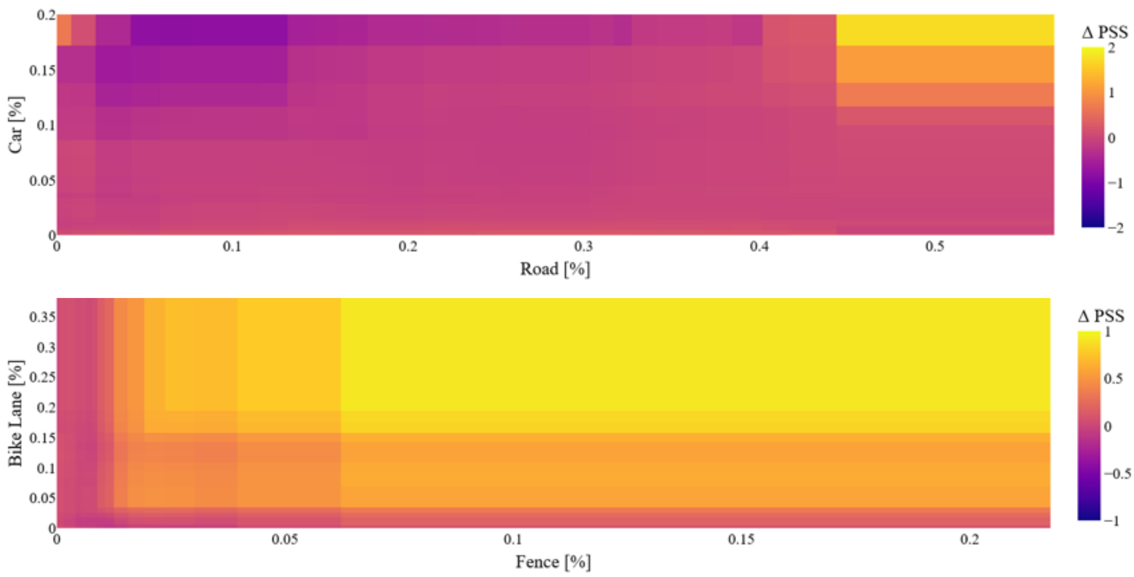

Figure 9.7: Impact of pairwise variable interactions on the perception of safety. Plots show the direct impact of a paired interaction between the two variables shown and the corresponding variation on the perception of safety scores (△PSS).

safe in general terms (i.e., crime-related safety aspects are being included in individuals perceptions). The bottom graph shows the perception of safety impact from the interaction between *bike lanes* and *fences*. Here, we see a more straightforward relation, increasing the sense of safety when both the amount of *bike lane* and *fence* increase. On the other hand, for images with fewer than 2% of *fences*, there is no impact on the perception of safety with any variation of *bike lanes*. The same can be seen on the opposite spectrum, with no impact on the sense of safety for any variation on the amount of *fence* for any images with fewer than 3% of *bike lane*. In all, we can notice that having *bike lanes* together with *fences*, which may serve to separate bicycle traffic from cars or pedestrians, increases the individuals' perception of safety.

Next, to globally understand what environment factors have more impact on the perception of safety, I have grouped variables and analyzed their importance in predicting safety perceptions. For this, I have performed a taxonomy split between elements from the segmentation and mapping information. Using each group, I then computed its average absolute contribution to explaining all available samples, i.e., I computed the average joint impact of each group of variables in modeling the perception of safety scores. I have divided variables into the following groups between segmentation data: Users (e.g., animals, persons, cyclists, motorcyclists), Vehicles (e.g., cars, trucks, bicycles), Physical elements (e.g., buildings, bridges, fences, walls), Road (e.g., roads, rails, crosswalks, bike lanes), Roadside (e.g., sidewalks, curbs, pedestrian areas), Roadside objects (e.g., street furniture, traffic signs, vegetation), Others (e.g., mountains, sand, snow); and mapping data: Places (e.g., restaurants, bars, cafes), Landuse (e.g., residential, commercial, industrial), Circulation Spaces (e.g., roads, cycleways, motorways), Habitat (e.g., mountains, lakes, rivers), Barriers (e.g., fences, garage entrances), Street elements (e.g., street furniture, vegetation), Transportation-related (e.g., taxi stops, bus stops). Figure 9.8 depicts the different groups' importance in modeling the perception of safety given the data

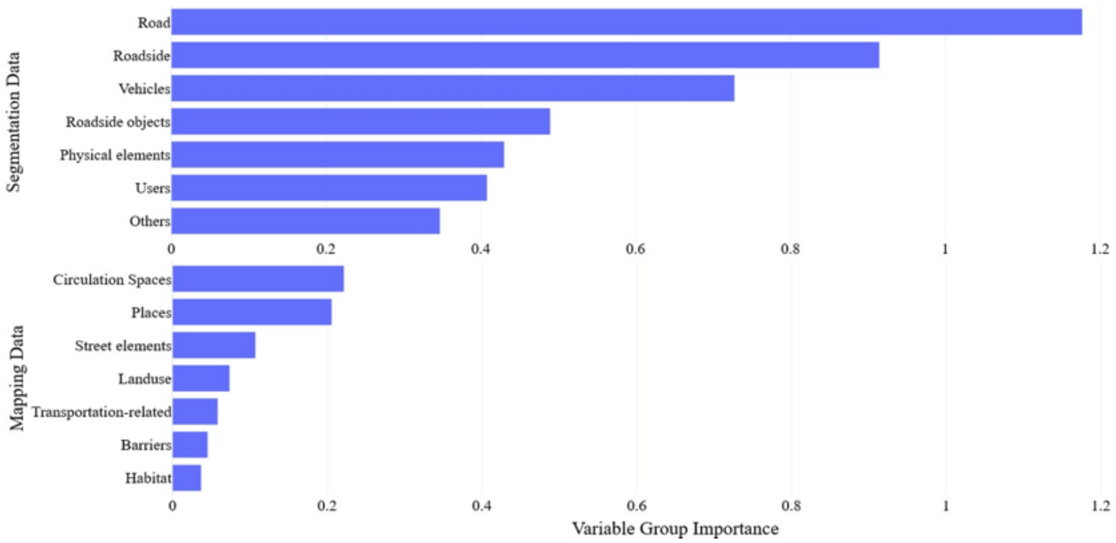

Figure 9.8: Variable importance for different groups of urban elements on the perception of cycling safety from both the segmentation and mapping data.

used. As shown, on average, variables extracted directly from the street-view images are more important than those retrieved from mapping data. As expected, the most important variables relate to the road, roadside infrastructure, vehicles, and roadside objects.

Finally, I present how individual samples can be analyzed in detail to understand how a unique environment is being perceived by individuals using EBM. For this, I present three observations in Figure 9.9 and plot the top ten image factors for that particular image as they increase or decrease each image's subjective safety score from the average perception of safety score. First, image A (top) viewpoint is centered in the middle of the road and snow is clearly visible on its side. The environment depicted is perceived to be dangerous ($PSS = 27.82$). Looking at the main factors for such a low score, we notice that *snow*, a visible *bridge*, no paved *sidewalk* and *bike lanes* exist, and a great area on the image is covered by *road*, which decrease the sense of safety, while only the inexistence of cars and buildings contribute to a slight increase in safety perceptions. Next, I focus on image B (middle), where an environment perceived as neither dangerous nor safe ($PSS = 47.33$) is shown. Here, the existence of a *bike lane*, *lane markings*, and *vegetation* contribute to an increase in the sense of safety, whereas the non-visible *sidewalk* and *curbs*, and the existence of several *cars* (covering 11% of the image) decrease the sense of safety. Lastly, image C (bottom) shows an environment perceived as slightly safer ($PSS = 57.50$), where a dedicated cycling lane, next to the sidewalk and separated from the road is shown. In this image, a very low area occupied by *road* (only 3%), the existence of a *bike lane*, large *sidewalk*, *vegetation*, and no visible *cars* heighten the sense of safety, while only the lack of visible *curbs*, existence of metal *poles*, and low amount of *lane markings* lower safety perceptions.

Figure 9.9: Interpreting street-view images' perceptions of cycling safety given the urban elements present. On the left, each characteristic effect on increasing (green) or decreasing (red) perception of safety scores is shown, together with its attribute value (in parenthesis).

9.5 Discussion

The present chapter examined the non-linear effects of various urban characteristics on the perception of cycling safety, shedding light on the complex interplay between urban environment factors and individuals' subjective safety assessments. Its findings have important implications for urban planning and the promotion of cycling as a sustainable mode of transportation, in addition to how street-view images can be used to study this topic.

The results revealed that the relationship between urban characteristics and cycling safety perception is not strictly linear. While some variables, such as the presence of dedicated or shared bike lanes and the existence of various types of street furniture, displayed a clear and consistent influence on safety perception, others showed a more subtle pattern. For example, the presence of other cyclists, road lane markings, and snow had apparent non-linear effects, suggesting that there may be an optimal threshold beyond which additional improvements do not significantly enhance safety perception. These findings emphasize the importance of considering the interaction between multiple factors in urban design rather than focusing on individual characteristics. More, some particular results, such as those pertaining to urban form, suggest that further in-depth analysis needs to be conducted to analyze the impact of urban network-extracted data on the perception of cycling safety.

The model used and its subsequent results analysis follow such principle, where a more significant number of elements can be incorporated together to understand safety perceptions better. Not only that, but it can also account for pairwise interactions between factors, enabling researchers to diver deeper into such an important topic. Another essential aspect of EBM is that it works with continuous dependent variables, such as the perception of safety scores used here. This steps away from traditional research methods where perception is often assessed using ordinal scales (i.e., Likert-point scales) together with ordered or multinomial logit models. Such endeavor allows one to increase the number of included factors easily (we have included 250 distinct variables), which is usually unfeasible and leads to nonconvergent logit models.

Such an advantage also poses challenges. Individually analyzing such a large number of urban factors is time-consuming and requires that many factors be combined for evidenced-based urban design. To counter this challenge, elements can be grouped to analyze significant components of urban environments. Our analysis found that road, roadside characteristics and objects, and vehicles are the main contributors to increase or decrease the sense of safety. Having well-delineated spaces for cyclists is vital, both from other motorized vehicles and pedestrians. Having environments where lane markings, sidewalks, curbs, or bike lanes are present and easily identifiable leads to a higher sense of safety, as does seeing other bicycles and cyclists.

While such study provides valuable insights, it is important to acknowledge some limitations. First, the perception of safety is subjective and can be influenced by individual characteristics, past experiences, and cultural factors, something not explored here. Future research should explore these aspects in greater detail to provide a more comprehensive understanding of the phenomenon. Additionally, longitudinal studies and more extensive data collection efforts could offer a more robust analysis of the non-linear relationships discussed here.

Overall, the non-linear effects identified in this chapter underscore the need for tailored urban planning strategies that consider the unique characteristics and needs of looking at urban spaces as a whole. Urban environments are diverse, and the factors affecting cycling safety perception may vary greatly from one location to another. Engaging with local communities to understand their specific concerns and preferences and design interventions accordingly is also important.

9.6 Summary and conclusions

In this chapter, we have explored how different urban elements impact cycling safety perceptions. I modeled both mapping and image-extracted data using an explainable boosting machine. This methodology allows one to understand the non-linear effects of various urban characteristics on individuals' perceptions, uncover pairwise interactions between different factors, and, at the same time, model a vast number of factors jointly, something often overlooked in the literature. This analysis uncovered several insights, suggesting that such non-linear understanding is crucial in capturing individuals' perceptions when evaluating the sense of safety from street-view images. Recognizing the complex interplay of urban factors and tailoring interventions is essential for creating cities conducive to safe and enjoyable cycling experiences.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/mncosta/cycling_safety_subjective_interpreting. Code is available for Python3. The code is available under MIT license (https://opensource.org/licenses/MIT).

Part B: Summary of Key Findings

In this part, I focused on the perception of cycling safety. The following items emerged as crucial remarks from the research carried out.

Using pairwise image comparisons is a viable choice to learn subjective safety perceptions

Pairwise image comparisons offer a valuable method for studying subjective cycling safety, allowing for a nuanced exploration of visual stimuli related to safety perceptions. They offer the use of real-world scenarios to facilitate gathering preferences and priorities regarding safety features, aiding in the development of targeted interventions or infrastructure improvements. This method leverages the individuals' inherent subjectivity to safety and contributes to a more cyclist-centric approach to addressing cycling safety concerns via a semi-naturalistic data collection process.

Perception of cycling safety scores: an indicator to measure perceived safety

Introducing a novel perception of safety score can be a valued metric in the study of cycling safety. By assigning numerical values to these perceptions, one can establish a standardized and comparable framework for assessing subjective safety across diverse cycling scenarios. This offers a systematic way to analyze and interpret perceived safety levels, allowing for statistical analyses and robust comparisons between different conditions or interventions. Such scores could be used in the future to enhance the precision of safety assessments and facilitate the tracking of changes over time, enabling researchers and policymakers to evaluate the effectiveness of safety interventions.

Lack of individuals' personal data: cyclists' profiles should be explored in the future

The absence of cyclists' profiles in the analysis presented in this thesis represents a significant limitation as it overlooks the individual nuances and preferences that can play a role in influencing safety perceptions. Integrating cyclists' profiles, including experience level, habits, and personal preferences, is essential for a more personalized and contextually relevant safety assessment. By considering these individual characteristics, researchers can tailor interventions and recommendations to specific user groups, acknowledging that perceptions of safety may vary widely among cyclists with different backgrounds and (especially) experiences. Additionally, incorporating cyclists' profiles enables a more nuanced understanding of how demographic factors, such as age, gender, or cycling frequency, may impact safety perceptions. This should be included in a future iteration of the perceived safety scores introduced so that the diverse needs of the cycling community can be better catered to.

Importance of including ties in pairwise comparisons

Including ties in pairwise comparisons is crucial for a more accurate and realistic representation of subjective perceptions. Ties, or situations where participants perceive two images as equally safe, provide valuable information that should not be discarded. In a cycling safety context, this recognition of ties leverages the fact that specific urban scenarios may be perceived similarly, highlighting situations where individuals might equally perceive multiple design alternatives. Ties introduce a level of relevancy of the results found, increasing the robustness and validity of the findings.

Using machine learning to predict perceived safety at a city-wide level from real-world images

Utilizing a trained siamese-convolutional neural network to explore perceived safety at a city level represents a promising approach in cycling safety analysis. Siamese networks, specifically designed for image comparison tasks, can effectively capture intricate visual patterns and relationships within pairs of images. It enables a scalable and data-driven method for analyzing vast urban imagery in the applied context. The network can learn and generalize patterns indicative of perceived safety across different locations within a city. This approach facilitates the identification of specific urban sites and areas that consistently impact cyclists' perceptions of safety. However, it's crucial to ensure that the dataset used for training is diverse and representative of the varied conditions cyclists may encounter across different parts of the city.

Non-linear impact of urban elements on perceived safety

The non-linear impact of different urban elements on the perception of cycling safety introduces a layer of insight-retrieval compared to previous approaches that demand careful consideration. Urban environments are complex, featuring diverse aspects such as road infrastructure, vehicles, signage, and landscaping. As we have seen, the influence of these elements on the perception of accident risk is not always linear, and their combined effects can lead to interesting interactions, as seen from the pairwise interactions shown. Recognizing the non-linear nature of these impacts is crucial for a comprehensive understanding of subjective safety perceptions. Certain urban features may disproportionately affect safety, varying their influence depending on the overall composition of the urban context. This necessitates a nuanced analysis beyond simplistic linear relationships, considering potential synergies or oppositions between elements. Future research should employ similar methods to the one used here to capture the complexity of these interactions, ensuring that interventions and recommendations address the complex web of factors shaping cyclists' perceptions of safety.

Part C

Objective and Subjective Cycling Safety

What have we learned so far

Until now, we have explored both objective (in Part A) and subjective (in Part B) cycling safety and how both can be independently analyzed using more scalable data-driven approaches. In both analysis, new strategies were devised to make of use of authoritative data and/or VGI, together with machine learning tools that enables researchers and planners to understand the two cycling safety types from a different perspective than that of previous research. From the knowledge and modelling developed, one can also look at objective an subjective safeties at a macro- and micro-scale, i.e., at a city-wide levels or at an observation-level, enabling a more contextual approach to studying cycling safety.

What we will explore next

Next, we will explore if past research has tried to analyze both safety types together and whether any relation between the two has been found. While considerable efforts have been put forward before to understand how policies and urban design changes can make cyclists be and feel safer, not much attention has been paid to understanding this intricate relation. I will try to contribute to addressing this problem. Taking advantage of the approaches used in this thesis's previous parts, I will explore whether such relation exists and, if so, what it consists of.

Research Questions

3. *What is the connection between objective and subjective cycling safety?*

3.1. *What do we currently know about the objective–subjective cycling safety relation?*

3.2. *Does an increase in objective risk relate to an increase in perception of risk? Or does the opposite happen, does a decrease in objective risk relate to an increased perception of risk?*

The last part of this thesis delves into the complex connection between objective and subjective cycling safety. As we will explore, such a relation is not always straightforward, and intervention in one type of safety may negatively affect the other. As such, it is vital to analyze and understand more about such a relation. This part presents my contributions in this area. Its highlights, linked with each of its chapters, are depicted in Figure C.

Chapter 10 overviews the current literature to provide a scoping background on how past research has explored the relation between objective and subjective safety. Results indicate a complex relation, where both alignments and discrepancies have been found between actual and perceived safety. Additionally, behavior change plays a crucial role in molding such a relationship, with several authors pointing toward how objective safety and subjective safety contribute to changing behaviors. Lastly, further research must analyze this topic, as measures to increase one type of safety might have opposite effects on the other.

Chapter 11 analyzes the effects of several urban features on objective and subjective cycling safety. It uses similar approaches with a machine learning algorithm to classify either accident outcomes or whether environments are perceived as safe or unsafe. This dual modeling strategy then allows for comparing elements' effects on each type of safety. Results highlight that some features' influences are similar on objective and subjective safety, while others present opposing impacts. Lastly, types of urban environments are compared, and a reverse influence is noted: environments with low perceived safety are actually safer. In contrast, environments perceived as safer are associated with low actual safety.

Lastly, I finalize Part C by providing an overview of its main highlights, discussing their implications in advancing cycling safety research.

Part C: Objective and Subjective Cycling Safety
(Chapters 10 and 11)

Scoping review on the relation
between objective and subjective safety
(Chapter 10)

⇒ Literature is reviewed on the relation between objective and subjective cycling safety;

⇒ Main findings showcase that such relation is often complex and context-dependent;

⇒ Understanding this relation is vital to ensure effective measures to increase both objective and subjective cycling safety.

Urban elements influence on
objective and subjective cycling safety
(Chapter 11)

⇒ Urban elements effects on accidents outcomes and perceptions of safety are analyzed;

⇒ Results showcase some elements have similar effects on both safety types, while other have opposing effects;

⇒ Findings points towards a context-oriented relation between objective and subjective safety;

⇒ Cycling environment typologies analyzed indicate an inverse relation, with environments having a higher actual risk being perceived as safer and environments with low actual risk being perceived as unsafer.

Figure C: Summary of research for Part C: Objective and Subjective Cycling Safety. Part C is divided in two chapters and main highlights are listed for each chapter.

Chapter 10

The *Status Quo* on the Relation between Objective and Subjective Cycling Safety

This chapter is currently being prepared to be submitted as a journal article: "Costa, M., Siebert, F. W., Azevedo, C. L., Marques, M., Moura, F. (N/A). The status quo of the relation between objective and subjective cycling safety: A scoping review and future directions [Manuscript in preparation]."

10.1 Introduction

Today, many cities are seeking to transition to more sustainable transportation modes. Cycling plays a key role in such a transition. Cycling can improve health (Oja et al., 2011b; Götschi et al., 2016), reduce greenhouse gas emissions and air pollutants (Mason et al., 2015; Neves and Brand, 2019), and serve as a valid option for shorter trips, including first-and-last-mile links to transit. However, for such a transition, individuals must want to switch to cycling. Cycling safety is often considered a pivotal talking point for those who cycle or intend to do so. Keeping cyclists and potential cyclists from being involved in incidents is vital to prevent minor or life-changing injuries and death. Not only that, but it is also crucial they feel safe while riding, or they will revert to other transport modes if they do not.

Objective cycling safety research studies and analyzes where, how, and why cycling accidents occur, aiming at reducing the number of accidents and the impacts of such accidents. Factors such as street elements (Chen, 2015), road network (Marshall and Garrick, 2011), and land use (Kaplan and Prato, 2015) are some of the many components that have been studied and found to have a statistically significant impact on cycling accidents. The measures and policies that are drawn from such studies can help to decrease the risk faced by cyclists and lead to the creation of safer environments for all.

Conversely, subjective cycling safety questions what factors increase or decrease the perception of accident risk. Concerns of being involved in an accident are often considered a major deterrent to cycling (Parkin et al., 2007; Winters et al., 2012; Sanders, 2015; Aldred, 2016; Aziz et al., 2018; Félix et al., 2019), leading individuals to decrease their cycling activity compared to their potential because of motorized traffic associated risks (Jacobsen and Rutter, 2012). They assess the likelihood of getting injured while cycling and act based on that evaluation (Jacobsen and Rutter, 2012), which may lead to opting for other transport modes and posing a challenge to any city's efforts to boost cycling rates.

Despite considerable efforts in studying objective and subjective safety, the relation between the two has remained rather unexplored. Are perceptions of cycling risk influenced by an actual higher accident risk? Is there a alignment between the occurrence of cycling accidents and the public perception of these incidents? Such questions delve into the potential associations between the two types of safety, which, for the most part, persist as fair unknowns in the field of cycling safety research.

As such, this chapter aims to review and examine current efforts being carried out to identify, analyze, and understand the relation between objective and subjective cycling safety. To accomplish this, I began by reviewing the current body of work on the subject and analyzing what approaches are being used to study this problem. Next, from this analysis, I compile how transport policies and infrastructure design can impact cycling safety in general and, more specifically, the relation between the two types of cycling safety.

This chapter is structured as follows: after this introductory section, I detail the methodological approach in Section 10.2; Section 10.3 examines the results, which are then discussed in Section 10.4; and, finally, Section 10.5 highlights the main findings and outlines future research leads.

10.2 Methodology

A scoping review strategy is employed in this study (framework previously outlined by Arksey, Hilary and O'Malley, Lisa (2005)). Contrary to systematic literature reviews that focus on a well-defined question and aim at providing answers to a relatively narrow topic, a scoping literature review tends to tackle a wider scope (typically covering multiple study approaches and designs) and a broader research question (Arksey, Hilary and O'Malley, Lisa, 2005). Scoping reviews can also serve as a preliminary approach to cover a research area's body of work and identify potential areas with enough background to warrant a future systematic review (Munn, Zachary and Peters, Micah DJ and Stern, Cindy and Tufanaru, Catalin and McArthur, Alexa and Aromataris, Edoardo, 2018). Importantly, findings are typically not aggregated, nor are assessed qualitatively (Arksey, Hilary and O'Malley, Lisa, 2005), but it serves to identify critical gaps and current limitations (Arksey, Hilary and O'Malley, Lisa, 2005), which can be used to devise possible paths forward to tackle such gaps.

As aforementioned, here I aim to find the answer to the question: "What do we currently know about the objective–subjective cycling safety relation" This chapter examines and summarizes past and current approaches to identify and understand whether such a relation exists. Next, I describe the methodology used in this scoping review.

10.2.1 Search strategy and study selection

To retrieve relevant manuscripts to this review, a search strategy was developed. Three electronic research databases were used for the search: Web of Science (WoS)[1] (Clarivate, 2023), Transport Research International Documentation (TRID)[2] (The National Academies of Sciences, Engineering, and Medicine, 2023), and Scopus[3] (Elsevier, 2023). These scientific databases contain millions of publications which include numerous records on transportation research compiled from multiple journals and publishers.

Table 10.1: Search terms and criteria used in all databases.

Category	Search criteria
Keywords	(("OBJECTIVE SAFETY" AND "PERCEIVED SAFETY") OR ("OBJECTIVE SAFETY" AND "PERCEPTION OF SAFETY") OR ("OBJECTIVE SAFETY" AND "SUBJECTIVE SAFETY") OR ("OBJECTIVE SAFETY" AND "PERCEIVED RISK") OR ("OBJECTIVE SAFETY" AND "PERCEPTION OF RISK") OR ("OBJECTIVE SAFETY" AND "SUBJECTIVE RISK") OR ("OBSERVED SAFETY" AND "PERCEPTION OF SAFETY") OR ("OBSERVED SAFETY" AND "PERCEIVED SAFETY") OR ("OBSERVED SAFETY" AND "SUBJECTIVE SAFETY") OR ("OBSERVED SAFETY" AND "PERCEIVED RISK") OR ("OBSERVED SAFETY" AND "PERCEPTION OF RISK") OR ("OBSERVED SAFETY" AND "SUBJECTIVE RISK") OR ("ACTUAL SAFETY" AND "PERCEIVED SAFETY") OR ("ACTUAL SAFETY" AND "PERCEPTION OF SAFETY") OR ("ACTUAL SAFETY" AND "SUBJECTIVE SAFETY") OR ("ACTUAL SAFETY" AND "PERCEIVED RISK") OR ("ACTUAL SAFETY" AND "PERCEPTION OF RISK") OR ("ACTUAL SAFETY" AND "SUBJECTIVE RISK") OR ("CRASH RISK" AND "PERCEIVED SAFETY") OR ("CRASH RISK" AND "PERCEPTION OF SAFETY") OR ("CRASH RISK" AND "SUBJECTIVE SAFETY") OR ("CRASH RISK" AND "PERCEIVED RISK") OR ("CRASH RISK" AND "PERCEPTION OF RISK") OR ("CRASH RISK" AND "SUBJECTIVE RISK")) AND (CYCLING OR CYCLIST*)
Dates	2000 – 2023
Publication types	JOURNAL ARTICLE, CONFERENCE ARTICLE, BOOK, BOOK CHAPTER

Notes: "OR" and "AND" are a boolean operators used to find records containing a combination of the specified keywords and "*" means any character used to break off the query word.

The three databases were searched to identify published and indexed materials using specified keywords in their title, abstract, or keywords. All search criteria, including the keywords used, range of years to search, and publication types, are detailed in Table 10.1. The terms used a combination of "objective safety" (and similar designations), "subjective safety" (and similar designations), and

[1] https://www.webofscience.com/
[2] https://trid.trb.org/
[3] https://www.scopus.com/

“cycling” (and similar designations). To answer the above question, the inclusion criteria were designed to ensure the search includes entries covering and mentioning both safety types. All material considered in this process was published or accepted to be published as of December 19th, 2023.

After searching the databases using the above criteria, 58 publications were identified. From these, 43 were excluded for being duplicated, being irrelevant, or within the scope of this review after manually reviewing the full-text article. From the full-text review, five publications were further added from their references and included in this review. In the end, twenty publications were reviewed. I will now detail the results of the full-text review of these publications.

10.3 Results

I will now explore the results from the full-text review of the publications that met the above criteria. The next subsections explore an overview of the selected publications, the methodologies used to explore the relation between the two types of safety, and the results found between such relation. Table 10.2 summarizes the publications included.

Overview of Reviewed Publications

Cycling safety research is gaining popularity with a growth in publications on the topic. Figure 10.1 shows the number of publications per year for publications on cycling safety. To compare the attention that has been paid to exploring both aspects of safety in the same publication, the number of publications about objective cycling safety only and subjective cycling safety only are also displayed. These numbers were compiled using a similar approach to the one described in Section 10.2.1, but using either the objective or subjective safety keywords at one time, respectively. As we can see, the growing trend of publications on cycling safety is clear, showing a steady increase in objective safety and a more dramatic increase in the interest in subjective safety, which can be explained by a growing interest from municipalities and the general public in active mobility. From 2005 onwards, researchers have started to explore the relationship between objective and subjective safety. Yet, despite a slight increase in the number of publications that explore both cycling safety types in the same publication, those represent a very small fraction (below 4% of all publications in 2023) of the total number of publications on cycling safety.

Publications on both objective and subjective cycling safety are authored by an average of 1.5 authors, with seventeen being journal articles, one book chapter, one conference article, and one report. Of the journal articles, eight were published in Accident Analysis & Prevention, four in Transportation Research Part F: Traffic Psychology and Behaviour, two in Transportation Research Record, and the remaining journals contained only one publication of the included articles. European affiliated authors were responsible for thirteen publications, six from North America, three from Oceania, and Africa and Asia having one publication each. von Stülpnagel, R., Winters, M., and Delhomme, P., were the

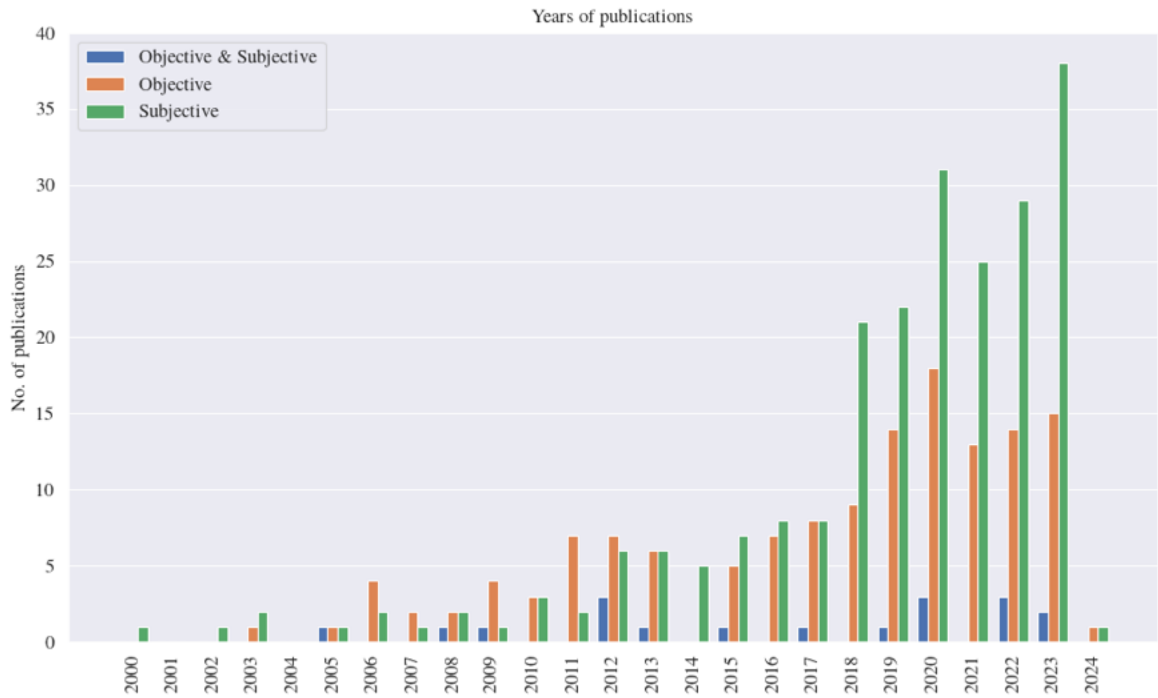

Figure 10.1: Years of publications. A comparison is displayed between publications pertaining to objective safety only, subjective safety only, and those that include both aspects.

most prolific authors with two publications each, while the remaining authors were only responsible for authoring one publication.

Table 10.2: Summary of reviewed publications.

Authors	**Title**	**Case Study**	**Methodology**	**Main results and conclusions**	**Objective–subjective relation found**
Elvik and Bjørnskau (2005)	How accurately does the public perceive differences in transport risks?: An exploratory analysis of scales representing perceived risk.	Norway	Exploratory analysis of how perceived risk is related with observed risk in Norway.	Positive correlation between statistically estimated risk and perceived risk for men cycling, and negative for women cycling	In certain circumstances
Ichikawa and Nakahara (2008)	Japanese high school students' usage of mobile phones while cycling	40 Japanese high schools	Inspect the perception and actual use of mobile phones among high schoolers while cycling and the experience of crashes/near-crashes	Crashes/near-crashes were less prevalent for those with a higher perception of danger of using the phone while riding	Yes
Cho et al. (2009)	The role of the built environment in explaining relationships between perceived and actual pedestrian and bicyclist safety	Washington, DC (United States of America)	Investigate how perceived and actual crash risk are related between each other and with respect to built environment characteristics using path analysis	Higher crash risk increases perceived crash risk and higher perceived risk is negatively associated with actual crash risk, as an effect of behavioral change	In certain circumstances
Sørensen and Mosslemi (2009)	Subjective and objective safety: The effect of road safety measures on subjective safety among vulnerable road users	Literature Review of more than 200 artciles	Compilation of available road safety measures for objective and subjective safety for pedestrians and cyclists and assess relationships and discrepancies between their effects on both types of safety.	From 125 total measures, 78 have a positive effect on both objective and subjective safety. Within the remaining 47, 20 have unclear effects on objective and subjective safety, and 25 have opposite effects on objective and subjective safety	In certain circumstances

Branion-Calles et al. (2020)	Cyclist crash rates and risk factors in a prospective cohort in seven European cities	Antwerp (Belgium), Barcelona (Spain), London (United Kingdom), Örebro (Sweden), Rome (Italy), Vienna (Austria), and Zürich (Switzerland)	Quantify exposure-adjusted crash rates and model adjusted crash risk factors, including sociodemographic characteristics, attitudes about transportation, neighbourhood built environment features and location	Alignment between objective and perceived safety, with individuals who agreed that cycling was a safe were at lower risk for a crash than those that were neutral or disagreed	Yes
Castanier et al. (2012)	Risk of crashing with a tram: Perceptions of pedestrians, cyclists, and motorists	10 French cities	Investigate the link between comparative judgements of risky behaviors, previous risky behaviors, and experiences of incidents or crashes involving trams	No significant results for cyclists between subjective assessments of risk and experiences of incidents or crashes	No
Winters et al. (2012)	Safe cycling: How do risk perceptions compare with observed risk?	Toronto and Vancouver (Canada)	Look into the relation between perceived and observed injury risk using logistic regression	Routes types perceived as risker were found to be so, while routes perceived as safer were also found to be so. Some infrastructure types (e.g., cycle tracks and multiuse paths) showed discrepancies	In certain circumstances
Washington et al. (2012)	Relationships between Self-Reported Bicycling Injuries and Perceived Risk of Cyclists in Queensland	Queensland (Australia)	Explore the relation between injuries resulting from crashes and perceived risk as a function of exposure, risk aversion, and rider ability using simultaneous regressions.	Perceived risk does not appear to influence injury rates, nor do injury rates influence perceived risks of cycling	No
Chaurand and Delhomme (2013)	Cyclists and drivers in road interactions: A comparison of perceived crash risk	Paris (France)	Evaluate perceived risk in car-car, car-bike and bike-bike interactions and their likelihood of crashes	Discrepancy between perceived and objective risk which can help to mold behavior	No
Sanders (2015)	Perceived traffic risk for cyclists: the impact of near miss and collision experiences.	San Francisco Bay Area (United States of America)	Investigate whether experiences with collisions or near misses are associated with perceived traffic risk for cyclists.	Both near misses and collisions influenced cyclists' perceptions of risk in various degrees	Yes

Poulos et al. (2017)	Near miss experiences of transport and recreational cyclists in New South Wales, Australia. Findings from a prospective cohort study	New South Wales (Australia)	Analysis of exposure-based rate of near misses and their circumstances from travel diary data	Near misses involving motor vehicles were perceived as more serious than those of involving other types of near misses	Yes
Schmidt and von Stülpnagel (2018)	Risk Perception and Gaze Behavior during Urban Cycling—A Field Study	Freiburg im Breisgau (Germany)	Investigate the relation between subjective risk perception during cycling and gaze behavior in a naturalistic setting. Gaze is then compared with known objective and subjective dangerous locations.	Cyclists change their behavior when they thought a road segment to be dangerous, decreasing the probability of an accident. Areas with no accidents may only remain so because cyclists feel at risk. Conversely, actual danger may result from feeling comparatively safer at other locations, making cyclist miss potential threats	No
Useche et al. (2019)	Healthy but risky: A descriptive study on cyclists' encouraging and discouraging factors for using bicycles, habits and safety outcomes	20 Countries in Latin America, North America, and Europe	Analyze the relationship between encouraging and discouraging factors for cycling and cycling crashes suffered within the last 5 years	Individuals with a lower perception of risk are more likely to suffer cycling crashes and injuries	In certain circumstances
Osama et al. (2020)	Determining if walkability and bikeability indices reflect pedestrian and cyclist safety	Vancouver (Canada)	Explore the association between bike score and cyclist crashes in Vancouver using multivariate Bayesian crash models with random and spatial effects	City areas with increased bikeability (which includes perceived safety and comfort) were associated with greater cyclist crash risk	Yes
von Stülpnagel and Lucas (2020)	Crash risk and subjective risk perception during urban cycling: Evidence for congruent and incongruent sources	Freiburg im Breisgau (Germany)	Analysis accident statistics and citizens' reports concerning cycling risks for a broad range of infrastructure and traffic network elements	General alignement between objective risk and subjective risk perception. However, in some situations there is a high deviation between the two	In certain circumstances

Amiour et al. (2022)	Objective and Perceived Traffic Safety for Children: A Systematic Literature Review of Traffic and Built Environment Characteristics Related to Safe Travel	Literature review of 38 articles	Comparison of literature results to investigate objective and perceived safety for children while walking or cycling	Empirical results from comparison of studies' results highlight that some built environment characteristics are aligned between safety types for walking and cycling safety, while for others there is no correlation or are not aligned	In certain circumstances
Janstrup et al. (2022)	Predicting injury-severity for cyclist crashes using natural language processing and neural network modelling	Denmark	Use of natural language processing to evaluate hospital admissions of perceived safety and injury reports	Strong correlation between identified topics from perceived safety questinnaires and actual safety	Yes
Rasch et al. (2022)	Drivers' and cyclists' safety perceptions in overtaking maneuvers	Vårgårda (Sweden) and Valencia (Spain)	Analysis of objective safety metrics and perceived safety of drivers and cyclists in overtaking maneuvers	Strong link between objective and perceived safety, with an alignment when perceived risk is higher and cyclists are subeject to the greatest threats	Yes
von Stülpnagel et al. (2022)	Crash risk and subjective risk perception during urban cycling: Accounting for cycling volume	Munich (germany)	Spatial distribution of cycling crashes and crowdsourced data on subjective risky locations to investigate the effects of different infrastructure types, speed limits, and cycling volumes on both types of safety	Objective and subjective risks are mostly well aligned, but there are specific scenarios where cyclists underestimate the actual crash risk	In certain circumstances
Fuest et al. (2023)	I bet you feel safe! assessing cyclists' subjective safety by objective scores	Braunschweig (Germany)	Comparison of two distinct subjective safety metrics, and their comparison to known crash locations	Perceived scores using two different metrics could not deduce the occurrence of a crash, suggesting subjective safety is independent from objective safety	No

Methodologies used

Interestingly, many approaches have been used to analyze the relationship between objective and subjective cycling safety. These include rigorous statistical analyses based on solid evidence to find a link between objective and subjective cycling safety, including logistic regression (Winters et al., 2012), path analysis (a special case of structural equation modeling) (Cho et al., 2009), spatial models (Osama et al., 2020), machine learning tools (Janstrup et al., 2022), and gaze path analysis (Schmidt and von Stülpnagel, 2018). More nuanced qualitative assessments have also been used, including model result comparison (von Stülpnagel and Lucas, 2020; von Stülpnagel et al., 2022) or comparing results from previous literature (Amiour et al., 2022; Sørensen and Mosslemi, 2009).

Subjective risk perceptions are typically captured from surveys, questionnaires, or interviews. In contrast, objective risk data originates from crash records, hospital admissions, historically dangerous locations, or from questionnaires to capture non-reported incidents to the police, which did not lead to any medical help being needed.

Yet, despite the methodological strategy used, the vast majority seek to find correlation terms between both types of safety and conclude whether there is any connection between the two. Although such approaches do not prove causality (i.e., saying that one kind of safety directly affects the other), researchers may conclude that there is some connection between the two. On the other hand, other publications have geared more towards the latter approach, identifying one-way effects from one type of safety that is not true in the opposite case. This has implications for future planning strategies, as such insights can help planners and authorities prioritize which safety type should be tackled first, and, therefore, special attention should be paid to such strategies.

Another key aspect shared between most studies included in this review is their approach to analyzing only one particular aspect of the possible relation between objective and subjective safety. Here, most studies have emphasized analyzing exposure to risk, common built environment typologies, near misses, or its impact on children. Despite shedding light on the convergence and divergence between objective risky situations and the subjective feelings of safety among cyclists, conducting such particular studies may not provide a holistic understanding of the factors influencing cycling safety as a whole.

Main findings

The reviewed publications show a complex interplay between objective and subjective cycling safety. Seven of the twenty reviewed publications have identified a link between the two, and eight have demonstrated that they are related under some circumstances. At the same time, the remaining five have found no connection between the two. Such findings suggest a nuanced perspective that objective and perceived safety are sometimes related but dependent on the context and topic of study. Table 10.3 summarizes such relations found in the reviewed publications.

Table 10.3: Summary of relations found between subjective and objective cycling safety.

Publication	No relation	Relation exists with limited evidence	High SS → High OS	Low SS → High OS	High SS → Low OS	Low SS → Low OS
			Relation found			
Elvik and Bjørnskau (2005)			✓	✓	✓	✓
Ichikawa and Nakahara (2008)				✓		
Cho et al. (2009)				✓		✓
Sørensen and Mosslemi (2009)			✓	✓	✓	
Branion-Calles et al. (2020)			✓			
Castanier et al. (2012)	✓					
Winters et al. (2012)			✓	✓	✓	
Washington et al. (2012)	✓					
Chaurand and Delhomme (2013)	✓					
Sanders (2015)		✓				
Poulos et al. (2017)		✓				
Schmidt and von Stülpnagel (2018)	✓					
Useche et al. (2019)					✓	
Osama et al. (2020)					✓	
von Stülpnagel and Lucas (2020)			✓	✓	✓	✓
Amiour et al. (2022)			✓	✓	✓	✓
Janstrup et al. (2022)		✓				
Rasch et al. (2022)						✓
von Stülpnagel et al. (2022)			✓	✓	✓	✓
Fuest et al. (2023)	✓					

Note: SS: Subjective Safety, OS: Objective Safety.

First, consider the studies that have found an unequivocal link between objective and subjective cycling safety, regardless of the circumstances. Here, Ichikawa and Nakahara (2008) found that crashes and near-crashes were less prevalent for those with a higher perception of risk while cycling and using a mobile phone; Branion-Calles et al. (2020) identified that individuals who thought cycling was safe were a lower risk of crash; Sanders (2015) noticed that both near misses and collisions influenced perception of cycling risk in various degrees; Poulos et al. (2017) found that perceived risk and objective risk were aligned, albeit with various magnitudes; Janstrup et al. (2022) found a strong correlation between identified topics of perceived safety and actual safety; Rasch et al. (2022)

discovered a strong alignment between objective and subjective safety, with individuals feeling less safer when exposed to greater threats in being overtaken; and Osama et al. (2020) identified city areas where bikeability was higher (associated with higher perception of safety) were associated with greater crash risk; . Although these studies identified such relations, they do not all point in the same direction, with some supporting an alignment between the two, while others found that lower levels of subjective safety may imply higher levels of objective safety and vice-versa.

Second, the vast majority of studies identified that sometimes a connection exists between objective and subjective safety, but that depends entirely on the circumstances, often highlighting situations where a link was not found or was opposite to that for most cases. Within this set of publications Elvik and Bjørnskau (2005) found a positive relation between perceived risk for men, and negative for women; Cho et al. (2009) highlighted that higher crash risk increased perceived risk, but increase perception of risk led to a decrease in actual risk; Sørensen and Mosslemi (2009) reviewed a number of road safety measures and their impacts on objective and subjective safety, finding that the vast majority improves both safety types, but some have unclear effects or may increase one safety type while decreasing the other; Winters et al. (2012) found that particular cycling routes and environments where perceived risk and actual risk was congruent, but in some particular environments there were discrepancies between the two; Useche et al. (2019) found that individuals with lower perceived risk were more probable to be involved in a cycling crash; von Stülpnagel and Lucas (2020) found a general alignment between safety types, but in some situations there were some discrepancies, such as in one-way streets with bikeways in opposing direction or in locations with tram stops; Amiour et al. (2022) noticed a general alignment between subjective and objective safety for numerous built environment elements, while others showed no relation or were not aligned; and von Stülpnagel et al. (2022) found a general alignment between safety types, but in some specific scenarios cyclists' would underestimate the actual crash risk.

Finally, the remaining studies (Castanier et al., 2012; Washington et al., 2012; Chaurand and Delhomme, 2013; Schmidt and von Stülpnagel, 2018; Fuest et al., 2023) found no link between objective and subjective cycling safety, suggesting that subjective safety is a construct independent from objective safety. However, despite no connection, several studies pointed out that behavior changes may play a role in such discrepancies. In this sense, areas with no reported accidents may owe their accident-free status to cyclists' heightened perception of risk, showcasing the intricate relationship between perception and reality in the context of cycling safety. Ultimately, this raises additional challenges to how such relations can be identified and such complex dynamics analyzed.

10.4 Discussion

Lessons learned from the literature

This scoping review on the relation between objective and subjective cycling safety has analyzed twenty articles from various research indexing databases. Cycling safety research has gained much popularity in recent years, growing about 15% over the last decade (Scarano et al., 2023). However, despite a growing body of work on objective and subjective cycling safety, the relation between the two has remained rather unexplored so far, accounting for only a fraction of those that focus on objective safety or subjective safety.

The publications reviewed here have pointed out an intricate and nonobvious relation between the two types of cycling safety. Such association appears to be highly context dependent and contingent upon specific circumstances. For example, Elvik and Bjørnskau (2005) has pointed out gender-dependent variations, while Winters et al. (2012), von Stülpnagel and Lucas (2020), and von Stülpnagel et al. (2022) have highlighted environments where there are discrepancies between objective risk and perception of risk. In this sense, Amiour et al. (2022) further underscored such variability by identifying elements in the built environment that either align, show no relation, or are opposite between subjective and objective safety. Sørensen and Mosslemi (2009)'s review of road safety measures and their impacts on objective and subjective safety further strengthen such complex relation. Nevertheless, understanding such relations is vital to developing effective strategies to safeguard cyclists and improve cycling numbers. If such a relation is not considered, devising policies or interventions to improve one type of safety may have opposite effects on the other, hindering any existing strategy to improve cycling safety or requiring other types of strategies to be thought out.

Several studies, including those by Chaurand and Delhomme (2013), Cho et al. (2009), and Schmidt and von Stülpnagel (2018), found partial or no direct link between objective and subjective cycling safety. Despite this lack of connection, these studies acknowledge the potential role of behavior changes in influencing the discrepancy between perceived and actual safety. The revelation that areas with no reported accidents may owe their accident-free status to cyclists' heightened perception of risk adds a layer of complexity to the relationship, suggesting that behavior changes or self-selection phenomenons may influence both perception and actual cycling safety.

Mobility behavior, self-selection and cycling safety

As identified by a few publications, cyclists may change their behavior due to high perceived safety, leading to lower objective risk (Cho et al., 2009; Chaurand and Delhomme, 2013; Schmidt and von Stülpnagel, 2018). As Schmidt and von Stülpnagel (2018) puts it, a heightened sense of risk exposure may instigate cyclists to look out for potential dangers, leading to lower levels of objective risks. Conversely, feeling safe may prompt cyclists to miss actual potential threats. Such effects may also be underpinned by individual skill, as cyclists who feel more in control (i.e., with higher levels of perceived safety) might feel they are more able to avoid any crash, leading to more risky behaviors (Lund and Rundmo, 2009) and higher actual risk (Chaurand and Delhomme, 2013; Cho et al., 2009; Rosenbloom et al., 2008). Similarly, one's experience may also act as a positive reinforcement to such behaviors (Chaurand and Delhomme, 2013), leading to lower levels of perceived safety, contributing to complexity in the relation between objective and subjective safety.

In this sense, if the aim is to minimize objective risk, increasing the sense of risk may be beneficial. Changes to the urban environment or use of education and training programs may increase or maintain perceived risk levels (Rosenbloom et al., 2008). However, such overestimation may cause undue stress and overload of attention resources, leading individuals to drop cycling and choose another mode of transportation (Chaurand and Delhomme, 2013). In addition, such a heightened sense of risk may also cause and reinforce an absence or underestimate of objective risk data. Conversely, if the aim is to provide cyclists with a higher sense of safety, then that might negatively affect the objective side of safety.

Ultimately, however, this intricate connection between objective and subjective safety is also closely linked to individuals' behavior, and measures should not be made entirely without considering the consequences of both types of safety. Hence, understanding how behavior is constructed from efforts that target one or both types of safety is vital for successful cycling safety policies.

Additionally, self-selection phenomenons may pay a fundamental role in how the objective-subjective relation is constructed. Such concept has been studied before relating to residential location and is linked with individuals' tendencies to opt for places of residency based on their abilities, needs, preferences, attitudes and socioeconomic characteristics (Mokhtarian and Cao, 2008; De Abreu e Silva, 2014). Such concept has since been extended to other dimensions, including travel choice and modal preference (Van Wee, 2009). In cycling mobility it revolves around individuals choosing to cycle in urban environments based on personal preferences, perceptions, and comfort levels. Therefore, it can be influenced by factors such as subjective safety or risk perception. From the review and discussion presented before, one can hypothesize that self-selection of cycling relates to the dichotomy of objective safety versus perception of risk in cycling.

In terms of "self-selection and objective safety", cyclists who opt for urban cycling may do so because they perceive the built environment, infrastructure, or traffic conditions to be suitable and safe. This self-selected group may actively choose cycling because they perceive positively cycling safety in the presence of well-designed bike lanes, low traffic speeds, or other objective safety measures that align with their safety priorities.

Conversely, when considering "self-selection and perception of risk", individuals who choose cycling as their mode of transportation may have a lower perceived risk compared to those who opt for alternative modes. The self-selected group of cyclists may perceive the risks associated with cycling differently, contributing to their decision to actively choose this mode of transport.

Research should delve into whether the self-selection process leads to an overestimation or underestimation of the actual risk cyclists face and analyze whether the principle of self-selection might play a pivotal role in the intricate relationship between cycling mobility and the dichotomy of "objective safety versus perception of risk.". Examining how objective safety measures align with the self-selection of cyclists and their perceptions provides valuable insights into the complex dynamics of cycling behavior.

Challenges and possible future directions

In light of this review, I specify four areas of research that could add substantial value to uncovering the true relation between objective and subjective safety and address current shortcomings and limitations in cycling safety.

First and foremost, more emphasis must be placed on the relationship between objective and subjective cycling. Despite its demonstrated importance in ensuring that policies and measures are successful in both observed and perceived safety, understanding the connection between them has remained under the radar. We need a more considerable prominence of strategies and approaches to underline the understanding of this relation as its unique research topic. Only then can we ensure that whatever engineering, social, and management measures are devised effectively improve cycling safety as a whole.

Second, a greater understanding of how cycling skill, cycling experience, cycling proficiency, and social factors (e.g., age, gender, education level) impact this relationship is needed. As pointed out, different studies have focused on some of these topics. Still, we need greater knowledge of how a variety of these factors impact the connection of objective and subjective safety and how they may facilitate measures that target a particular population group. This is especially important when examining how actions affect children's or older people's safety, whose perceptions and associated behaviors might differ substantially from adults.

Third, given the complexity of such a relation, newer and broader modeling tools need to be tested and developed. Given the nature of typical data, qualitative and quantitative methods must enhance how researchers retrieve insights from surveys and accident records. GIS mapping, micro-simulation, and virtual reality environments can be used to analyze spatial patterns, exposure to diverse circumstances and traffic flows, and evaluate users' responses under more realistic scenarios while controlling safety concerns. Similarly, cognitive load analysis and behavioral modeling can help identify possible conflicts and evaluate users' reactions under several conditions. Lastly, using fusion machine learning models or other data mining techniques can help integrate both objective (accident data, infrastructure) and subjective (user feedback, perception surveys) data to provide a more comprehensive understanding of the complex interactions between objective and subjective elements of cycling safety.

Fourth, considering the nature of such a relationship, a more interdisciplinary and holistic approach is needed. By this, I mean that traffic psychologists and road safety engineers must work together to devise strategies that boost each other's strengths and knowledge. This multidimensional approach will allow for more informed decision-making in designing safer cycling environments and more effective implementation of measures.

10.5 Summary and conclusions

In summary, the studies reviewed in this chapter present a complex and multi-sided picture of the relationship between objective and subjective cycling safety. While some studies support a direct link, others emphasize context-dependent connections or suggest that both concepts are independent. The intricate dynamics between the two safety types reveal a need for a deeper understanding of the factors influencing cyclists' perceptions, their behaviors, and the accidents they are involved in. Such knowledge, together with newer approaches seeking to uncover such intricacies, has the potential to lay the groundwork for future cycling safety research and, more effectively, target interventions to improve cyclists' safety.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/mncosta/obj_subj_cyclingsafety_litreview. Code is available for Python3. The code is available under MIT license (https://opensource.org/licenses/MIT).

Chapter 11

Comparing Urban Elements Effects on Objective and Subjective Safety

This chapter is currently being prepared to be submitted as a journal article: "Costa, M., Siebert, F. W., Azevedo, C. L., Marques, M., Moura, F. (N/A). How do urban elements influence objective and subjective cycling safety? Using machine learning to analyze congruencies and discrepancies [Manuscript in preparation]."

11.1 Introduction

Cycling safety research refers to research that can lead to develop policies or measures that aim to minimize the number of crashes and/or injuries or increase the sense of safety for those who cycle. Conceptually, it revolves around measuring risk, exposure to risk, and travel behavior (Schepers et al., 2014). It is often divided into objective risk (also known as observed or actual risk) and subjective risk (or perceived risk). While the former relates to the number of accidents (the count of fatalities, injuries, or material damage resulting from the accident), the latter is the risk that is assumed to exist or the sense of safety regarding a particular environment, route, or behavior. Considerable efforts have been carried out in both safety research areas, respectively. However, only a few studies explored how elements impact both safety types simultaneously (cf. Chapter 10, Winters et al., 2012; von Stülpnagel and Lucas, 2020; von Stülpnagel et al., 2022; Amiour et al., 2022).

With this in mind, this chapter explores the impact of different urban elements on both objective and subjective cycling safety. This analysis enables a better understanding of how road elements, roadside characteristics, and vehicles affect both cycling safety types, allowing researchers and urban planners to spot congruencies and discrepancies between objective and subjective cycling safety. Discrepancies are especially important to understand as it may lead to under or overestimation of accident risk, causing a decrease in cycling or leading to more accidents.

Next, we explore relevant background on the topic in Section 11.2. Section 11.3 presents the methodological approach used throughout this chapter. Section 11.4 presents its results, which are then discussed in Section 11.5. Finally, Section 11.6 concludes the work explored and provides some directions for future work.

11.2 Background

Multiple methods and tools have been used to understand how the urban setting impacts objective and subjective cycling safety. For objective safety, these often use discrete outcome models (Kaplan et al., 2014; Behnood and Mannering, 2017) or generalized linear models (Chen and Shen, 2016b; Pedroso et al., 2016). Subjective safety studies typically rely on analysis through logistic regressions (Lawson et al., 2013; Wang and Akar, 2018) or other survey qualitative tools (Aldred and Woodcock, 2015; Useche et al., 2019). Newer approaches have begun to employ data mining and machine learning frameworks to analyze how different urban characteristics are associated with cycling accidents and their perceptions. These explore a multitude of methods, including clustering methods, computer vision algorithms, neural networks, and decision tree-based algorithms (Jeong et al., 2018; Zhao et al., 2019; Wu et al., 2019; Janstrup et al., 2022; De Bock and Verstockt, 2022; Graystone et al., 2022). Often, these data mining approaches prove useful to unravel insights from large and complex datasets, yielding good performance metrics while requiring relatively short data preparation (Mannering et al., 2020; Rella Riccardi et al., 2022).

However, understanding the outputs of such machine learning approaches is not always easy, especially for those called "black box" methods, which achieve better results than their counterpart, interpretable, glass box methods. A few tools have been created to overcome such obstacles and enable users to interpret highly accurate yet complex methods. These include Shapley Additive Explanations (SHAP, Lundberg and Lee, 2017), Local Interpretable Model-agnostic Explanations (LIME, Ribeiro et al., 2016), DeepLIFT (Shrikumar et al., 2016), Partial Dependency Plots (Friedman, 2001), or Morris Sensitivity Analysis (Morris, 1991). From these, SHapley Additive exPlanations (SHAP) is probably the most popular tool due to its ease of use and consistency with human interpretation and evaluations.

These approaches have been used to understand objective and subjective cycling safety. Yet, most studies analyze each safety type separately, with only a few trying to hypothesize and understand the link between the two types of safety. Overall, the scarce number of studies that have investigated this topic has found mixed results. Findings suggest a non-linear relation, dependent on contexts or circumstances. For example, Chaurand and Delhomme (2013), Cho et al. (2009), and Schmidt and von Stülpnagel (2018), found partial or no direct link between objective and subjective cycling safety, while Winters et al. (2012), von Stülpnagel and Lucas (2020), and von Stülpnagel et al. (2022) have highlighted environments where there are discrepancies between the two. Understanding how the two safeties are related and how the built environment, cycling context, and policies modulate such connections is vital to developing effective strategies that safeguard cyclists and improve cycling numbers.

11.3 Methodology

I now describe the methodology used in this chapter. I begin by detailing the data used to account for the objective risk, the subjective risk, and the urban context elements. Next, I explain the modeling used to compare the influence of the urban elements on both objective and subjective safety. All materials and code used are publicly available at the end of the chapter.

Objective Safety: Cycling Accident Records

Objective cycling safety data is often available as accident records captured by the police, hospitals, or transportation authorities (Costa et al., 2022). Here, we use a subset of CYCLANDS (cf. Chapter 3, Costa et al., 2022), namely cycling accidents from Berlin, Germany. Accidents include road accidents based on police reports where personal injury occurred (excluding property damage-only accidents) and are divided per accident outcome: light injury, serious injury, and fatality. The police registered observations, and a multi-stage check process ensures data quality (Statistische Ämter des Bundes und der Länder, 2021). For this chapter, we use a set of 7516 cycling accidents where geographic coordinates of the accident location are available. Further details of this dataset were already explored and can be seen in Chapter 5. Additionally, I group accident outcomes into two possible classes: i) fatalities (killed) and serious injuries (KSI), and ii) Light Injuries (LI), as is often done in cycling safety literature (Chen and Shen, 2016b; Eriksson et al., 2022).

Subjective Safety: Perceived Safety Scores

As an indicator of subjective cycling safety, I use the perceived safety scores (PSS) estimated earlier (cf. Chapter 8, Costa et al., 2023). These include PSS for 3850 SVI. Each image depicts real-world cycling environments, which correspond to accident locations where a cycling accident is known to have occurred. Again, the locations of these images match the available data for the objective risk mentioned above. For brevity, I refer the reader to Chapter 8 for details on this dataset. Additionally, as performed in Chapter 7, I classify all available environments in two classes: perceived as safer (when $PSS_i \geq \overline{PSS}$) and perceived as unsafer (when $PSS_i < \overline{PSS}$), with PSS_i corresponding image i PSS, and $\overline{PSS}$ being the average PSS over all available images.

Urban Context Data

Finally, to analyze the impact of urban elements on both cycling safety types, I use VGI. Again, similar to the approach used in Chapter 9, I use both image semantic segmentation data and geographic mapping data extracted from images' locations. Both data sources contain context information about the built environment, cycling circumstances, and urban surroundings of known accident locations. For conciseness, details on how this data was acquired and its contents are available in Chapter 9.

In the end, I combine the available data into two datasets: i) one containing cycling objective safety data (accident outcomes) and their corresponding urban context elements, and ii) containing the subjective safety data (perceived safe and unsafe environments) and their associated urban context elements. Both datasets were filtered to contain matching observations (i.e., accident records match the perceived safety at that location). All observations where data was missing or unavailable were discarded, totaling 3850 observations. Appendix H presents a description and overview of the data used in this chapter.

Analysis

I aim to analyze the impact of different urban elements on objective cycling safety and subjective cycling safety, respectively. For this, I use machine learning techniques, namely XGBoost (Chen and Guestrin, 2016), known for its efficiency and flexibility when dealing with complex data. Next, to interpret the modeled results, I use SHAP (Lundberg and Lee, 2017; Lundberg et al., 2020), a widely popular approach often used to explain machine learning models derived from game theory. I now detail each of these steps.

XGBoost (eXtreme Gradient Boosting Tree)

XGBoost (Chen and Guestrin, 2016) is a fast and efficient implementation of gradient boosted decision trees that uses an ensemble learning technique over a sequence of decision trees to achieve a stronger learner (Friedman, 2001). I now provide an overview of XGBoost, but readers are referred to Chen and Guestrin (2016) for further details.

A tree ensemble model seeks to predict a given output $\hat{y}$ using i independent variables x_i (also known as features) using K additive functions:

$$\hat{y} = \sum_{k}^{K} f_k(x_i), \tag{11.1}$$

where $f_k \in F$ are independent tree structures in a F space of trees. Learning is based on traditional gradient tree boosting where the learning objective is to minimize the regularized training loss L_l, defined as

$$L_k = \sum_{i}^{N} l(y_i, \hat{y}_i) + \sum_{k}^{K} \Omega(f_k) \tag{11.2}$$

where l is a loss function computed over observed output y_i and its current predicted value $\hat{y}_i$ and Ω a regularizer defined as

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_i^T w_{ik}^2 \tag{11.3}$$

with T being the number of leaves, γ and λ hyperparameters, and w the score of the i-th leaf. Overall learning uses Eq. 11.2 to learn the optimal values for each tree leaves and its splits. The above hyperparameters and others (such as tree depth, learning rate, and split parameters) must be set *a priori* and are usually found through random or grid search. Hyperparameter details used in this problem are described below.

We use XGBoost in two very similar approaches in our setting. First, we are interested in finding the effect of urban elements on objective cycling safety. In other words, we use XGBoost as a classification technique using the aforementioned urban elements as predictors to classify the outcome of a given cycling accident. As such, this binary classification (Class 0: KSI, Class 1: SI) problem finds the relation between each urban element x_i and its effect on modulating the probability of an accident outcome. Second, we use the same strategy for the subjective cycling safety problem, where we use urban elements as predictors to classify whether an environment was perceived as unsafer (Class 0) or safer (Class 1). Again, we have a binary classification problem in which we find how urban elements impact the probability of an environment being perceived.

SHAP (SHapley Additive exPlanations)

Albeit being a highly fast and accurate machine learning model, XGBoost's results (i.e., features contributions to a given outcome) are not easily interpretable and can lead to inconsistent evaluations when looking at feature importances (Lundberg et al., 2018). To best interpret XGBoost's results I use SHAP (Lundberg and Lee, 2017; Lundberg et al., 2020). SHAP is a popular method for interpreting the output of machine learning models. It derives from game theory and provides a way to understand the contribution of each feature to a model's predictions. It quantifies the impact of including a particular feature in a model compared to not by computing an "explanation model" following a binary addictive feature attribution function to interpret a model's output based on their marginal contribution (Shapley et al., 1953). SHAP is often considered superior to other methods because it enables consistent interpretations and provides local feature importances. However, SHAP can be expensive to compute as it increases exponentially with the number of features. Yet, an efficient algorithm has been derived for decision trees and ensembles of decision trees (including XGBoost) (Lundberg et al., 2018, 2020).

In summary, SHAP is a powerful tool for understanding machine learning models, providing insights into feature importances. In our setting, I use SHAP to interpret XGBoost's outputs, analyze how urban elements influence objective and subjective safety and compare their effects between the two types of safety.

Table 11.1: Binary XGBoost classification models' hyperparameters grid search. Hyperparameters corresponding to the best model are shown in bold.

Model	Hyperparameters
Objective Safety	Max depth $= \{5, 6, 7, 8, 9, \mathbf{10}\}$,
	N Estimators $= \{100, 200, 300, \mathbf{400}, 500\}$,
	Learning Rate $= \{0.001, 0.01, 0.1, 0.2, \mathbf{0.5}\}$,
	Subsample $= \{.6, .7, .8, .9, \mathbf{1.}\}$,
	Feature sample by tree $= \{.6, \mathbf{.7}, .8, .9, 1.\}$
Subjective Safety	Max depth $= \{5, 6, 7, 8, \mathbf{9}, 10\}$,
	N Estimators $= \{\mathbf{100}, 200, 300, 400, 500\}$,
	Learning Rate $= \{0.001, 0.01, 0.1, 0.2, \mathbf{0.5}\}$,
	Subsample $= \{.6, .7, .8, \mathbf{.9}, 1.\}$,
	Feature sample by tree $= \{.6, \mathbf{.7}, .8, .9, 1.\}$

11.4 Results

Experimental Setup

All models were implemented in Python using the `xgboost` and `shap` packages. I ran a 5-fold cross-validation random search for each model over the tunable hyperparameters and presented the results for the best model. Non-specified parameters used the respective package's default values. Table 11.1 shows the search space and best hyperparameters found. I computed the average accuracy (Acc) and the mean receiver operating characteristic area under the curve (AUC) to evaluate each model.

Classification Results

First, we look at the models' goodness of fit indicators. As aforementioned, I train two XGBoost models to perform binary classification: Model OS (Objective Safety) predicts accident outcomes based on urban characteristics, and Model SS (Subjective Safety) predicts how environments are perceived using (the same) urban characteristics. Both models achieved good results, indicating that they could effectively learn their respective objectives from the urban context information. Model OS had $Acc = 0.978$ ($std = 0.01$) and $AUC = 0.946$ ($std = 0.02$), while Model SS had $Acc = 0.782$ ($std = 0.01$) and $AUC = 0.850$ ($std = 0.01$). Next, we analyze each model individually, looking at the effect of how urban elements are associated with objective safety and subjective safety, respectively. Finally, we compare both models and analyze the congruencies and discrepancies between objective and subjective safety.

Figure 11.1: Urban elements mean absolute SHAP values (i.e., average feature importance on the model's output). Shared elements between the two safety types are shown in the same color while elements appearing in only one type are shown in gray. Please note the different SHAP value scales between the two types of safety.

Urban elements effects on Objective Safety

We now analyze the influence of urban factors on cycling accident outcomes. Figure 11.1 (left) shows the average absolute feature importance in predicting an accident's outcome. On the whole, we notice that the most relevant urban characteristics, on average, that explain accident outcomes are related to roadside objects (poles, vegetation, street lights, traffic signs), roadside elements (curb, curb cuts, sidewalk), and road elements (road, lane markings).

Figure 11.2: Selected effects of urban elements on the objective and subjective safety. SHAP values correspond to log-odds of a feature on the prediction of the respective outcome (please notice the different scales). Color represents features values.

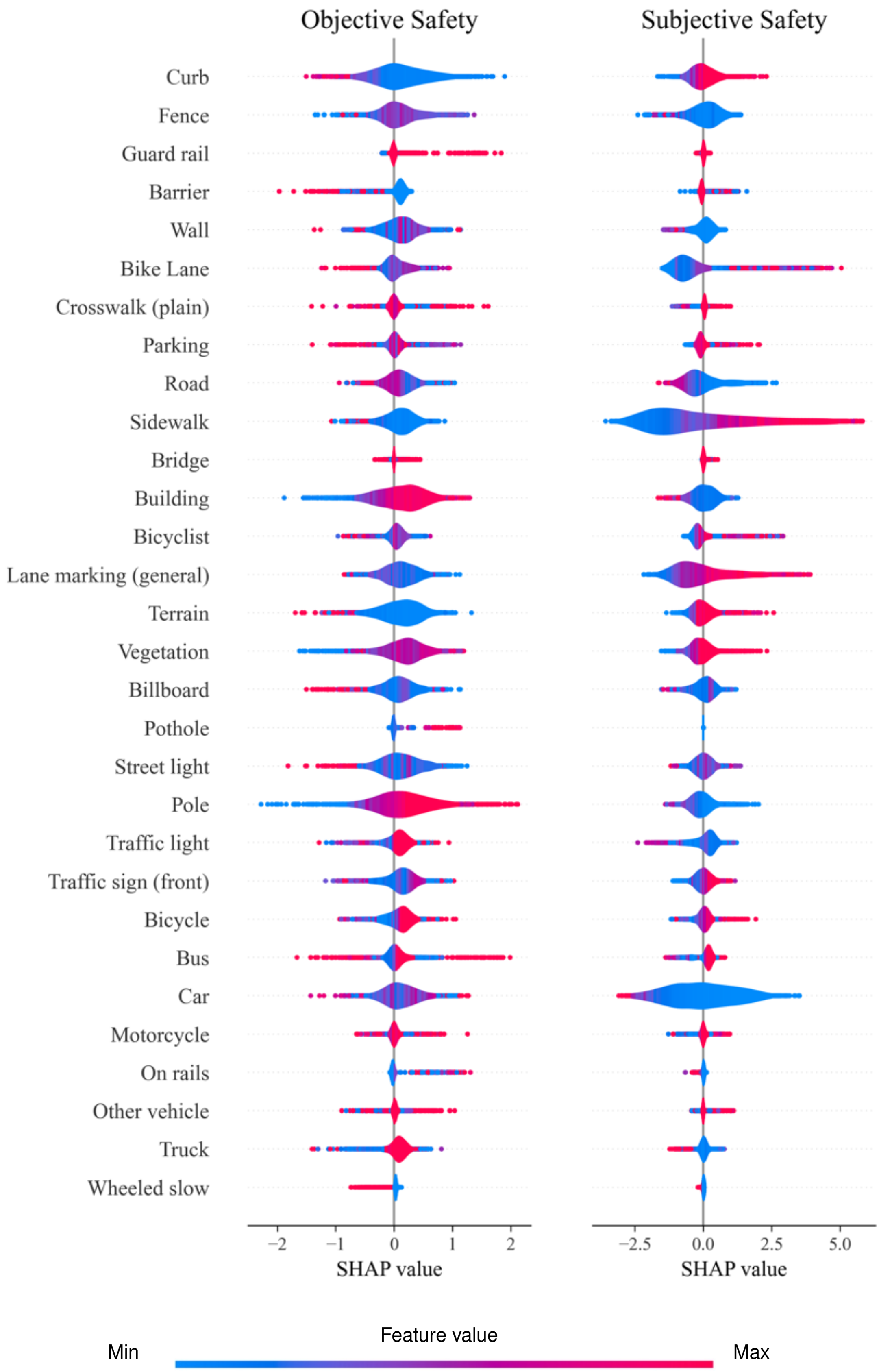

Figure 11.2: *Figure continued.*

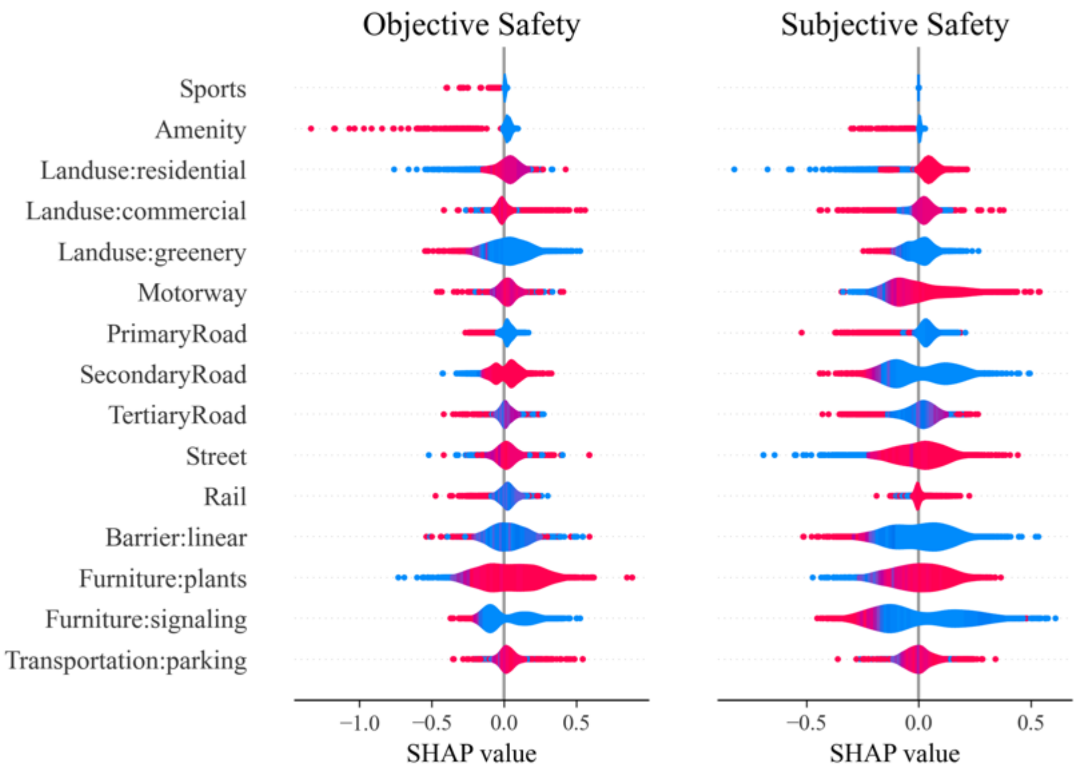

Figure 11.2 (left) (full results are available in Appendix I) shows the relationship between urban features and their effect on Model OS's outcomes. SHAP values correspond to log-odds of each variable on the prediction of accident outcomes (KSI *vs.* LI) as measured by SHAP. Colors represent a given feature's values ranging from low (blue) to high (red). If red points are plotted for lower SHAP values and blue ones towards higher SHAP values, then safety increases as values decrease (i.e., negative correlation to safety). If red points are plotted with higher SHAP values and blue ones with lower SHAP values, then safety increases as the feature's values increase (i.e., positive correlation to safety).

Taking a closer look at urban characteristics' effects on objective safety, one can analyze in more depth how variables influence cycling accident outcomes. For example, while increased curbs and curb cuts decrease objective safety, an increase in poles increases safety. While both serve to delineate urban space, their impact on cycling accidents is opposite of one another. This suggests that more severe accidents occur in locations where their images depict cycling environments where cyclists are riding on roads or cycling lanes next to curbs (as opposed to riding on sidewalks or cycling lanes built on top of sidewalks). On the other hand, poles indicate that they indeed serve to protect those more vulnerable, leading to increased actual safety.

While such an understanding can be extracted directly, the effects of other variables are more nuanced and harder to grasp linearly. For example, the presence of crosswalks is not linearly linked with observed safety as its effect varies for different levels of crosswalks. Both high levels of cars and buses produce an increase and decrease in safety, suggesting that a more in-depth analysis is needed to understand their effects correctly.

Urban elements effects on Subjective Safety

Next, we look at the influence of urban elements on the perception of cycling safety. Again, we begin by inspecting Figure 11.1 (right) to identify the features that have an average higher importance on subjective safety. Here, we see that sidewalks, cycling lanes, cars, roads, and cyclists are among the features considered as having the highest importance.

Looking at their effects on perceiving environments as safe or unsafe in Figure 11.2 (full results are available in Appendix I), we see that increasing the amount of sidewalks and cycling lanes is associated with an increase in subjective safety, as is the increase of lane markings, cyclists, and other bicycles. On the other hand, increasing the presence of rails, crosswalks, and cars decreases the log-odds of an environment being perceived as safe.

Objective Safety *vs.* Subjective Safety

Finally, I analyze and compare urban elements' effects on objective and subjective safety, seeking to answer our initial research question. From Figure 11.1, we notice that several urban elements are considered among the most important for both objective and subjective safety. These include road-side elements, such as poles, billboards, terrain, vegetation, sidewalks, and curbs; road elements, including the road itself and lane markings; and cars and buildings.

Although SHAP values cannot be directly compared between the two models, one can identify how increasing one variable increases the log-odds of both safety types or whether they have opposing effects on each safety type. For instance, curbs have opposing effects as they increase subjective safety and decrease objective safety. Similarly, sidewalks, buildings, poles, street lights, and construction spaces have opposing influences on objective and subjective safety.

Comparatively, some characteristics are aligned in their effects on objective and subjective safety. These include pedestrians, vegetation elements, and bicycles, which increase safety levels as they also increase. Similarly, amenities, greenery land use zones, and primary roads are also aligned between both safety types, with a decrease in objective and subjective safety as these values increase. Finally, commercial land use areas and shops, utility poles, and public benches have complex relationships to both objective and subjective safety, suggesting the non-linear effects of such urban elements.

Another possibility of using XGBoost and SHAP to analyze objective and subjective safety in such a fine-grained analysis of urban elements is to explore specific urban environment typologies and analyze levels of subjective and objective safety in those locations. With this in mind, I recall the reader to the six built environment typologies found in Chapter 5, which were associated with different levels of cycling objective risk, and which I now analyze under a different approach (please note that although classes remain the same, a new naming strategy was used to more adequately describe each environment type based on its urbanistic characteristics):

- **Class 1 - Cycle haven:** Residential area with cycling infrastructure and connections to public transport, bars, cafes, and restaurants. Street furniture is present with fewer amounts of vegetation.
- **Class 2 - Green transit hub:** Large intersection with high presence of cycleway, sidewalks, and pedestrian crossings. Not many buildings are present, yet trees, plants, and flowers exist. Public transportation networks for buses, trams, or subways exist, with some on-street parking.
- **Class 3 - Cozy pedal haven:** Residential area with some vegetation, bars, cafes, and restaurants, little parking, and no heavy vehicles or primary road infrastructure.
- **Class 4 - Crossroads transit hub:** Main road intersections, where heavy vehicles are typically seen, together with buses and trains. There are many traffic signs and walls/fences and lower amounts of vegetation.
- **Class 5 - Industrial artery zone:** Commercial and predominant industrial area, highly accessible by main roads, where usually there is little infrastructure for pedestrians and cyclists. There are more vegetation and on-street parking than average and little traffic signage.
- **Class 6 - Drive-centric commercial zone:** Car-driven infrastructure with many commercial buildings, focused on signalized primary roads and parking spaces, with fewer opportunities for cycling.

For this, I explore how elements are associated with observed and perceived cycling risk in each of the above clusters and explore whether elements have different influences among these clusters. Figure 11.3 shows the average impact of the top ten features for each safety type for the six environment classes. Looking at the effects of the different elements on objective safety, we notice that, for example, in the cases of curbs, vegetation, and lane markings, their results are somewhat similar throughout the six classes. However, that is not the case for poles, with Class 3 poles having a greater average impact, and for Class 4, the effect is nearly none when compared with the remaining classes. The same analysis can be done for the subjective safety. Here, we see that, for example, fences have similar average log-odds of influencing the outcome of perceived environments, whereas for the remaining variables that is not the case. For instance, for sidewalks, there are large differences between almost all classes. Such analysis showcases the importance of the urban environment context on both objective and subjective safety.

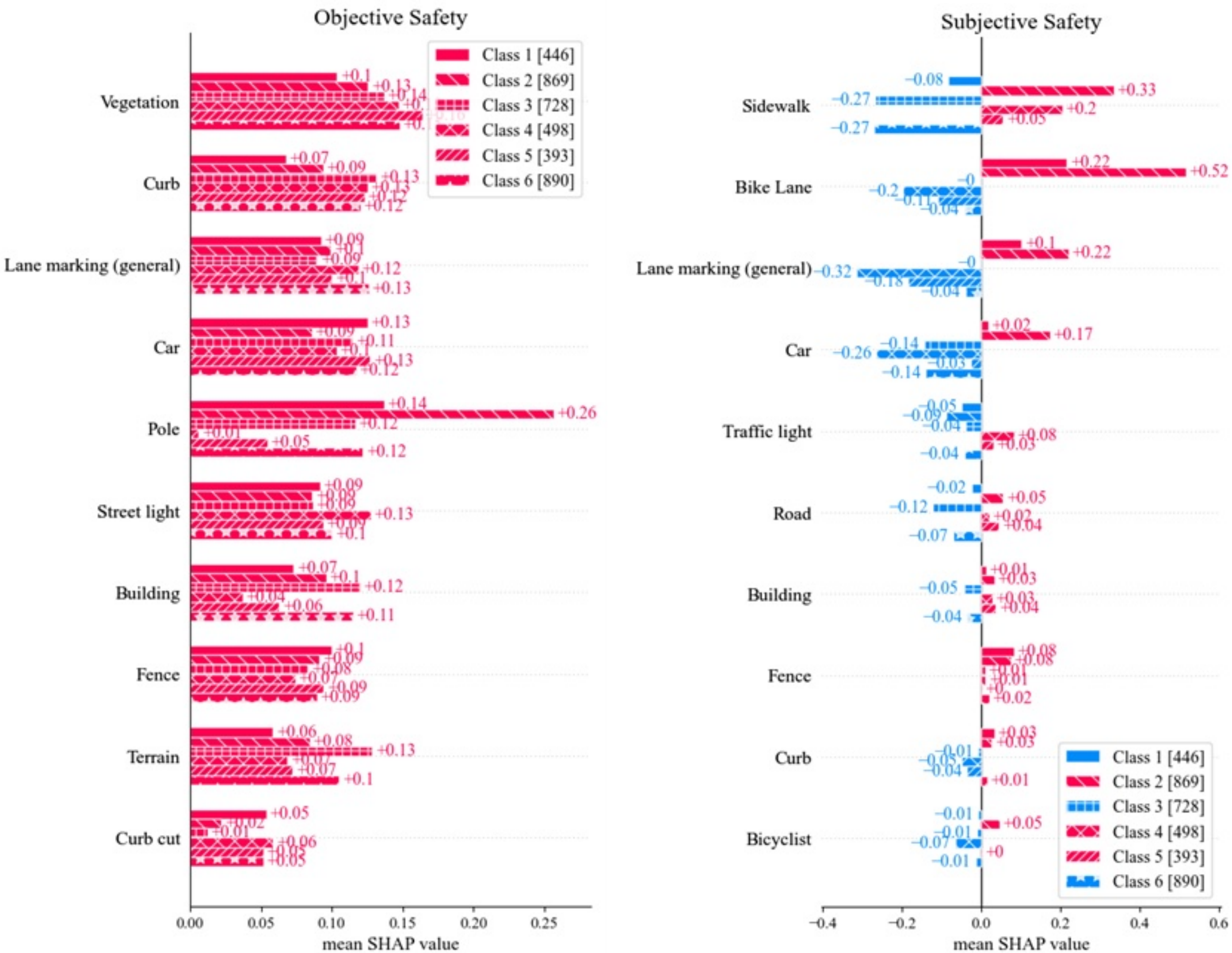

Figure 11.3: Urban elements effects on objective safety and subjective safety for the built environment typologies found in Chapter 5

A global analysis of all included elements can be done to identify the environments that are safer or more dangerous globally. For this, I computed the global effect of all elements for each of the six classes. Ordering the environment classes in terms of objective safety we have that:

$$\text{CLASS 1} < \text{CLASS 2} < \text{CLASS 5} < \text{CLASS 4} < \text{CLASS 3} < \text{CLASS 6}.$$

As such, *Cycle Havens* and *Green Transit Hubs* present the highest objective risk, while *Cozy Pedal Havens* and *Drive-centric Commercial Zones* correspond to the lowest objective risk environments. For the subjective safety, we have that:

$$\text{CLASS 3} < \text{CLASS 6} < \text{CLASS 4} < \text{CLASS 5} < \text{CLASS 1} < \text{CLASS 2}.$$

In this case, *Cozy Pedal Havens* and *Drive-centric Commercial Zones* correspond to environments with the highest perceived cycling risk. At the same time, *Cycle Havens* and *Green Transit Hubs* exhibit the lowest cycling risk. Interestingly, such results indicate a (almost entirely) reverse relation between the objective and subjective safety for these particular types of environments. Figure 11.4 shows a graphical representation of the six urban environment classes in terms of their objective and subjective cycling safety levels. Overall, although only these six environment typologies were analyzed, the employed approach enables the direct comparison of different urban settings and analysis of objective and subjective cycling safety at these locations.

11.5 Discussion

This chapter explored the effects of various urban elements on objective and subjective cycling safety. In sum, I used XGBoost and SHAP to quantify and understand these effects. Results have important implications for urban planning and design as they allow us to pinpoint directly the impact of individual elements on either cycling accidents or the perception of cycling safety. In turn, such knowledge can be used to better equip cycling environments with characteristics that lower actual risk and create environments where cyclists feel safer, potentially increasing cycling numbers in general.

My findings allude to a context-oriented effect of urban elements on objective safety and subjective safety. While some elements are shown to be aligned in terms of safety types, others suggest that an opposite influence exists between objective and subjective safety. Understanding when the second case occurs is vital, and two situations may arise. On the one hand, there may be an overestimation of unsafety (i.e., subjective unsafety much higher than objective unsafety), leading to individuals being discouraged from cycling (Sanders, 2015; Aldred, 2016; Félix et al., 2019). On the other hand, accident unsafety may be underestimated, leading to cyclists not paying attention to potentially dangerous elements and presumably generating cycling accidents, as pointed out in other studies (Schmidt and von Stülpnagel, 2018).

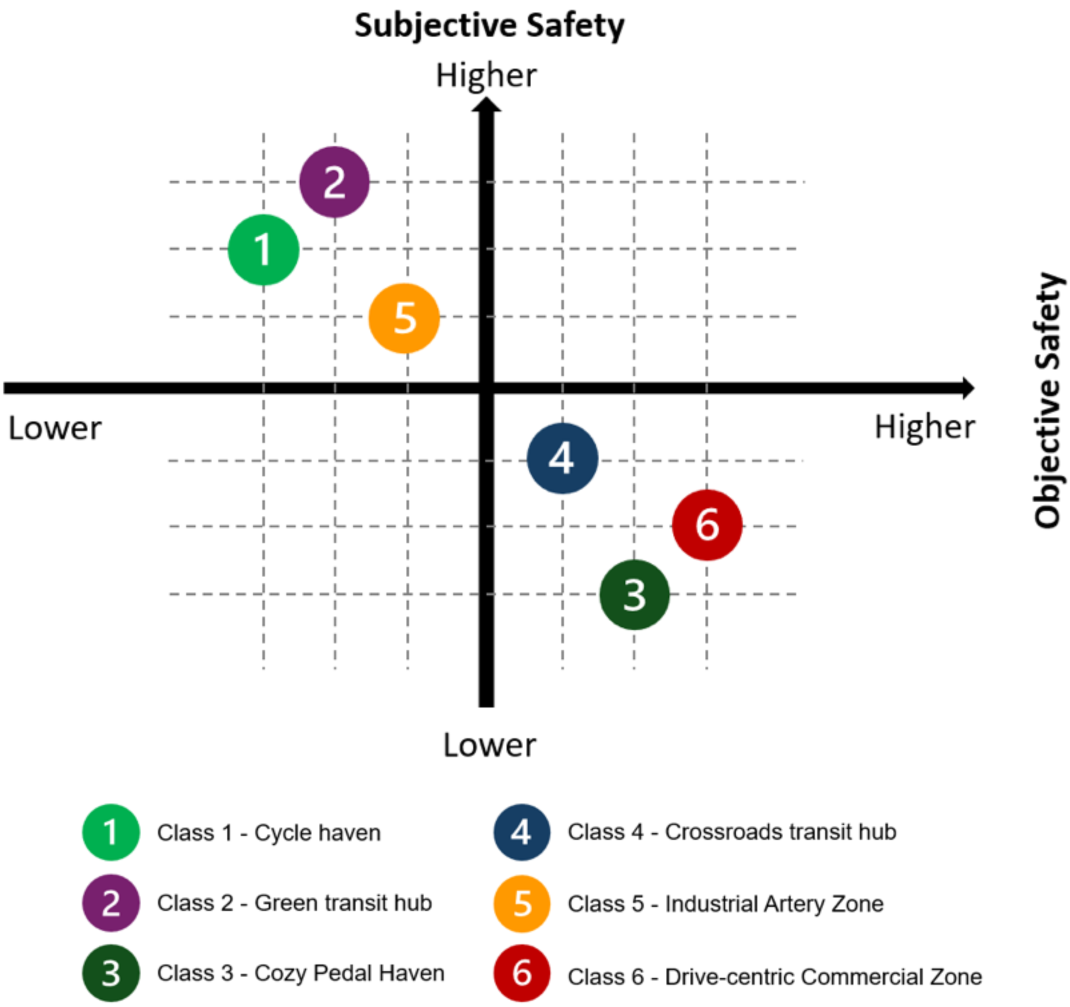

Figure 11.4: Urban environment classes ranked according to their objective and subjective cycling safety.

Compared to other studies that have explored the relationship between objective and subjective safety, the approach used throughout this chapter has the advantage of analyzing the influence of individual urban characteristics. This contrasts with most studies that have examined environment typologies holistically. This detailed knowledge may help better understand how objective safety is related to subjective safety as deeper insights may be recovered. This can also help in understanding how some studies have found both safety types to be aligned (Poulos et al., 2017; Branion-Calles et al., 2020; Osama and Sayed, 2017; Rasch et al., 2022), while others have found discrepancies in some particular situations (Winters et al., 2012; von Stülpnagel and Lucas, 2020; von Stülpnagel et al., 2022).

Furthermore, this approach also enables posterior analysis by constructing/simulating environments and analyzing how these are scored regarding actual and perceived risk. The study of cycling environment types showcased a (nearly perfect) reverse misalignment for the six typologies analyzed, suggesting a broad discrepancy between objective and subjective safety for environments where we know cycling accidents have occurred. Ultimately, this can help determine when objective safety is aligned with subjective safety and in what circumstances they are distorted.

Policy implications

Results have essential practice implications. Understanding where and how risk is underestimated or overestimated is of the utmost importance to adequately provide cyclists with environments where they are and feel safe. Failing to do so may result in increased accidents or a reduced number of cyclists.

First, tackling underestimation of actual risk may be done by possibly raising cyclists' awareness of the dangers faced at particular locations or specific situations via traffic lights or traffic signs, retraining sessions, or education programs. Other research has suggested that cycling workshops and community initiatives may provide cyclists with the necessary information about the road rules and safe practices for cycling (Lawson et al., 2013), especially for those with less experience. Here, authorities may play a fundamental role in incentivizing participation as low rates for voluntary participation in cycling education programs are expected (Sanders, 2013). Additionally, greater efforts must address possible distracted or aggressive cycling behaviors, which may relieve cyclists' attention and, thus, contribute to an underestimation of cycling accident risk. Here, officials need to take measures to counteract possible distractions and stimulate cyclists to pay close attention to specific situations that may arise, such as signage or usage of particular urban elements known to raise cyclists' awareness.

On the other hand, accident risk overestimation may be tackled by better communication strategies to cyclists and potential cyclists. As noted before, heightened perceptions of accident risk jeopardize policies seeking to increase cycling numbers. Thus, policies are needed to convey better the real dangers cyclists face. Here, targeted marketing campaigns and incentives for cycling addressed to potential cyclists may better inform cyclists of the real risks they face and how misperceptions of such risks may occur. Additionally, incentivizing individuals to register their experiences in travel diaries may also be helpful for users to establish better how their perceptions misalign with actual risky experiences.

More detailed practice implications can be extracted from analysing urban elements individually. Figure 11.5 shows six of the top urban elements often considered when looking at cycling safety, which include cycling elements and urban space dividing elements (Christ et al., 2024): poles, barriers, sidewalks, cycleways, residential streets, and presence of other bicycles. Looking at these specific findings, important practical recommendations can be drawn. First, designing an urban environment that suits the promotion of cycling as a mean of transportation by providing cyclists with features they feel safer, may actually increase the risk they face on their trips. For example, a larger and bigger sidewalks seem to increase the perception of cycling safety, but they are also associated with a decrease in actual safety, which may result from increase interactions with pedestrians. On the other hand, increasing the amount of poles increases the objective safety, while decreasing the sense of safety felt by cyclists. Such examples showcase how hard it is to plan and design environments where cyclists are safe and feel safe while cycling. Remarkably, an increase in bicycles is mostly associated with an increase in objective and subjective safety, which may reflect that environments are more suited for cyclists or other road users are perhaps more aware of cyclists' presence, which is also aligned with cycling-in-numbers phenomenons (Elvik and Bjørnskau, 2017). Yet, clearly such analysis here lacks the information about exposure effects, which have been shown to be important (von Stülpnagel et al., 2022) and should be considered when moving to practical changes.

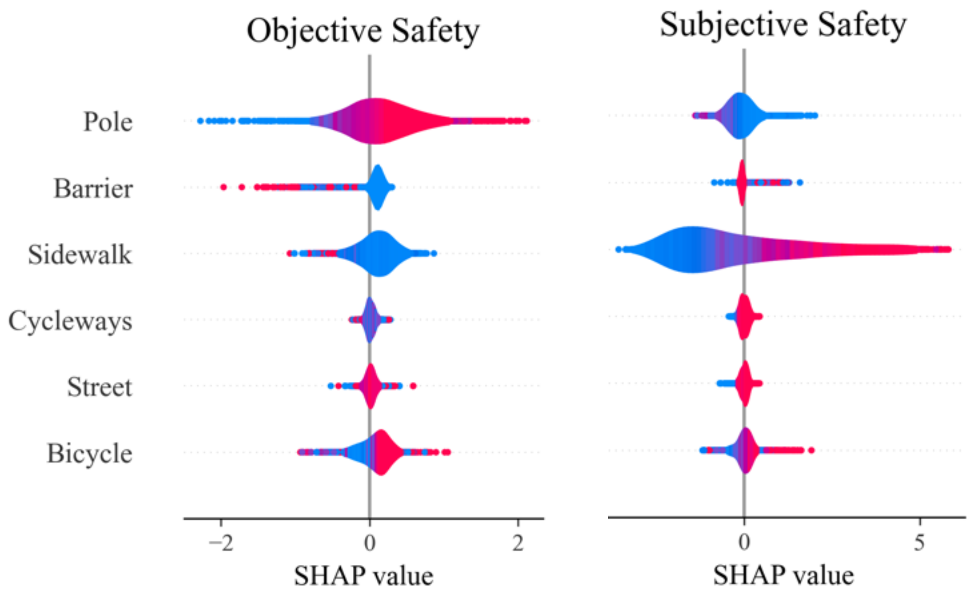

Figure 11.5: Selected urban elements and their SHAP effects in objective and subjective cycling safety.

Notwithstanding the practical information that can be retrieved from such analysis, it is important to acknowledge that singling out one element and acting on its expected effects may not results in a complete change of safety levels. Naively, simply increasing the amount of poles in urban environment may not highly increase cyclists' objective safety or simply by removing cycling lanes we increase cyclists' attention to reduce possible accidents outcomes. Urban environments are complex with many interplaying elements. Yet, such detailed knowledge can be used by policymakers and researchers to understand better how risk relates to exposure and individuals' perceptions. When combined with observational studies, practitioners can form a deeper and more holistic idea of how observed risk relates to perceived safety and how "risk re-alignment" procedures can be implemented (Sanders, 2013). Yet, ultimately, it is also key that changes and implemented policies tackling cycling safety are well delivered to cyclists. Only then can one viably promote cycling as a means of transportation (Lawson et al., 2013).

Limitations

However, this study has its limitations and caveats. First, the methods and results used bring forth correlations between urban characteristics and the respective safety type. This means that causality cannot be drawn from these results. Nonetheless, they partially meet the conditions to establish causality, namely those of association and plausibility (Van de Coevering et al., 2015). As such, care should always be exercised when devising policies based on correlations and the safety of cycling

(Götschi et al., 2016). Further experiments are needed to understand the causal effects between the two safety types and cycling environment elements, especially those considering time precedence and non-spuriousness (Van de Coevering et al., 2015), although I have tried to control such unaccounted effects by defining urban environment typologies.

Second, the data used throughout this analysis was primarily based on volunteered geographical information. Its value has been used and proved before in this thesis (cf. Chapter 4–9) and in understanding cycling safety and other domains (von Stülpnagel and Lucas, 2020; von Stülpnagel et al., 2022; Ito and Biljecki, 2021). Yet, past chapters have analyzed this data jointly with accident contributing factors for the observed risk or perceptions about the cycling environment for the perceived risk. Ideally, such data would also be included in this objective–subjective safety analysis, but to have a fairer evaluation, they were removed. In the future, accident-contributing factors, socio-demographic characteristics of individuals, and other data can be included to retrieve further insights about this relationship further. Furthermore, the analysis could gain value if data concerning such factors is available for both safety types. For example, this could include perceptions about accident circumstances (i.e., those typically available in accident records) or risky maneuvers, as has been evaluated before for the case of overtaking situations or near misses (Ichikawa and Nakahara, 2008; Chaurand and Delhomme, 2013; Sanders, 2015; Poulos et al., 2017; Rasch et al., 2022), and cycling volumes (von Stülpnagel and Lucas, 2020; von Stülpnagel et al., 2022).

Finally, the data used was extracted from known accident locations. While a distinction could be made between different levels of observed risk using accident outcomes, it constrained an evaluation and comparison between objective and subjective risk in these locations. To further explore the intricate relation between objective and subjective safety, future analysis should incorporate non-accident areas, as sometimes is done in road safety research to compare accident versus non-accident locations (Ma et al., 2019; Chang et al., 2022). Such a broader encompassing study can bring forth even more insights to fully understand the objective–subjective cycling safety relation.

11.6 Summary and conclusions

This chapter has explored how various urban elements are associated with objective and subjective cycling safety. A machine learning approach was used to model such effects. Data used included accident records for the observed safety, cycling environments perceived safety scores for the subjective safety, and volunteered geographic information for the urban context and its elements. Results showcase how different elements are sometimes perceived differently from their actual risk, while others are congruent between perceived and actual risk. Ultimately, however, the explored approach presents a new strategy to uncover the true objective–subjective safety relation and understand how different environments and contexts modulate such connection.

Supporting materials

Supporting materials, namely the code used, for this section are available at https://github.com/mncosta/objective_subjective_safety_xgboost. Code is available for Python3 and is available under MIT license (https://opensource.org/licenses/MIT).

Part C: Summary of Key Findings

In this part, I focused on the relation between objective and subjective cycling safety. The following items emerged as crucial remarks from the research carried out.

Limited understanding of the relation between objective and subjective cycling safety

While research has deepened the knowledge of actual and perceived safety in the past years, the same focus has yet to translate into exploring and understanding a possible relation between the two. Findings from the few studies that have done so found mixed results. Some highlight a congruent link, while others found disparities, especially for particular urban environment typologies. Given its importance in ensuring that policies and measures are successful in both observed and perceived safety, more research is needed to understand the connection between objective and subjective safety.

Cycling behavior and self-selection in cycling safety

As previously hypothesized, behavior changes may pay a particular important role in how the objective–subjective safety relation is constituted. Additionally, cycling self-selection phenomenons (associated with cycling preferences and environments where to do so) may also play a role in such relation. In the future, it it important to analyze whether such phenomenons (both related to behavior change and self-selection) contribute to how perception of safety is modulated and objective safety is influenced as, for example, more proficient cyclists may better reckon where is safe to cycle or not (and vice-versa).

Individual effects of urban elements on cycling accident outcomes and perceptions of the safety of cycling environments

Urban elements' influence on objective and subjective cycling safety was evaluated using a machine learning approach that allows researchers to understand the individual effect of a given urban characteristic on actual or perceived safety. Furthermore, the method enables the direct comparison of elements effects between the two safety types. Results showed that some elements had a similar impact (increased or decreased both safety types), while others had the opposite effects. Findings suggest and allow for a more context-oriented study of the objective–subjective relation.

Inverse relation between objective and subjective cycling safety for analysed environment typologies

Results for urban environment typologies on how they are linked with observed and perceived risk suggested an inverse connection between actual and perceived safety. Low observed risk was correlated with high perceived risk, and high actual risk was associated with low perception of risk. This has important implications for practice. An overestimation of accident risk may lead to lower cycling rates among individuals, while an underestimation may increase the severity of accidents. Further experiments should analyze these results further and understand whether these discrepancies are causing or being caused by behavior changes that lead to such misalignments or if any other factors influence such connections.

Chapter 12

Conclusions and Leads for Future Research

Cycling plays a fundamental role in cities' transitions towards sustainability. Cycling has been found to have many benefits, including health, the environment, and the economy. However, many deterrents exist for those seeking to pick a bicycle. Within these, safety aspects are often regarded as the primary barrier for potential cyclists. If cities want to successfully improve cycling numbers, improving cyclists' safety and sense of safety is vital.

This thesis tackled such needs by delving into understanding objective safety, subjective safety, and the relation between the two. It focused on the particular case of Berlin, Germany, but the approach employed focused on a scalable methodology that can continuously and ubiquitously monitor cycling safety and analyze where changes ought to be made to improve cyclists' safety. Its main objective was to "*Combine authoritative and volunteered geographical data to automatically and continuously identify, understand, and draw recommendations to improve urban objective and subjective cycling safety.*" Through the use of multiple data sources and types, it explored a range of methodologies that allow researchers, urban planners, and authorities to monitor and identify urban characteristics that either increase or decrease cycling safety. This thesis was divided into three main parts to achieve such an objective. Their main conclusions and contributions are enumerated in the following sections.

The remainder of this chapter concludes this thesis and presents the main scientific contributions and findings in Section 12.1. Section 12.2 answers the original research questions posed in Chapter 1. Section 12.3 provides an overall summary of the work carried out. Section 12.4 lists research limitations and shortcomings. Finally, Section 12.5 presents possible leads for future research.

12.1 Research Scope and Contributions

This thesis has positioned itself at the intersection of two distinct areas of research: needs to address problems related to cycling safety (from the Transportation Systems side) that were studied under a data processing approach (from a Data Science perspective). Several methodologies were used under this scenario which have contributed to advancing knowledge in cycling safety. The next paragraphs summarizes and contextualizes this thesis main contributions.

Objective Cycling Safety

First, Part A addresses objective cycling safety. It begins by filling a need for more accessible data about cycling accidents. The compiled collection of cycling accidents is then used with volunteered geographical information to understand differences between accident and non-accident locations and model accident severity outcomes.

While various cities and countries already publish their datasets on cycling accidents, there is a need for a standardized and unified repository of cycling crash information. CYCLANDS tackles this problem. CYCLANDS, a collection of thirty individual datasets, is a compilation of cycling accident data encompassing nearly 1.6 million records, unprecedented in cycling safety research. Ultimately, CYCLANDS aims to lower the difficulty barrier, enabling any individual less proficient in data processing tools to access and explore such valuable resources and laying the ground for more accident severity modeling research, which can lead to evidence-based improvements to cyclists' safety.

Next, this thesis delves into how typical accident records can be augmented using volunteered geographical information. This process provided crucial attributes about the built environment in locations where accidents occurred. A comparison is made between accident versus non-accident sites, and significant differences were found in city areas where cycling accidents are prone to occur.

I expand on the previous findings and employ an accident severity model to investigate the relationship between the built environment and cycling accidents. Through a novel modeling framework that combines the power of unsupervised machine learning and econometric models, risk factors are analyzed based on their impacts, contingent upon the location and specific built environment typology in which accidents occurred. Researchers can use such an approach to examine the inherent risk associated with accidents occurring in particular urban environments.

Subjective Cycling Safety

Second, Part B tackles subjective cycling safety. It uses a pairwise image comparison survey to capture individuals' perceptions of cycling environments regarding safety. Comparisons are processed and used to score environments, analyze the impact of urban characteristics, and understand how environments can be changed to improve the sense of safety.

I begin by showcasing how pairwise image comparisons about perceived safety can be transformed into perceived safety scores using paired models. Researchers can use these scores to compare cycling environments easily via a continuous scale. Next, I build upon such strategies to develop a deep learning model that can accurately predict an image's perceived score based entirely on image features. Such a model can simulate human perception of cycling safety and analyze subjective cycling safety at a city-wide scale.

Although such an approach is highly scalable, it needs more direct interpretability of what makes an environment being perceived safe or unsafe. Therefore, the next step consisted of analyzing the influence of built environment elements, road users, and urban morphology on perceived safety. Non-linear and pairwise interaction effects of urban elements were explored, and results showed that while some factors can be analyzed linearly, others cannot. This indicates that careful considerations ought to be made when designing policies or recommendations for urban changes to make cyclists feel safer.

Objective and Subjective Cycling Safety

Third, Part C delves into the objective–subjective cycling safety relation. As shown, this complex relation is not always straightforward, and intervention in one type of safety may negatively affect the other. As such, it is vital to analyze and understand more about such a relation and the interplay between objective safety, subjective safety, and behavior changes induced by such a relation.

Finally, I have analyzed congruencies and discrepancies between urban elements' effects on objective and subjective safety through a dual modeling approach. Findings highlight that some features' influences are similar on objective and subjective safety, while others present opposing impacts. Interestingly, when comparing known risky environments in Berlin, a reverse situation is noted for perceived risk: environments with low perceived safety are actually safer; in contrast, environments perceived as safer are associated with low actual safety.

12.2 Answering the Research Questions

I now attempt to concisely answer the main and supporting research questions outlined in Section 1.2.

RQ1. What is the relation between cycling built environments and cycling accidents?

Several urban environment elements affect cycling accident outcomes by increasing or decreasing the risk cyclists face on their journeys. This thesis explored this relation in several aspects, including understanding individual effects of elements, more holistic manners through built environment typologies and analyzing non-linear effects on accident severity outcomes. The following support questions help to answer this question, as do the results from Chapters 4, 5, and 11.

SRQ1.1. How can one tackle the lack of data on objective cycling safety?

Cycling accident records are the basis of objective cycling research. However, most incidents involving cyclists are often not reported (or go unreported). Hence, there needs to be a concerted effort to improve the quantity and quality of data available to researchers and urban planners. CYCLANDS (cf. Chapter 3) is a first step towards this goal, providing standardized access to nearly 1.6 million cycling accident observations. Creating such a collection lowers the barrier to cycling safety research and, I hope, serves as a stepping stone to more standardization and availability of accident records. Moreover, such records might not contain a complete description of the context in which accidents occurred. The approaches used in Chapters 4 and 5 contribute to filling this data gap as well by adding VGI (including mapping and imagery data) on accidents' locations.

SRQ1.2. Are there built environment differences between cycling accident locations and non-accident locations?

Results suggest that, indeed, there are differences between accident and non-accident locations. Although only circulation spaces (i.e., urban road networks) were evaluated in Chapter 4, a broader analysis could be made using the remaining available data on the urban context. Moreover, such results are not location-dependent (i.e., strict to one city) but appear to be spread to other locations (as shown for the cases of Barcelona and New York).

SRQ1.3. What is the link between the built environment, accident contributing factors, and accident outcomes?

Cycling accident outcomes result from many distinct factors. Results from Chapter 5 showed an interesting interplay between cycling environments (including the built environment) and accident contributing factors. As mentioned, not all accident contributing factors were found to be statistically significant in all built environment typologies analyzed, which suggests that some contributing factors are more relevant in particular scenarios when compared to others. Similarly, outcome base levels (i.e., probability of an accident resulting in a fatality, serious injury, or light injury when no other factors are considered) also showed significant differences, suggesting that some environment typologies are inherently more dangerous than others. Research should explore this in greater depth to understand how such particular environments can be re-designed to protect cyclists better.

RQ2. What urban factors impact the perception of cycling safety?

Similar to the case of objective cycling safety, several urban elements and factors impact the perception of safety. Factors studied included roads, roadside elements, users and vehicles, some weather conditions (snow), and urban form metrics. Results indicate that various factors were found to increase perceived safety, while others seemed to decrease the sense of safety while cycling. More in-depth results and insights can be seen in Chapters 7, 9, and 11. The following support research questions also help answer this question.

SRQ2.1. Can we capture cycling safety perception through street-view images?

Yes, we can. Part B of this thesis used pairwise comparisons of street-view images to study subjective cycling safety. Results show that street-view images, particularly comparing them, is a valid and valuable strategy to capture perceived levels of safety and understand how the depicted elements impact those levels.

SRQ2.2. Can we understand the cycling perception of safety in a scalable and continuous manner?

Chapters 7, 9, and especially Chapter 8 delved into how scalable approaches using machine learning techniques can be used to understand how individuals perceive cycling accident risk at a micro-level. First, pairwise comparisons require fewer survey answers than traditional ordinal-response approaches, improving scalability. Second, a particular deep learning approach was developed to score cycling environments based on users' comparisons of street-view images. As demonstrated, this deep learning approach is highly scalable as it can be used to analyze perceived safety at a city-wide scale and, therefore, "zoom out" to map subjective safety at a macro-level as well.

SRQ2.3. How do different urban elements influence the perception of risk?

This thesis' findings support that urban elements have a non-linear influence over perceived safety, with elements impacts changing depending on the elements' appearance on the analyzed images. Some elements impact perceived safety positively and negatively, depending on their values. Similarly, depending on the context of where the element is inserted, that also appears to change its respective influence. This supports a hypothesis that elements must be analyzed at a micro- and macro-level to understand their influence on subjective safety fully.

RQ3. What is the connection between objective and subjective cycling safety?

Findings suggest that a complex and not linear relation exists between what is perceived as safe (and risky) and what is actually safe (and risky). Yet, that relation still needs to be fully understood today. An element, environment, and personal assessment needs to be conducted to explore such connections further.

SRQ3.1. What do we currently know about the objective–subjective cycling safety relation?

There is currently limited knowledge of the relationship between objective and subjective cycling safety. Few studies have analyzed its connection, with several indicating a direct correlation, others finding no correlations, and others finding positive and negative associations between the two safety types. More research is needed to grasp better how such a relation is formed and molded. Care is especially required as behavior change might play a crucial role in such relation.

SRQ3.2. Does an increase in objective risk relate to an increase in perception of risk? Or does the opposite happen, does a decrease in objective risk relate to an increased perception of risk?

At the urban element level, this thesis' findings suggest that elements may influence both objective and subjective safety, may have complex relations that are hard to understand linearly or might have opposite influences over the two. At an environment typology level, when compared to objective safety levels, environments were inversely perceived. This means there may be an overestimation or underestimation of perceived risk versus actual risk. Again, more research is needed to unveil the objective–subjective cycling safety relation altogether.

12.3 Overall Summary

Cycling numbers have increased recently in many cities. Concurrently, the number of stressful situations cyclists face, and the number of accidents resulting in fatalities in Europe have also increased. Objective cycling safety research (which analyses cycling accidents and their outcomes) seeks to understand how to minimize accidents and their consequences. In recent years, significant research has been conducted to explore various factors contributing to accidents. Yet, research often faces scarce accident records and information about when, how, and where cycling accidents occur.

On the other hand, one's decision to cycle revolves around many factors. However, safety concerns are often cited as the major deterrent for potential cyclists and non-cyclists. Creating environments where cyclists feel safe is vital to promoting cycling as a mode of transportation and further increasing cycling numbers. Subjective cycling safety research (which analyzes individuals' perceptions of safety) explores what urban, personal, and social factors impact one's sense of safety. As its relevance has been put forward in recent years with cities aiming to increase cycling numbers, research has delved into exploring what factors increase or decrease the sense of safety. Yet, most approaches are often labor-intensive and have limited scalability.

Moreover, understanding how objective safety is related to subjective safety has yet to gain much traction in the cycling safety research field. The few that have explored this connection have found mixed results. A deeper understanding of the objective–subjective relation is needed to more effectively target interventions to improve cyclists' safety on the whole and not jeopardize reversing changes that may only improve one type of safety.

This thesis contributes to advancing cycling safety knowledge as it builds upon existing research on cycling safety. It uses new methodologies to unveil deeper relations between the urban context and objective and subjective cycling safety. The contributions mentioned bring forth additional, more scalable tools for researchers to evaluate how the urban environment continuously impacts cycling safety. Moreover, the tools can be used within simulation scenarios, allowing a broader mapping of actual and perceived safety.

The overall approach used multiple methods to understand the impact of urban characteristics on cycling safety. Quantitative methods were mainly used, which included clustering techniques, latent class discrete outcome models, paired models, siamese-convolutional neural networks, explainable boosting machines, and gradient boosted decision trees. As most topics covered combined authoritative data, volunteered geographical information, and/or survey responses, most analyses exploited data mining techniques and machine learning tools to unveil and process such large and complex data streams. Yet, an effort has been made to employ mostly directly explainable methods. Ultimately, the methods used enable direct inspection of urban characteristics to retrieve actionable insights on improving cycling safety.

In conclusion, this research underscores the critical need for a comprehensive understanding of cycling safety, addressing both objective and subjective aspects. By delving into the intricate connections between urban context and cycling safety, this thesis contributes valuable insights to the field. By exploring various quantitative methods and machine learning techniques, the research navigates the complexities of different datasets and strives for direct explainability. Ultimately, the findings aim to provide actionable insights into urban characteristics, fostering a safer environment for cyclists and, in turn, encouraging the continued growth of cycling as a sustainable mode of transportation.

12.4 Main Limitations

The analysis in this thesis has explored the influence of numerous urban factors on cycling safety. Results were achieved using various methods and modeling tools. Yet, as with every research methodology, the approaches used have limitations. It is even more important to consider their limitations given the social and health aspects it indirectly covers. I now put forward this thesis's five main limitations.

First, while the findings here presented provide valuable insights into cycling safety within the context of Berlin, it is important to acknowledge the limitations associated with the generalization of my findings. The specific characteristics and dynamics of Berlin may not fully capture the diversity inherent to other urban settings, like Lisbon, Copenhagen, or Munich, for example. Therefore, caution should be exercised when generalizing this thesis's findings. Nevertheless, it is noteworthy that the methodology employed throughout this research process was designed to be adaptable and serve as a robust framework for similar studies in different cities and geographical contexts. Future research endeavors should apply such methodology to other locations which can, in turn, enhance the external validity of my findings and contribute to a more comprehensive understanding of objective and subjective cycling safety on a broader scale.

Second, most analyses have used volunteered geographical information. While the value of incorporating such data cannot be questioned, special attention should always be paid when utilizing it. While several checks and steps were used to ensure the data's validity and quality, all observations' characteristics could not be individually analyzed due to time constraints.

While considerable efforts sought to compile the complete set of accident records available, the analysis conducted throughout this thesis only used police records as accident observations. As such, results and findings can only highlight the effects of urban elements from these observations. Yet, accident records are known to be notoriously under-reported. Future endeavors should explore these records combined with other sources, such as hospital admissions or crowdsourced observations.

On the subjective safety side, it is essential to acknowledge that perceptions of safety are inherently subjective and can be influenced by individual characteristics and cultural factors, something not explored here. In addition to overlooking these factors, no longitudinal characteristics were captured to include cycling proficiency or past risky experiences.

Lastly, most of this work has found significant associations between numerous elements and cycling safety. However, causal influences were never tested. Acknowledging such a fact is highly important, given the impacts that urban changes might have on cyclists' safety. Therefore, results and findings should always be carefully considered when devising policies or urban design changes.

12.5 Leads for Future Research

Obvious leads for future research would be overcoming the abovementioned limitations. In addition, more cycling safety research knowledge could be drawn from the following five possible directions.

First, several methods used throughout this thesis could be used to understand cycling safety in other locations. For example, applying the approach used in Chapter 5 in Munich, Germany, could allow us to check whether the retrieved built environment typologies would be the same as extracted for Berlin and whether the same contributing factors are relevant in the same set environments.

The modeling approach used throughout Part A was based on severity-based modeling due to a lack of cycling traffic data, which is needed for more frequentist methodologies. Yet, such analysis becomes available with the advent of more open data in this domain (e.g., using mobile phone tracking applications) or with newer modeling tools to estimate cycling flow. Such a strategy could be used in conjunction with severity-based models to better understand the impact of the urban environment on cyclists' safety.

Next, a study using the model trained in Chapter 8 but using other cities' images and comparisons could allow researchers to analyze whether there are common factors in perceived safety between multiple locations or whether there are significant factors at play that restrict such knowledge transferability.

Another possible direction would be to use the collected data on cyclists' profiles. Such analysis would entail comparing whether different cycling profiles have different levels of perceived safety and if urban elements have distinct effects over distinct sets of individuals. This could be further developed by using eye-tracking technology to verify whether different profiles pay attention to different sets of environment characteristics.

Finally, multiple findings have underscored the need for tailored urban planning strategies that consider the unique characteristics and needs of looking at urban spaces as a whole. Ultimately, for the knowledge gained in this thesis to have practical implementations, engaging with local communities and authorities is a must. Future endeavors should also explore what urban changes or policies can be implemented. This would ensure more tailored insights are retrieved into the possibilities available for change in the urban space.

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Chapter A

CYCLANDS: Details on data provided in each dataset

In this appendix, further details on each datset in CYCLANDS is presented. Tables A.1 and A.2 delve deeper from Table 3.2, providing key characteristics from each dataset.

Table A.1: Information contained in each dataset. Details of accident locations, personal and vehicle characteristics involved, causes of the accident and data and time.

	Location Details							Personal Charact.			Vehicle Charact.					Accident Cause			Date & Time Details	
Dataset Location	**Lat & Lon**	**Address**	**Traffic Control**	**Speed Limit**	**Road Type**	**Intersection Type**	**Other[1]**	**Gender**	**Age**	**Other[2]**	**Type**	**Maneuvers**	**Collision Point**	**Direction**	**Other[3]**	**Contributing Factors**	**Human Factors**	**Vehicle Factors**	**Date**	**Time**
Barcelona, Spain	✓	✓						✓	✓	✓	✓								✓	✓
Cambridgeshire, UK	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		✓	✓				✓	
Chicago, USA	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓					✓	✓
Colorado, USA	✓	✓			✓	✓				✓	✓	✓	✓		✓		✓		✓	
Connecticut, USA	✓	✓			✓	✓	✓						✓			✓			✓	✓
Denver, USA	✓				✓	✓				✓	✓	✓	✓	✓			✓		✓	✓
Detroit, USA		✓				✓					✓								✓	✓
France	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓						✓	✓
Genebra, Switzerland	✓				✓	✓					✓					✓			✓	
Germany	✓										✓		✓						✓	✓
Helsinki, Finland	✓																		✓	
Las Vegas, USA		✓								✓	✓		✓	✓		✓			✓	
Los Angeles, USA	✓	✓						✓	✓		✓								✓	
Louisville, USA	✓	✓				✓							✓						✓	✓
Madrid, Spain		✓						✓	✓										✓	✓
Nantes, France	✓																		✓	✓
Nashville, USA	✓	✓									✓		✓						✓	✓
Netherlands	✓	✓		✓	✓			✓	✓		✓	✓	✓		✓				✓	✓
New York, USA	✓	✓									✓							✓	✓	✓
Pasadena, USA	✓	✓		✓				✓	✓		✓	✓	✓	✓		✓			✓	✓
Pennsylvania, USA	✓				✓	✓		✓	✓	✓					✓				✓	✓
Queensland, Australia	✓	✓	✓	✓		✓						✓				✓			✓[4]	
Richmond, USA	✓	✓																	✓	✓
Rome, Italy	✓	✓	✓		✓		✓	✓							✓				✓	✓
San Jose, EUA	✓	✓	✓			✓			✓						✓		✓	✓	✓	✓
Seattle, USA	✓	✓				✓									✓				✓	✓
UK (Collideoscope)	✓																		✓	✓
UK (.gov)	✓		✓		✓	✓													✓	✓
Victoria, Australia	✓				✓	✓		✓	✓										✓	
Washington DC, USA	✓	✓																	✓	✓

[1] Other information include information on Annual Daily Traffic, Nearby a School, Traffic Levels.
[2] Other information include Type of Occupant, School Trip, Trip Purpose, Human/Driver Action, or Human Vision.
[3] Other information include Overtaking, Defects, Action, Accident Type, Lights, or Speeding.
[4] Year only.

Table A.2: Information contained in each dataset. Details light conditions, road conditions and weather conditions available in each dataset.

Dataset Location	Light Condition Details						Road Condition Details										Weather Condition Details						
							Surface Conditions																
	Daylight	Dawn	Dusk	Dark	Dark Lighted	Dark Unlighted	Dry	Wet	Frost/Ice	Snow	Mud	Slush	Water	Other[1]	Road Alignment[2]	Surface Type[3]	Clear	Cloudy	Rain	Wind	Fog	Snow	Other[4]
Barcelona, Spain							✓	✓	✓	✓													
Cambridgeshire, UK	✓			✓			✓	✓	✓						✓		✓		✓	✓	✓		
Chicago, USA	✓	✓	✓	✓			✓	✓	✓	✓	✓				✓	✓	✓	✓	✓		✓	✓	✓
Colorado, USA	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓						✓		✓	✓	✓	✓	✓
Connecticut, USA	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓			✓		✓	✓	✓	✓	✓		
Denver, USA	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓		✓									
Detroit, USA	✓	✓	✓	✓			✓	✓		✓			✓				✓	✓	✓	✓		✓	
France	✓	✓	✓		✓	✓	✓	✓	✓				✓				✓	✓	✓	✓		✓	
Genebra, Switzerland	✓	✓	✓	✓			✓	✓									✓	✓	✓	✓		✓	
Germany	✓	✓	✓	✓																			
Helsinki, Finland							✓	✓															
Las Vegas, USA	✓	✓	✓		✓	✓											✓	✓	✓	✓			
Los Angeles, USA							✓	✓	✓	✓			✓		✓								
Louisville, USA	✓	✓	✓		✓	✓	✓	✓		✓				✓			✓	✓	✓		✓		
Madrid, Spain																	✓		✓		✓	✓	
Nantes, France																							
Nashville, USA	✓	✓	✓		✓	✓											✓		✓	✓		✓	
Netherlands																	✓		✓	✓	✓	✓	
New York, USA							✓	✓															
Pasadena, USA	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓	✓				
Pennsylvania, USA	✓	✓	✓		✓	✓	✓	✓							✓		✓		✓		✓	✓	✓
Queensland, Australia	✓	✓	✓		✓	✓											✓		✓		✓		✓
Richmond, USA							✓	✓							✓	✓							
Rome, Italy	✓			✓			✓	✓	✓	✓				✓									
San Jose, EUA	✓	✓	✓		✓	✓	✓	✓	✓	✓				✓			✓	✓	✓	✓		✓	
Seattle, USA	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓			✓			✓	✓	✓		✓	✓	
UK (Collideoscope)																							
UK (.gov)	✓				✓	✓														✓	✓		
Victoria, Australia																							
Washington DC, USA																							

[1] Other information include Debris, Gravel, Slippery, Sand, or Oil.
[2] Road alignment refers to the road being Straight, Curve, or On a Grade.
[3] Surface Types may be Concrete, Asphalt, Dirt, Paved, or others.
[4] Other information include Hail, or Smoke.

Chapter B

Accident Environment Types in New York

In this appendix, I present a collection of repeated experiments that supplement the research carried out in Chapter 4, providing additional materials to support the findings presented therein. The repeated experiments presented here offer valuable insights into the robustness and reliability of the main study's outcomes. Instead of using data from Barcelona, we apply the same procedure to cycling accidents in New York, USA. Again, all materials are available at https://github.com/mncosta/aet_cet.

Data & Methods

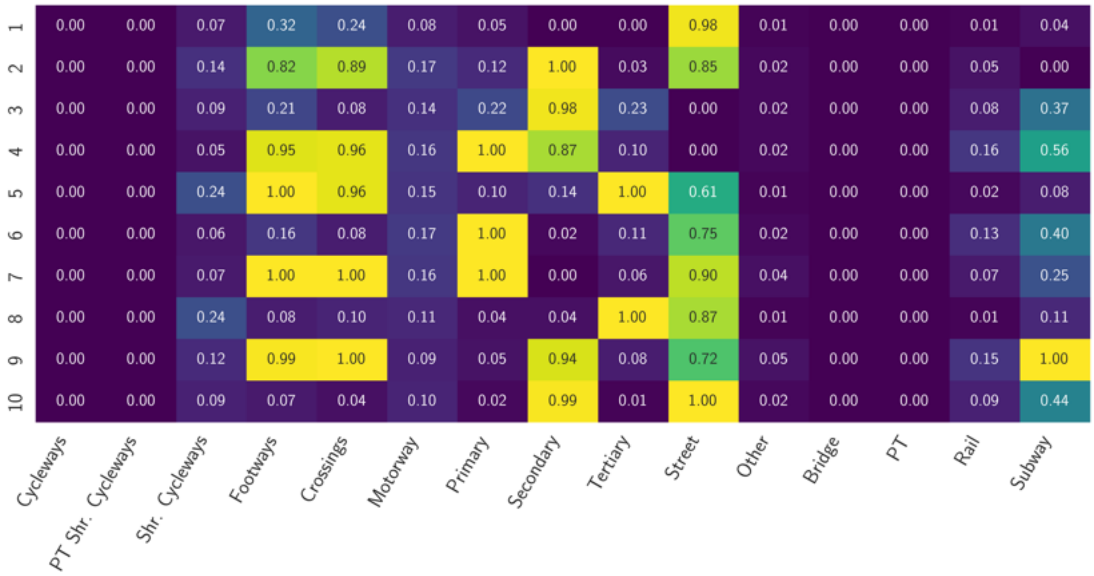
Cycling accidents include 40 838 cycling accidents that occurred between 2013 and 2019. Similarly to the Barcelona dataset, accident records include the geographic coordinates of the accident and the vehicles involved. In this case, observations have even fewer details than the Barcelona one, emphasizing a greater need for further contextual information about these cycling accidents.

The experiments in this appendix follow the same methodologies and data analysis techniques described in the main text. Mainly, I use accidents' geographic coordinates to extract information from OSM about network infrastructure and then apply SC to uncover Accident Environment Types in New York. Similarly to the Barcelona case study, I extract city-wide data to find City Environment Types. To achieve this, I randomly sample 80 000 points ($\sim$100 points/km^2), applying the same procedure as the accident locations.

Results

AET and CET for New York are shown in Figure B.1. Globally, when compared to CET, accidents happen more often in locations:

- with lower to no amounts of cycleways. Compared to CETs, cycleways are quite common in some environments (CET 2, 4, and 5), but they are inexistent in AETs. This suggests that cycling accidents tend to happen in locations not served by segregated cycleways;
- with shared cycleways and roads. Compared to CETs, shared cycleways are not common, whereas in AET, they appear throughout AET 2, 5, 8, and 9, indicating a possible increased risk for cyclists when sharing the road;
- with no motorways. Unsurprisingly, cycling accident environments exhibit little signs of motorway infrastructure when in CET, they are common;



(a)

(b)

Figure B.1: Accident Environment Types (a) and City Environment Types (b) cluster representations in New York, USA.

- where there are a greater presence of secondary, tertiary, and residential streets, and;
- connected to the subway that the CET. This suggests that locations served by the subway present a higher risk for cyclists, which may be linked to an increase in the area's complexity.

Similarly to the Barcelona case, several AET and CET are similar, such as AET and CET 1, AET and CET 2, and AET and CET 5, showing minor differences between AET and CET. On the opposite spectrum, CET 8 and 10, consisting almost entirely of motorways, do not appear on AETs, as bicycles cannot be used in such infrastructures.

The geographical distribution of AET is shown in Figure B.2. As one can see, there appear to be fundamental differences, such as a divergence of environment between Manhattan (greener), Brooklyn (bluer), and Harlem (yellowish). The main road axes, such as Broadway and Jamaica Avenues in Brooklyn, are also easily recognizable.

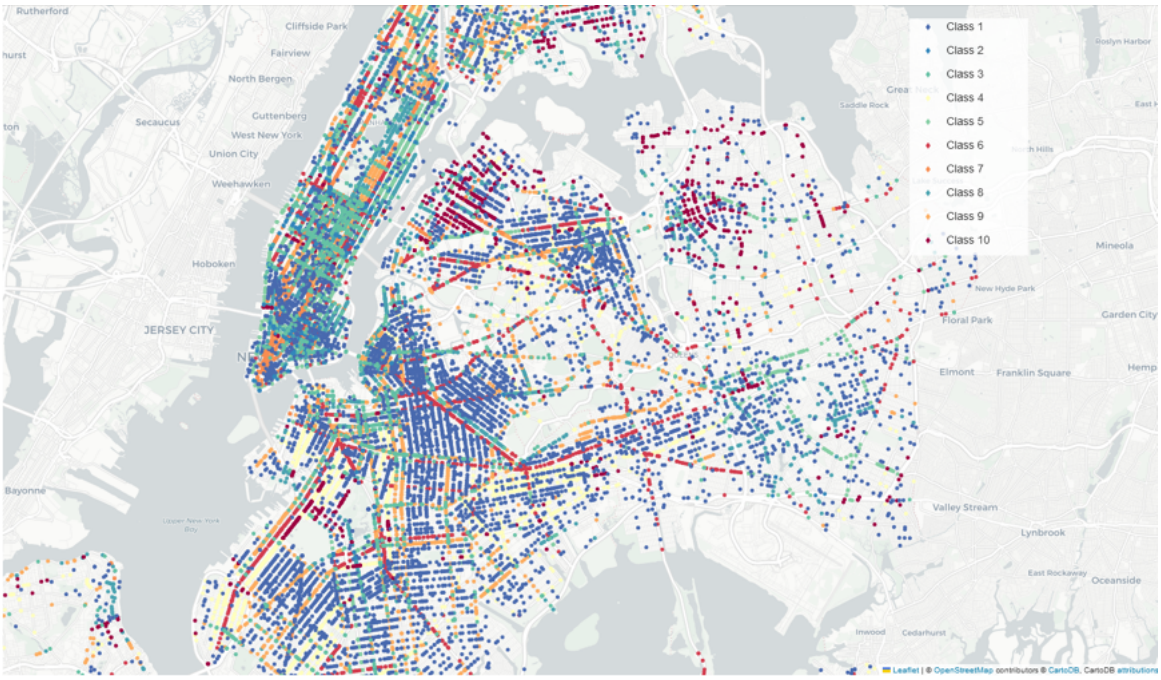


Figure B.2: Accident Environment Types in New York, USA.

Chapter **C**

GBM-LCDOM: Complete class membership results

This appendix provides complete details on the class membership results in Table C.2.

Table C.1: Summary of key class membership coefficients for the GBM.

μ_k=-1 μ_k=1

		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Image Objects	Road	0.1036	-0.0234	-0.0206	-0.0977	-0.0571	0.0769
	Sidewalk	0.0196	-0.0175	0.0095	0.1577	-0.1142	-0.0467
	Building	0.2019	-0.1155	-0.1815	0.1820	-0.1389	0.2052
	Wall	-0.1406	-0.1449	-0.0384	0.7926	-0.0570	-0.2205
	Fence	-0.1098	-0.1111	0.0239	0.4120	0.0796	-0.2264
	Pole	0.1405	-0.0746	-0.0722	0.1531	-0.1715	0.0838
	Traffic Light	0.1639	-0.0483	-0.1288	0.0434	-0.2471	0.3142
	Traffic Sign	0.1390	-0.1272	-0.0612	0.3203	-0.1155	-0.0856
	Vegetation	-0.2713	0.1919	0.2496	-0.3249	0.2315	-0.3052
	Person	0.3258	-0.2116	-0.2412	0.1336	-0.2448	0.4252
	Rider	0.4069	-0.2766	-0.2923	-0.0542	-0.2963	0.7183
	Car	-0.0883	0.0987	0.1118	-0.2241	0.0939	-0.1153
	Truck	0.3736	-0.2597	-0.2843	0.5162	0.0732	-0.1835
	Bus	-0.1870	-0.1925	-0.1608	0.3393	-0.1957	0.7023
	Train	-0.1488	-0.1529	-0.1548	1.1116	-0.1547	-0.1535
	Motorcycle	0.3548	-0.2222	-0.2637	-0.0755	-0.2046	0.5903
	Bicycle	0.4969	-0.3194	-0.3678	0.0015	-0.3467	0.7998
	Drive: Count of Streets	0.1440	0.4269	0.0325	0.0949	-0.6210	-0.1880

Drive: Count of Intersections	0.0307	0.6807	-0.1042	0.2187	-0.6522	-0.1383
Drive: Total Street Length	0.1509	0.2696	0.1600	0.1243	-0.7402	-0.1665
Drive: Betweeness Centrality	-0.1091	-0.7546	-0.0152	-0.0856	0.9773	0.1034
Drive: Closeness Centrality	-0.1105	-0.3533	-0.1360	-0.0253	0.7104	0.1036
Drive: Degree Centrality	-0.0961	-0.7446	0.0523	-0.1360	0.8785	0.0901
Bike: Count of Streets	-0.1665	0.6554	-0.2789	0.1627	-0.1770	0.0534
Bike: Count of Intersections	-0.2239	0.9188	-0.3299	0.2889	-0.3884	0.0341
Bike: Total Street Length	-0.1783	0.6443	-0.1709	0.1834	-0.4061	0.0923
Bike: Betweeness Centrality	0.1129	-0.7603	0.2219	-0.1190	0.4410	-0.0641
Bike: Closeness Centrality	-0.0292	-0.3898	-0.0573	-0.0522	0.5640	0.0592
Bike: Degree Centrality	0.1602	-0.7595	0.3368	-0.1565	0.2529	-0.1244
Walk: Count of Streets	-0.0134	0.5428	-0.1962	0.1344	-0.2911	-0.0407
Walk: Count of Intersections	0.0138	0.6875	-0.2516	0.2261	-0.4496	-0.0518
Walk: Total Street Length	0.0641	0.4912	-0.1818	0.1845	-0.4562	0.0160
Walk: Betweeness Centrality	0.0258	-0.5774	0.2255	-0.0996	0.3283	-0.0652
Walk: Closeness Centrality	-0.0453	0.0847	-0.0739	0.0319	0.1142	-0.0409
Walk: Degree Centrality	0.0926	-0.6442	0.3203	-0.1689	0.2289	-0.0980
Sports	-0.0414	-0.0705	0.0404	-0.0398	0.0685	0.0218
Kindergarten	-0.0126	-0.0504	0.0106	-0.0047	0.0452	0.0115
Primary School	0.0116	-0.0915	0.0171	-0.0134	0.0773	-0.0125
Building: Health-related	0.0368	-0.0410	0.0071	0.0277	-0.0308	-0.0084
Building:Religious	0.0145	-0.0402	0.0246	-0.0146	-0.0260	0.0195
Bank	0.0659	-0.0250	-0.0548	0.0231	-0.0729	0.1055
Bar/Cafe/Restaurant	0.1409	-0.1319	0.0817	-0.0424	-0.0853	-0.0705

Shop: General	-0.0161	-0.0095	-0.0190	-0.0436	0.1127	-0.0095
Shop: Big-box	-0.0148	0.0616	-0.0149	0.0141	0.0115	-0.0476
Shop: Supermarket	0.0450	-0.0620	0.0383	0.0034	-0.0207	-0.0459
Shop: Transport-related	-0.0686	0.0440	-0.0449	-0.0106	0.0999	0.0346
Shop: Other	0.0783	-0.0735	0.0237	-0.0718	0.0025	-0.0050
Building: Residential	0.0915	-0.2371	0.1108	-0.0546	0.0343	-0.0539
Building: Service	0.0239	-0.0995	0.0257	0.0412	-0.0167	0.0136
Building: Commercial	0.0405	-0.0372	-0.0299	-0.0361	0.0527	0.0248
Other Building	-0.0665	-0.1042	-0.0245	0.0336	0.2243	-0.0073
Leisure	-0.0027	-0.0652	0.0488	-0.0150	-0.0064	0.0035
Tourism	0.0368	0.0154	-0.0207	0.0128	-0.0428	0.0071
Land-use: Residential	0.0939	-0.1749	0.1361	-0.0120	-0.0977	-0.0790
Land-use: Industrial	-0.0666	-0.0276	-0.0559	-0.0024	0.1942	0.0302
Land-use: Commercial	-0.1083	0.0526	-0.1520	-0.0149	0.2354	0.1520
Land-use: Construction	0.0450	-0.0275	-0.0105	0.0003	-0.0071	-0.0007
Land-use: Greenery	0.0227	0.3060	-0.0311	0.0090	-0.2436	-0.0774
Cycleways	0.1554	0.0715	0.0262	0.0497	-0.2737	-0.1019
Cycling Shared Lane (PT)	-0.0338	0.0187	0.0529	-0.0555	-0.0145	-0.0155
Cycling Shared Lane	-0.0129	-0.0129	-0.0129	-0.0129	-0.0129	0.0837
Sidewalk	0.0051	0.3600	-0.1636	0.1457	-0.2459	0.0257
Sidewalk crossing	0.0813	0.4590	-0.0103	0.0778	-0.5738	-0.0896
Motorway	-0.6184	0.3572	-0.6042	0.1482	0.9298	0.5031
Primary Road	-0.0554	0.4043	-0.1534	0.0818	-0.2736	0.1231
Secondary Road	0.0161	0.2465	-0.0167	0.0278	-0.1858	-0.1059

Tertiary Road	0.0704	-0.0381	0.0575	-0.0034	-0.0595	-0.0995
Residentail Street	0.1093	-0.2105	0.1715	-0.0502	-0.1181	-0.0721
Public Transportation	0.0121	0.0682	-0.0274	-0.0170	-0.0536	0.0306
Rail	0.0047	0.1273	-0.0318	0.0184	-0.1216	0.0201
Rail subway	0.0875	0.1867	-0.0117	-0.0337	-0.2500	-0.0187
Park	-0.0910	0.1064	-0.0533	0.0547	-0.0374	0.0954
Barrier	-0.0035	0.1671	-0.1286	0.0041	-0.0051	0.0666
Barrier Access	-0.1676	-0.0698	-0.1601	0.0538	0.4186	0.1352
Vegetation/Trees	0.0060	0.0236	0.0287	0.0060	-0.0937	0.0011
Park Furniture	0.0594	-0.0528	0.0257	0.0461	-0.0897	-0.0166
Street Furniture	0.1205	-0.0447	0.0185	-0.0101	-0.0931	-0.0402
PT Stop	0.0284	0.0677	-0.0020	0.0322	-0.1252	-0.0101
Parking	-0.1353	0.1019	-0.2032	0.0848	0.2516	0.1248
Taxi Parking	0.0136	0.0241	-0.0071	-0.0129	-0.0670	0.0503

Chapter **D**

Perception of Cycling Safety Survey: Terms of Consent

RESEARCH PARTICIPATION CONSENT

1. General Information

The Research Ethics Committee of Instituto Superior Técnico, in order to ensure that studies are carried out within the appropriate legal framework and that the ethical standards are respected, require that participants in any study give their informed consent, as explained in Section 4.

2. Survey description

This study aims at understanding and classifying cyclists and is a part of a PhD Project entitled "Objective and Subjective Risk Mapping for Urban Cyclists: An Automatic, Ubiquitous, and Continuous Approach", financed by Fundação para a Ciência e Tecnologia (PD/BD/142948/2018) and developed at Instituto Superior Técnico. Professor Filipe Moura and Doctor Manuel Marques take responsibility for this survey, as well as the storage and analysis of the acquired data.

3. About your participation

As a participant, you will be asked to answer a set of questions about your preferences and opinions regarding the way you cycle as a means of transport. These questions are not to identify you, but only to characterize your cyclist's type, in general. Your participation in this study is voluntary and free, so you can withdraw at any time without having to provide any justification. Whenever you feel at risk, uncomfortable, you are free to give up. The information provided will only be recorded after your approval at the end of the questionnaire.

However, it is up to us to inform you that, in order to be able to compare responses between cyclists from different cycling contexts, you will be asked for the city where you live, your age group and gender. However, even in these cases, the probability of identification is very unlikely as this information does not unambiguously identify a specific location, person, or age (only the age group).

This study was reviewed and approved by the Ethics Committee of Instituto Superior Técnico (IST). The process will be overseen by the IST Data Protection Officer.

The collected data will be used for statistical purposes only, it will not be communicated to any entity other than those involved in this study and no response will be analyzed or presented individually.

After submitting your answers, you have the right, at any time, to ask the researchers for access to personal data concerning you, as well as the rights to rectify, erase, limit and oppose the treatment, including the right to withdraw consent at any time, without prejudice to the eventual lawfulness of the previously consented treatment. To do so, you must register the code that will be given to you at the end of the survey and send an email to the researchers responsible for the project, whenever you want. You also have the right to file a complaint with the Portuguese National Data Protection Commission (CNPD).

If you have any questions regarding the survey, you can contact one of the following researchers: Miguel Costa (mncosta@isr.tecnico.ulisboa.pt), Filipe Moura (fmoura@tecnico.ulisboa.pt), or Manuel Marques (manuel@isr.tecnico.ulisboa.pt).

4. Terms of consent

I declare that I am aware of the purpose of this research and the conditions of my participation in it, as set out below in detail:

1. I understand that my participation in this research consists of answering questions in a questionnaire freely and voluntarily;
2. I understand that the sociodemographic information that I disclose to researchers will not be used in any way for my subsequent identification;
3. I have been informed that my data will never be disclosed;
4. I authorize the scientific publication of the results obtained in this investigation, provided that the information is treated in such a way that my identification cannot be carried out;
5. I have been informed that my participation in the study is voluntary, does not involve any risk and that I will not receive any financial compensation for my participation in the study;
6. I understand that, if interested, I can access the study results once published in any scientific channel;
7. I have been informed that I can withdraw my consent and/or refrain from participating in the study without any problem;
8. I was informed that I can contact the researchers involved in case I need any clarification on any aspect related to this study through the emails indicated in this terms.

By answering the survey, I declare having been informed of the objectives and usefulness of the study. I may ask questions to clarify my doubts. I freely agreed to participate in the study.

NOTE: Your responses will remain anonymous throughout the entire process, and will be stored and encrypted in accordance with the European Parliament's EU Regulation 2016/679 on the protection of natural persons with regard to the processing of personal data.

Chapter **E**

Perception of Cycling Safety Survey: Cycling Profile Questionnaire

Perception of Cycling Safety

This study aims at understanding and classify cyclists and is a part of a PhD project entitled “Objective and Subjective Risk Mapping for Urban Cyclists: An Automatic, Ubiquitous, and Continuous Approach”, financed by Fundação para a Ciência e Tecnologia (PD/BD/142948/2018) and developed at Instituto Superior Técnico and Technical University of Denmark. Professor Filipe Moura (fmoura@tecnico.ulisboa.pt (mailto:fmoura@tecnico.ulisboa.pt)) and Doctor Manuel Marques (manuel@isr.tecnico.ulisboa.pt (mailto:manuel@isr.tecnico.ulisboa.pt)) take responsibility for this survey, as well as the storage and analysis of the acquired data.

The expected time to complete this survey is 5-10 minutes.

We thank you for your participation!

There are 18 questions in this survey.

Consent

General Information

This study aims at understanding and classifying cyclists and is a part of a PhD Project entitled “Objective and Subjective Risk Mapping for Urban Cyclists: An Automatic, Ubiquitous, and Continuous Approach”, financed by Fundação para a Ciência e Tecnologia (PD/BD/142948/2018) and developed at Instituto Superior Técnico and Technical University of Denmark. Professor Filipe Moura and Doctor Manuel Marques take responsibility for this survey, as well as the storage and analysis of the acquired data.

This study was reviewed and approved by the Ethics Committee of Instituto Superior Técnico (IST). The process will be overseen by the IST Data Protection Officer.

Terms of Consent

I declare that I am aware of the purpose of this research and the conditions of my participation in it, as set out below in detail:

1. I understand that my participation in this research consists of answering questions in a questionnaire freely and voluntarily;
2. I understand that the sociodemographic information that I disclose to researchers will not be used in any way for my subsequent identification;
3. I have been informed that my data will never be disclosed;
4. I authorize the scientific publication of the results obtained in this investigation, provided that the information is treated in such a way that my identification cannot be carried out;
5. I have been informed that my participation in the study is voluntary, does not involve any risk and that I will not receive any financial compensation for my participation in the study;
6. I understand that, if interested, I can access the study results once published in any scientific channel;
7. I have been informed that I can withdraw my consent and/or refrain from participating in the study without any problem;
8. I was informed that I can contact the researchers involved in case I need any clarification on any aspect related to this study through the emails indicated in this terms.

By answering the survey, I declare having been informed of the objectives and usefulness of the study. I may ask questions to clarify my doubts. I freely agreed to participate in the study.

If you have any questions regarding the survey, you can contact one of the following researchers: Miguel Costa (mncosta@isr.tecnico.ulisboa.pt), Filipe Moura (fmoura@tecnico.ulisboa.pt), or Manuel Marques (manuel @isr.tecnico.ulisboa.pt).

To download these terms, click here (https://ushift.tecnico.ulisboa.pt/~ushift.daemon/home/survey_consentterms/subjectivesafety/TermoConsentimento_EN.pdf).

Do you agree with the above terms? *

Please choose **only one** of the following:

- Yes
- No

Self Assessment

Do you agree or disagree with the statement "**I like to use a bicycle?**" *

❶ Choose one of the following answers

Please choose **only one** of the following:

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

How often do you cycle? *

❶ Choose one of the following answers

Please choose **only one** of the following:

- Never
- Rarely (a few times a year)
- Occasionally (a few times a month)
- Frequently (a few times a week)
- Daily (every day or almost every day)

How long have you been **cycling** for (more regularly)? *

Only answer this question if the following conditions are met:
((Frequency.NAOK (/~ushift.daemon/limesurvey/index.php/questionAdministration/view/surveyid/498185/gid/103/qid/2249) != 'AO01'))

❶ Choose one of the following answers

Please choose **only one** of the following:

- Less than 6 months
- Between 6 months and 1 year
- Between 1 year and 5 years
- More than 5 years

When do you cycle? (You can choose multiple answers) *

Only answer this question if the following conditions are met:
((Frequency.NAOK (/~ushift.daemon/limesurvey/index.php/questionAdministration/view/surveyid/498185/gid/103/qid/2249) != 'AO01'))

❶ Check all that apply
Please choose **all** that apply:

- ☐ During week days
- ☐ During weekends

What is the **main purpose** of your cycling trips? (You can choose multiple answers) *

Only answer this question if the following conditions are met:
((Frequency.NAOK (/~ushift.daemon/limesurvey/index.php/questionAdministration/view/surveyid/498185/gid/103/qid/2249) != 'AO01'))

❶ Check all that apply
Please choose **all** that apply:

- ☐ Commuting (i.e., Home-Work/School or Work/School-Home)
- ☐ Work-related (e.g., courier, deliveries, professional cyclist)
- ☐ Utilitarian (e.g., shopping, running errands)
- ☐ Leisure/Social
- ☐ Sports/exercise
- ☐ Taking kids to school

What is the **main reason** for you **not to cycle**? *

Only answer this question if the following conditions are met:
((Frequency.NAOK (/~ushift.daemon/limesurvey/index.php/questionAdministration/view/surveyid/498185/gid/103/qid/2249) == 'AO01'))

❶ Choose one of the following answers
Please choose **only one** of the following:

- ○ I don't want to
- ○ I am temporarily unable to (e.g. sprained ankle)
- ○ I am permanently unable to (e.g. permanent physical condition)
- ○ I don't know how to
- ○ I don't have access to a bicycle (my own or shared bicycle)

Would you consider **cycling if you could**?

*

Only answer this question if the following conditions are met:
((AutoAssessment04.NAOK (/~ushift.daemon/limesurvey/index.php/questionAdministration/view/surveyid/498185/gid/103/qid/1898) >= 'AO02'))

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Yes
- ◯ No

Cycling Comfort Profile

How would you **feel cycling here**?

*

Please choose the appropriate response for each item:

(Very Uncomfortable) 1	2	3	4	5	6	(Very Comfortable) 7
◯	◯	◯	◯	◯	◯	◯

How would you **feel cycling here**?

*

Please choose the appropriate response for each item:

(Very Uncomfortable) 1	2	3	4	5	6	(Very Comfortable) 7
○	○	○	○	○	○	○

How would you **feel cycling here**?

*

Please choose the appropriate response for each item:

(Very Uncomfortable) 1	2	3	4	5	6	(Very Comfortable) 7
○	○	○	○	○	○	○

How would you **feel cycling here**?

*

Please choose the appropriate response for each item:

(Very Uncomfortable) 1	2	3	4	5	6	(Very Comfortable) 7
◯	◯	◯	◯	◯	◯	◯

How would you **feel cycling here**?

*

Please choose the appropriate response for each item:

(Very Uncomfortable) 1	2	3	4	5	6	(Very Comfortable) 7
◯	◯	◯	◯	◯	◯	◯

Socio-demographic Characteristics

What is your **Age**? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ 0 - 10
- ◯ 11 - 20
- ◯ 21 - 30
- ◯ 31 - 40
- ◯ 41 - 50
- ◯ 51 - 60
- ◯ 61 - 70
- ◯ 71 - 80
- ◯ 81 - 90
- ◯ 91 - 100
- ◯ > 100
- ◯ Prefer not to answer

How would you describe your **Gender**? *

❶ Choose one of the following answers
Please choose **only one** of the following:

- ◯ Male
- ◯ Female
- ◯ Non-binary
- ◯ Other
- ◯ Prefer not to answer

What **city** are you based in? *

Please write your answer here:

Number for Contact

{code}

Use this code in case you want to contact us regarding your participation in this survey.

Submit your survey.
Thank you for completing this survey.

Chapter **F**

Perception of Cycling Safety Survey: Cycling Profile Classification Flow Chart

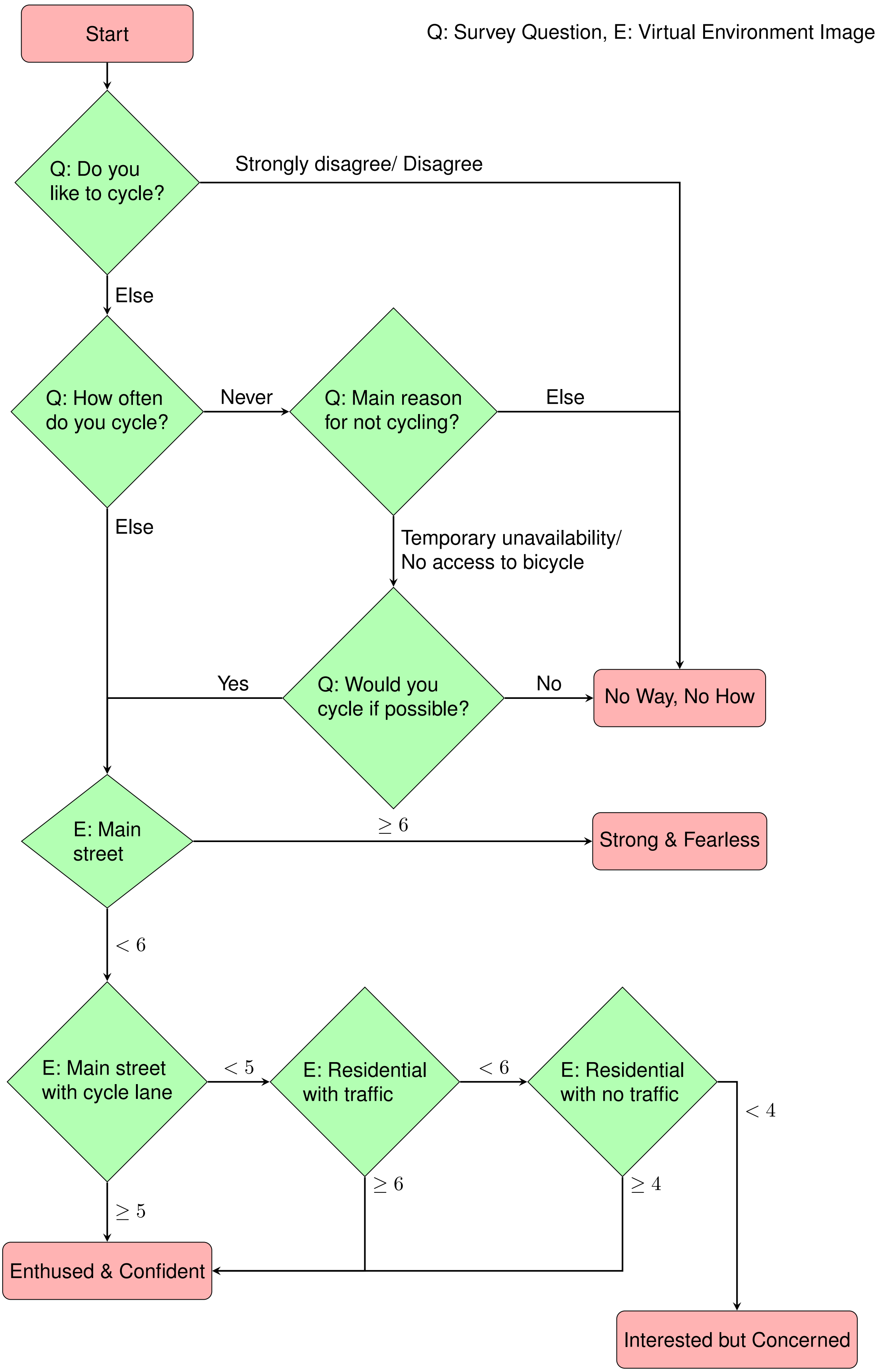


Figure F.1: Flow chart detailing the classification of individuals' cycling profiles.

Chapter **G**

Complete set of non-linear effects on the perception of cycling risk

Figure G.1: Impact of different elements from images' semantic segmentation on the perception of safety. Plots show the direct impact and variation on the perception of safety scores (ΔPSS) from different objects' areas (in %) pictured in the images and its associated error in grey (note the different scales).

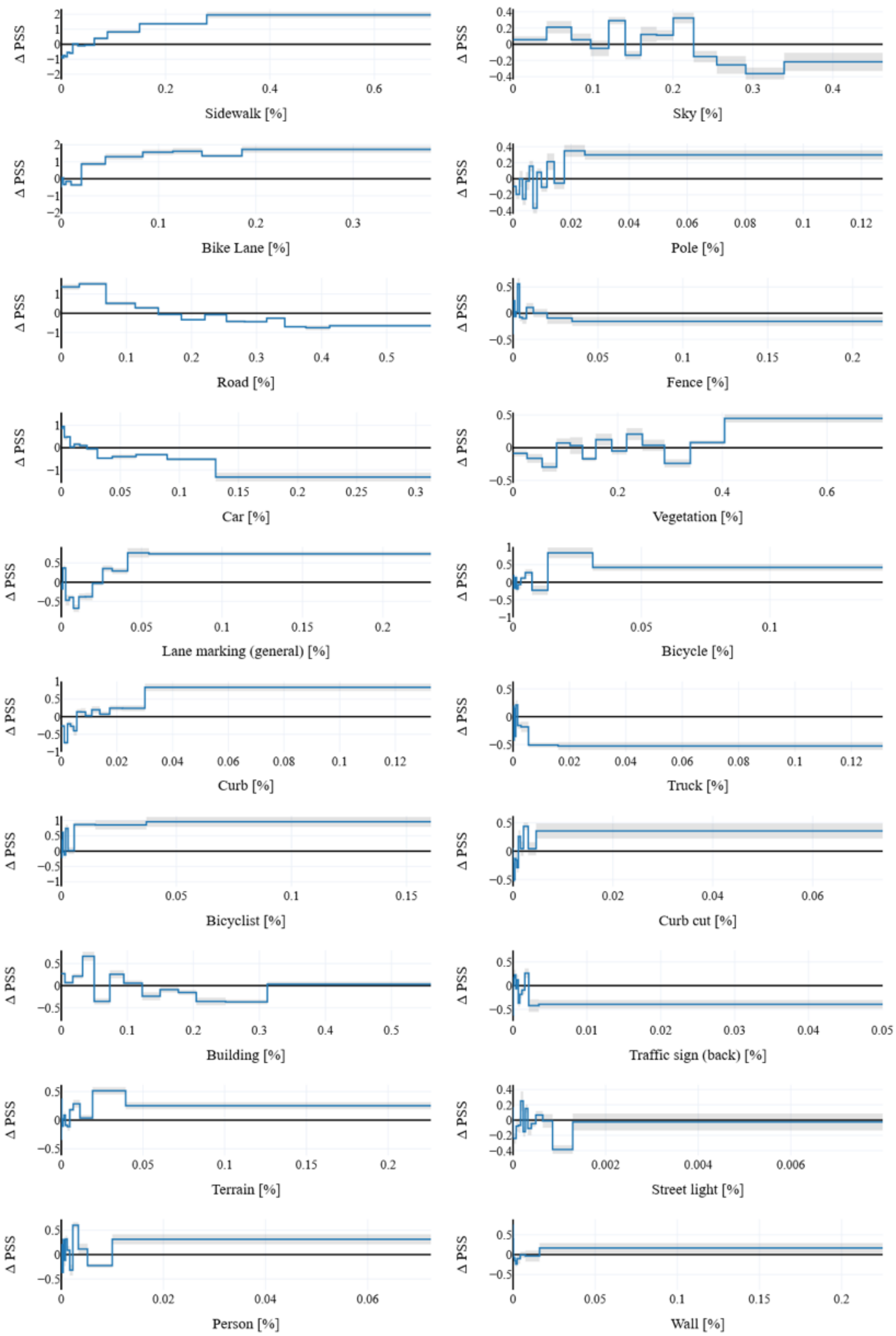


Figure G.2: *Figure continued.*

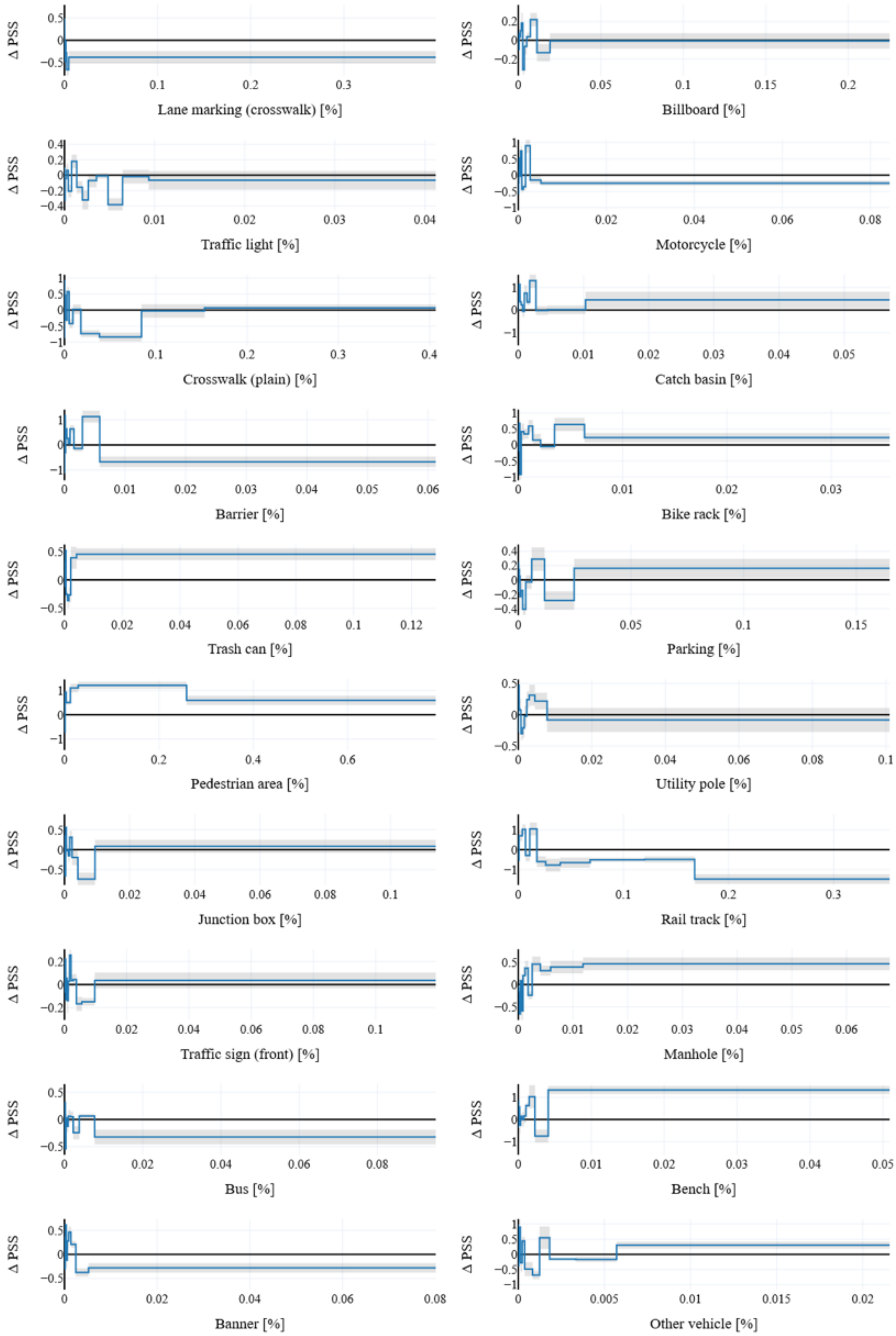


Figure G.2: *Figure continued.*

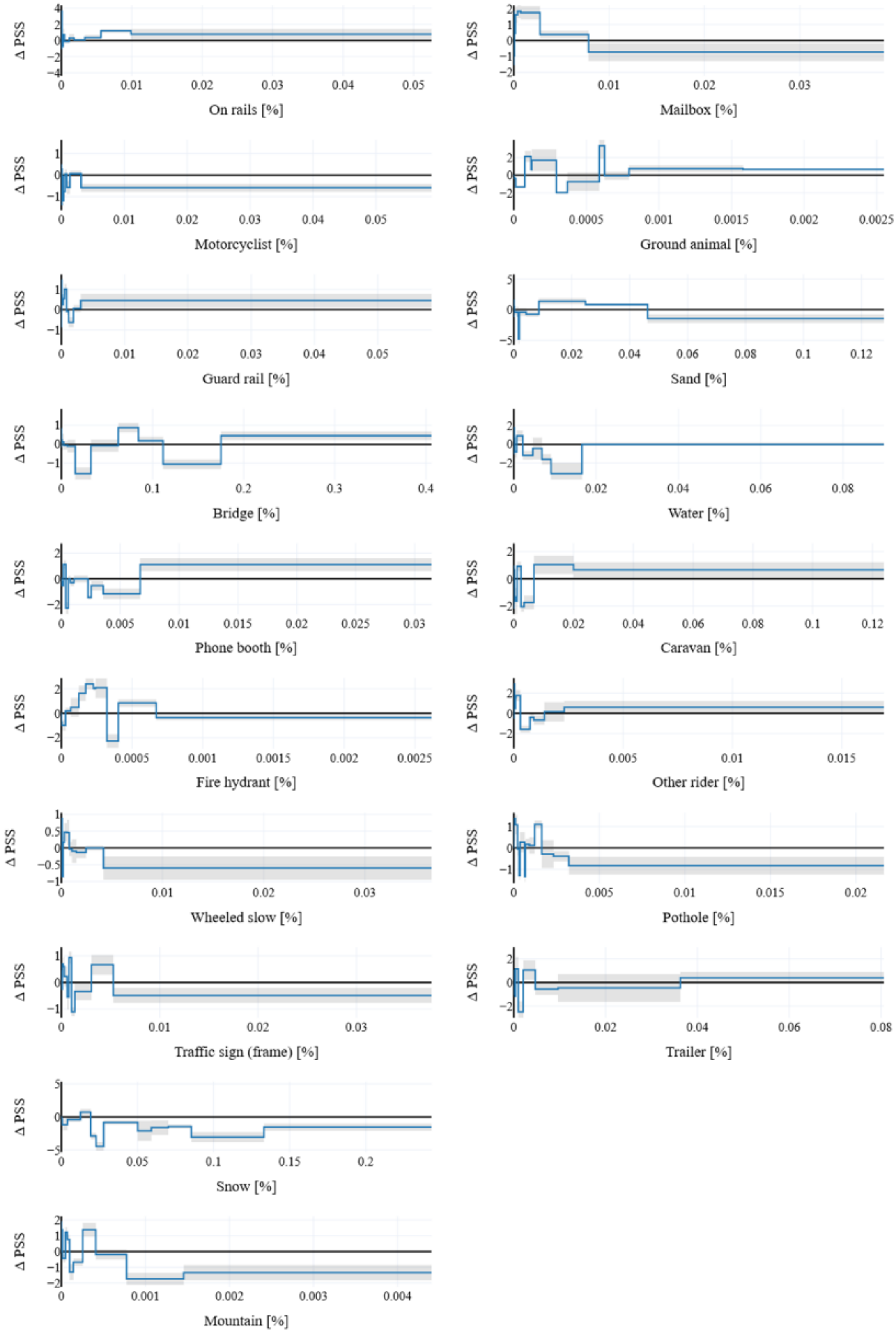


Figure G.2: Impact of different elements from mapping elements on the perception of safety. Plots show the direct impact and variation on the perception of safety scores (ΔPSS) from different urban elements and its associated error in (note the different scales).

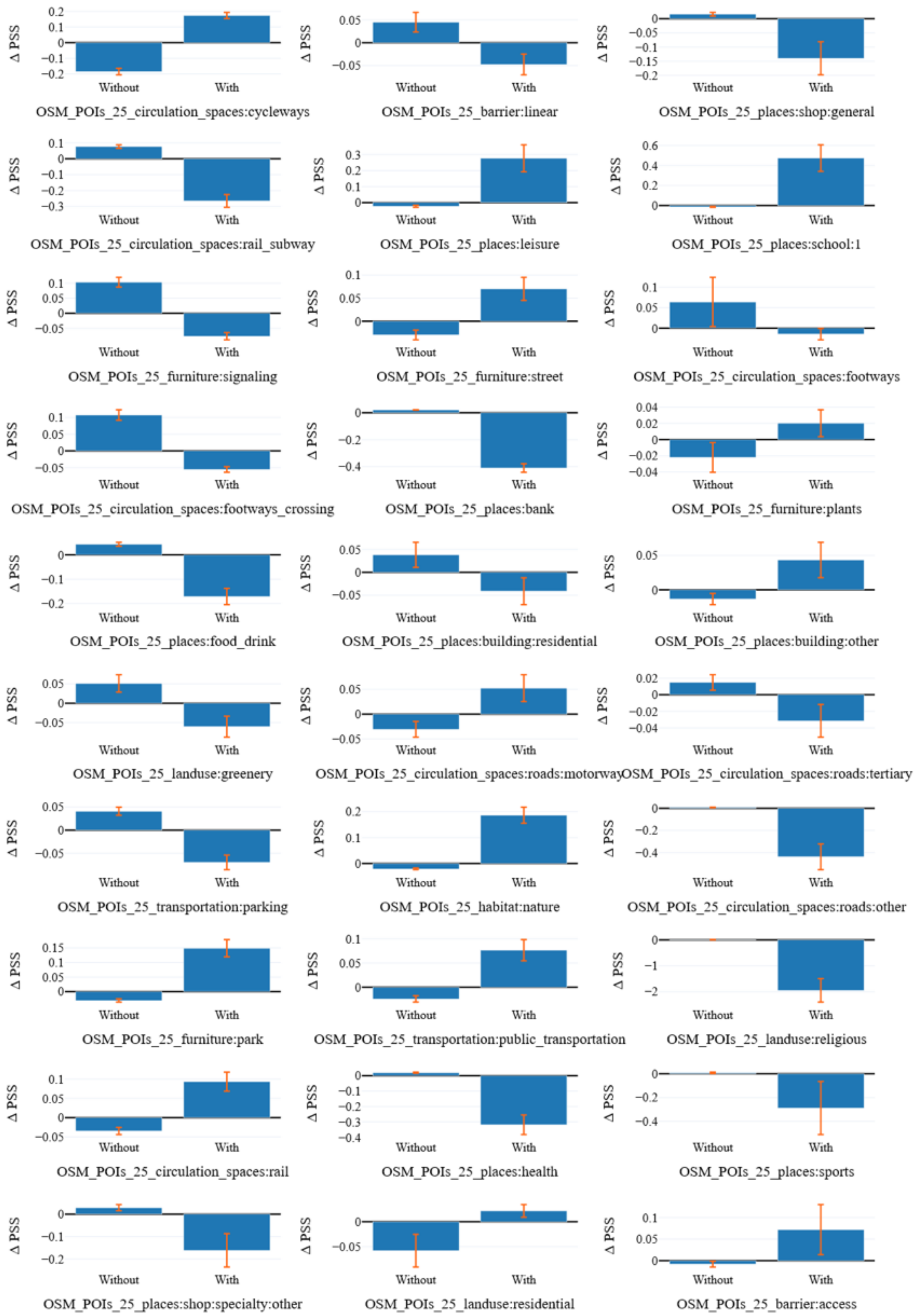


Figure G.3: *Figure continued.*

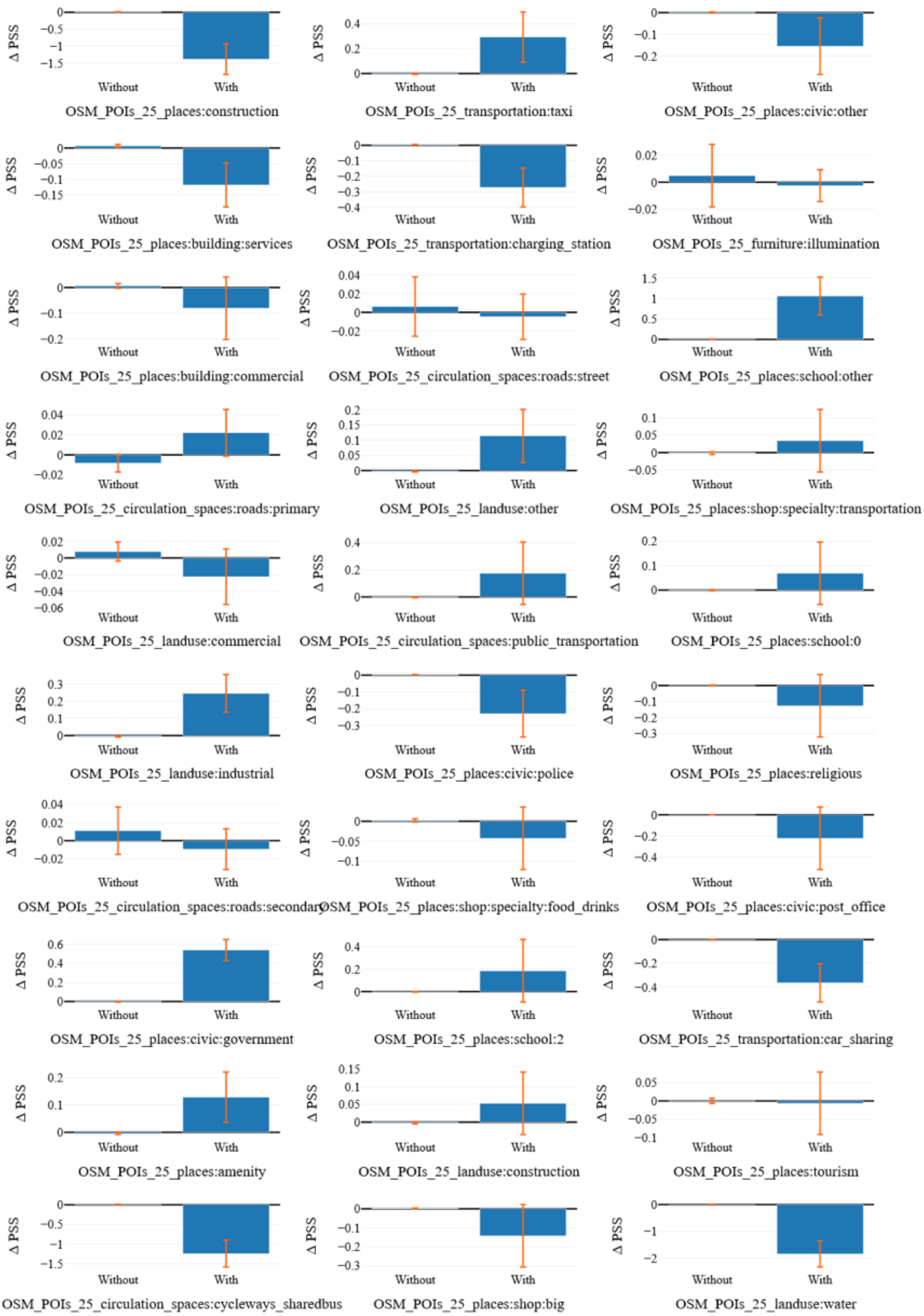
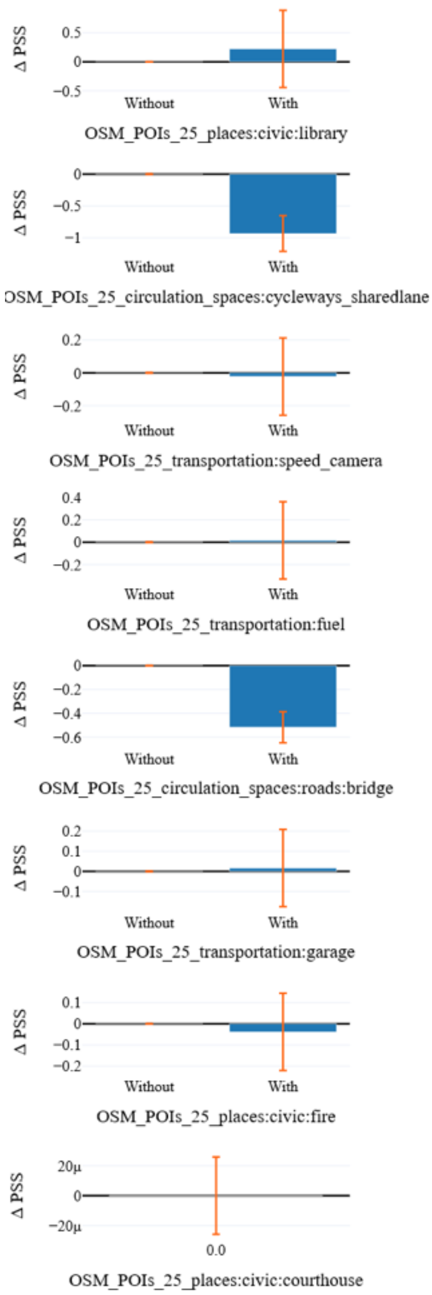


Figure G.3: *Figure continued.*



Chapter **H**

Overview of Data Used in Chapter 11

Table H.1: Data description summary of objective safety, subjective safety, and urban context data used in Chapter 11.

Variable	Variable Type	Description
Objective Safety		
Accident Outcomes	Binary	1=Light Injury (n=3279); 0=Killed & Serious Injury (n=545)
Subjective Safety		
Environments Perceptions	Binary	1=Perceived as Safer (n=1811); 0=Perceived as Unsafer (n=2013)
Urban Context		
Curb	Continuous	Percentage in image [0-1] (mean=0.0117)
Fence	Continuous	Percentage in image [0-1] (mean=0.01)
Guard rail	Continuous	Percentage in image [0-1] (mean=0.0001)
Barrier	Continuous	Percentage in image [0-1] (mean=0.0004)
Wall	Continuous	Percentage in image [0-1] (mean=0.0031)
Bike Lane	Continuous	Percentage in image [0-1] (mean=0.0288)
Crosswalk (plain)	Continuous	Percentage in image [0-1] (mean=0.009)
Curb cut	Continuous	Percentage in image [0-1] (mean=0.0009)
Parking	Continuous	Percentage in image [0-1] (mean=0.003)
Pedestrian area	Continuous	Percentage in image [0-1] (mean=0.0048)
Rail track	Continuous	Percentage in image [0-1] (mean=0.0046)
Road	Continuous	Percentage in image [0-1] (mean=0.2296)
Sidewalk	Continuous	Percentage in image [0-1] (mean=0.0712)

Bridge	Continuous	Percentage in image [0-1] (mean=0.0045)
Building	Continuous	Percentage in image [0-1] (mean=0.13)
Tunnel	Continuous	Percentage in image [0-1] (mean=0)
Persin	Continuous	Percentage in image [0-1] (mean=0.0022)
Bicyclist	Continuous	Percentage in image [0-1] (mean=0.0029)
Motorcyclist	Continuous	Percentage in image [0-1] (mean=0.0001)
Other rider	Continuous	Percentage in image [0-1] (mean=0)
Lane marking (crosswalk)	Continuous	Percentage in image [0-1] (mean=0.0015)
Lane marking (general)	Continuous	Percentage in image [0-1] (mean=0.0189)
Sand	Continuous	Percentage in image [0-1] (mean=0.0002)
Snow	Continuous	Percentage in image [0-1] (mean=0.0005)
Terrain	Continuous	Percentage in image [0-1] (mean=0.0095)
Vegetatiin	Continuous	Percentage in image [0-1] (mean=0.193)
Water	Continuous	Percentage in image [0-1] (mean=0.0001)
Banner	Continuous	Percentage in image [0-1] (mean=0.0006)
Bench	Continuous	Percentage in image [0-1] (mean=0.0001)
Bike rack	Continuous	Percentage in image [0-1] (mean=0.0003)
Billboard	Continuous	Percentage in image [0-1] (mean=0.0057)
Catch basin	Continuous	Percentage in image [0-1] (mean=0.0003)
CCTv camera	Continuous	Percentage in image [0-1] (mean=0)
Fire hydrant	Continuous	Percentage in image [0-1] (mean=0)
Junctiin box	Continuous	Percentage in image [0-1] (mean=0.0012)
Mailbox	Continuous	Percentage in image [0-1] (mean=0)
Manhole	Continuous	Percentage in image [0-1] (mean=0.0008)
Phine booth	Continuous	Percentage in image [0-1] (mean=0.0001)
Pothole	Continuous	Percentage in image [0-1] (mean=0)
Street light	Continuous	Percentage in image [0-1] (mean=0.0004)
Pole	Continuous	Percentage in image [0-1] (mean=0.0103)
Traffic sign (frame)	Continuous	Percentage in image [0-1] (mean=0.0001)
Utility pole	Continuous	Percentage in image [0-1] (mean=0.0008)
Traffic light	Continuous	Percentage in image [0-1] (mean=0.0016)
Traffic sign (back)	Continuous	Percentage in image [0-1] (mean=0.0006)
Traffic sign (frint)	Continuous	Percentage in image [0-1] (mean=0.0031)
Trash can	Continuous	Percentage in image [0-1] (mean=0.0006)
Bicycle	Continuous	Percentage in image [0-1] (mean=0.0038)
Boat	Continuous	Percentage in image [0-1] (mean=0)
Bus	Continuous	Percentage in image [0-1] (mean=0.0009)
Car	Continuous	Percentage in image [0-1] (mean=0.0405)
Caravan	Continuous	Percentage in image [0-1] (mean=0.0001)

Motorcycle	Continuous	Percentage in image [0-1] (mean=0.0004)
in rails	Continuous	Percentage in image [0-1] (mean=0.0002)
Other vehicle	Continuous	Percentage in image [0-1] (mean=0.0002)
Trailer	Continuous	Percentage in image [0-1] (mean=0.0001)
Truck	Continuous	Percentage in image [0-1] (mean=0.0018)
Wheeled slow	Continuous	Percentage in image [0-1] (mean=0.0001)
Sports	Continuous	Percentage in image [0-1] (mean=0.0256)
School	Binary	1=Element present; 0=Otherwise (mean=0.0531)
Health	Binary	1=Element present; 0=Otherwise (mean=0.0578)
Religious	Binary	1=Element present; 0=Otherwise (mean=0.0071)
Bank	Binary	1=Element present; 0=Otherwise (mean=0.0486)
Food_drink	Binary	1=Element present; 0=Otherwise (mean=0.2024)
Amenity	Binary	1=Element present; 0=Otherwise (mean=0.0363)
Shop	Binary	1=Element present; 0=Otherwise (mean=0.2746)
Building:residential	Binary	1=Element present; 0=Otherwise (mean=0.482)
Building:services	Binary	1=Element present; 0=Otherwise (mean=0.0575)
Building:commercial	Binary	1=Element present; 0=Otherwise (mean=0.0753)
Building:other	Binary	1=Element present; 0=Otherwise (mean=0.2364)
Civic	Binary	1=Element present; 0=Otherwise (mean=0.0335)
Leisure	Binary	1=Element present; 0=Otherwise (mean=0.0758)
Tourism	Binary	1=Element present; 0=Otherwise (mean=0.0785)
Cinstructiin	Binary	1=Element present; 0=Otherwise (mean=0.005)
Landuse:residential	Binary	1=Element present; 0=Otherwise (mean=0.7283)
Landuse:industrial	Binary	1=Element present; 0=Otherwise (mean=0.023)
Landuse:commercial	Binary	1=Element present; 0=Otherwise (mean=0.2563)
Landuse:cinstructiin	Binary	1=Element present; 0=Otherwise (mean=0.0335)

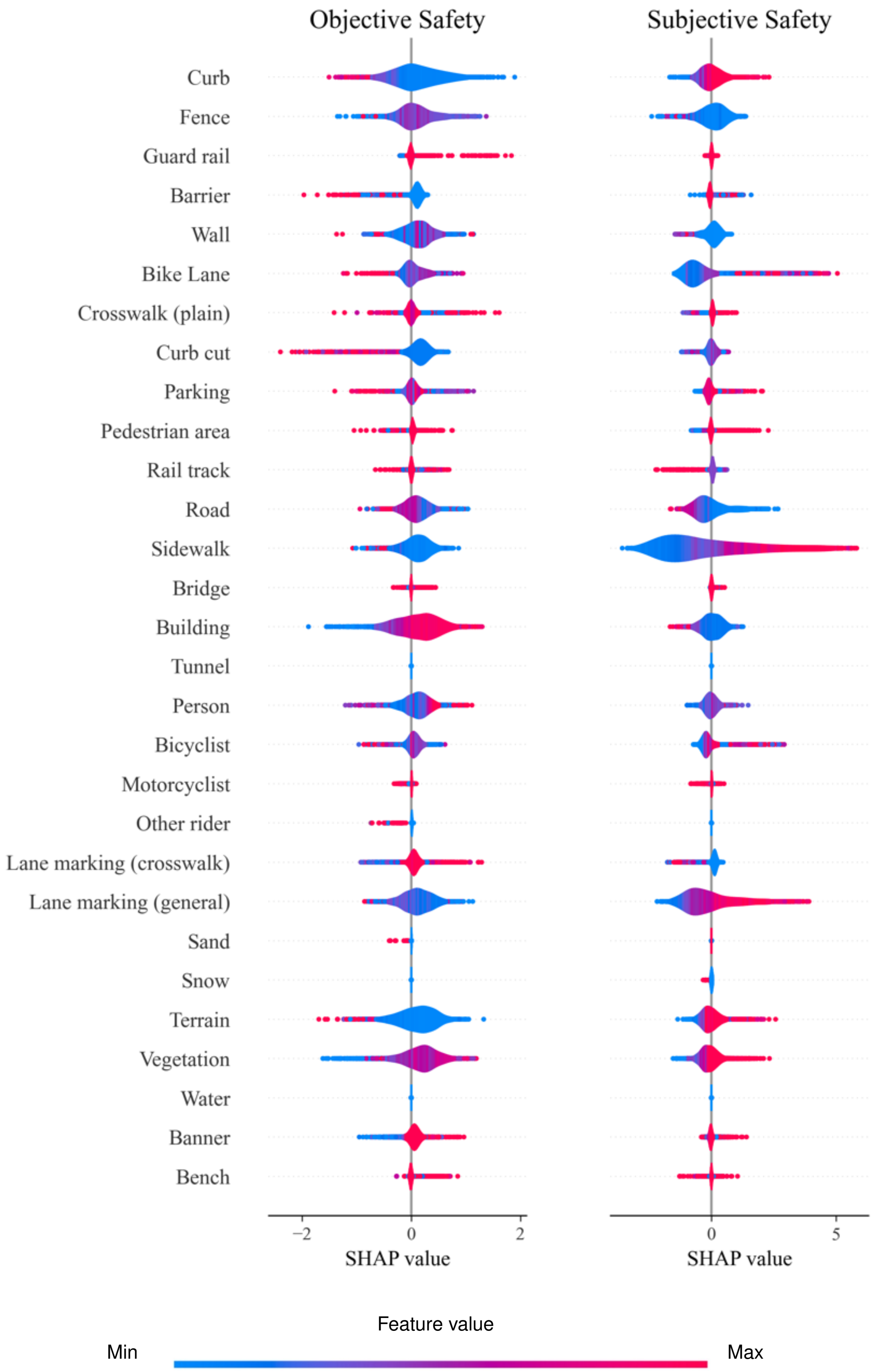
Landuse:religious	Binary	1=Element present; 0=Otherwise (mean=0.0037)
Landuse:greenery	Binary	1=Element present; 0=Otherwise (mean=0.4582)
Landuse:other	Binary	1=Element present; 0=Otherwise (mean=0.023)
Landuse:water	Binary	1=Element present; 0=Otherwise (mean=0.0003)
Cycleways	Binary	1=Element present; 0=Otherwise (mean=0.516)
Cycleways_sharedbus	Binary	1=Element present; 0=Otherwise (mean=0.0037)
Cycleways_sharedlane	Binary	1=Element present; 0=Otherwise (mean=0.0003)
Footways	Binary	1=Element present; 0=Otherwise (mean=0.8135)
Footways_crossing	Binary	1=Element present; 0=Otherwise (mean=0.658)
Motorway	Binary	1=Element present; 0=Otherwise (mean=0.3687)
PrimaryRoad	Binary	1=Element present; 0=Otherwise (mean=0.2704)
SecindaryRoad	Binary	1=Element present; 0=Otherwise (mean=0.5429)
TertiaryRoad	Binary	1=Element present; 0=Otherwise (mean=0.3201)
Street	Binary	1=Element present; 0=Otherwise (mean=0.5638)
Other	Binary	1=Element present; 0=Otherwise (mean=0.0178)
Bridge:	Binary	1=Element present; 0=Otherwise (mean=0.0003)
Public_Transportation	Binary	1=Element present; 0=Otherwise (mean=0.0149)
Rail	Binary	1=Element present; 0=Otherwise (mean=0.2704)
Rail_subway	Binary	1=Element present; 0=Otherwise (mean=0.2244)
Barrier:linear	Binary	1=Element present; 0=Otherwise (mean=0.4861)
Barrier:access	Binary	1=Element present; 0=Otherwise (mean=0.0999)
Furniture:plants	Binary	1=Element present; 0=Otherwise (mean=0.5238)
Furniture:park	Binary	1=Element present; 0=Otherwise (mean=0.1697)

Furniture:signaling	Binary	1=Element present; 0=Otherwise (mean=0.5761)
Furniture:illumination	Binary	1=Element present; 0=Otherwise (mean=0.6538)
Furniture:street	Binary	1=Element present; 0=Otherwise (mean=0.2989)
Transportation:public_Transportation	Binary	1=Element present; 0=Otherwise (mean=0.2408)
Transportation:parking	Binary	1=Element present; 0=Otherwise (mean=0.3706)
Transportation:charging_statiin	Binary	1=Element present; 0=Otherwise (mean=0.0141)
Transportation:speed_camera	Binary	1=Element present; 0=Otherwise (mean=0.0084)
Transportation:fuel	Binary	1=Element present; 0=Otherwise (mean=0.0086)

Chapter **I**

Complete set of SHAP results for the objective and subjective cycling safety

Figure I.1: Effects of urban elements on the objective and subjective safety. SHAP values correspond to log-odds of a feature on the prediction of the respective outcome (please notice the different scales). Color represents features values.



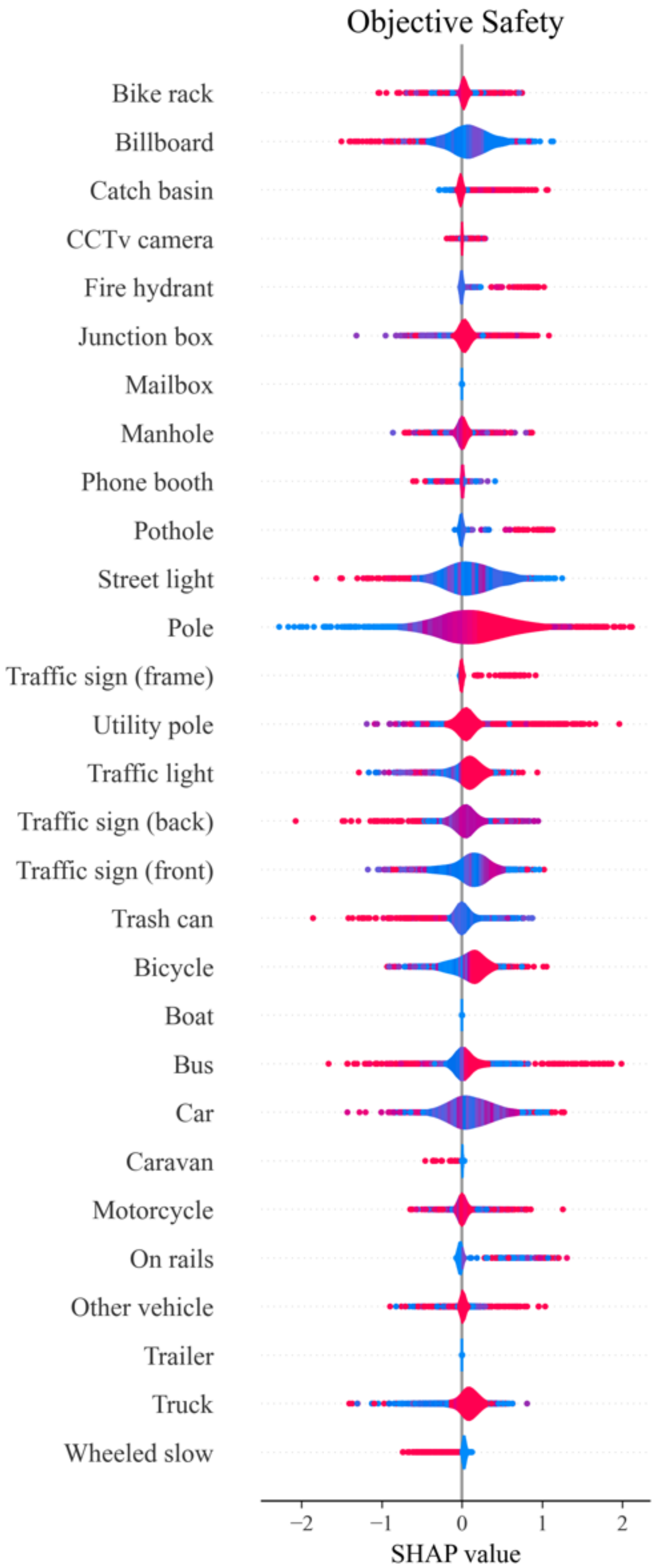
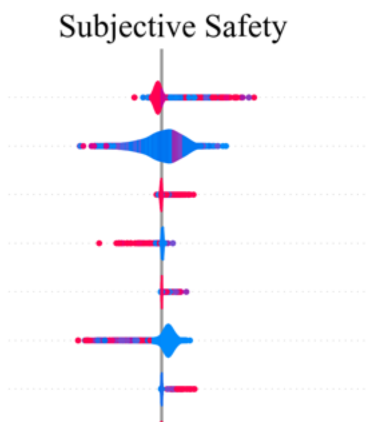


Figure I.2: *Figure continued.*



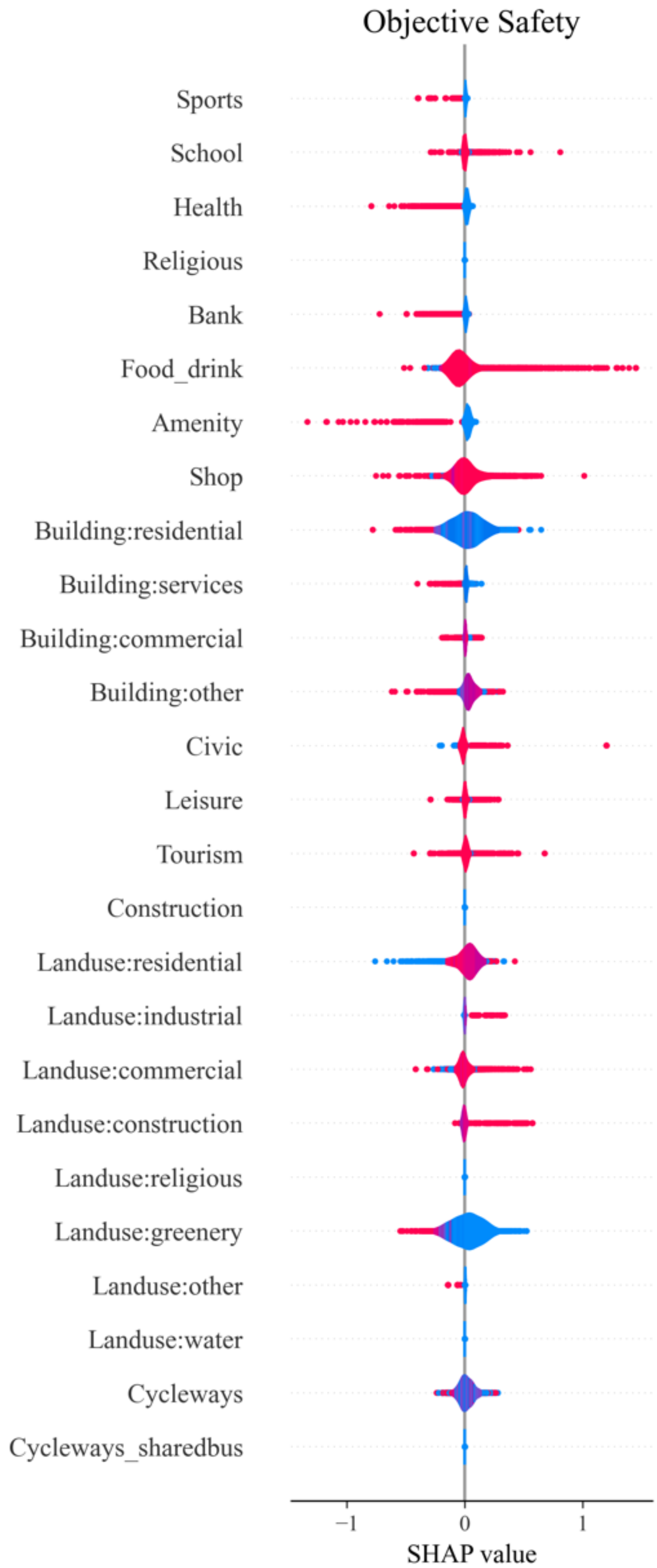
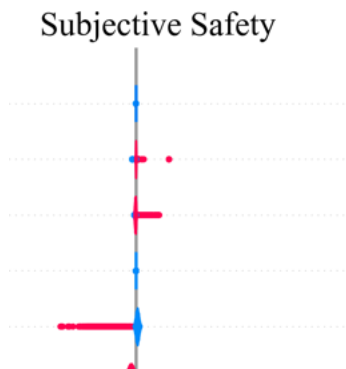


Figure I.2: *Figure continued.*



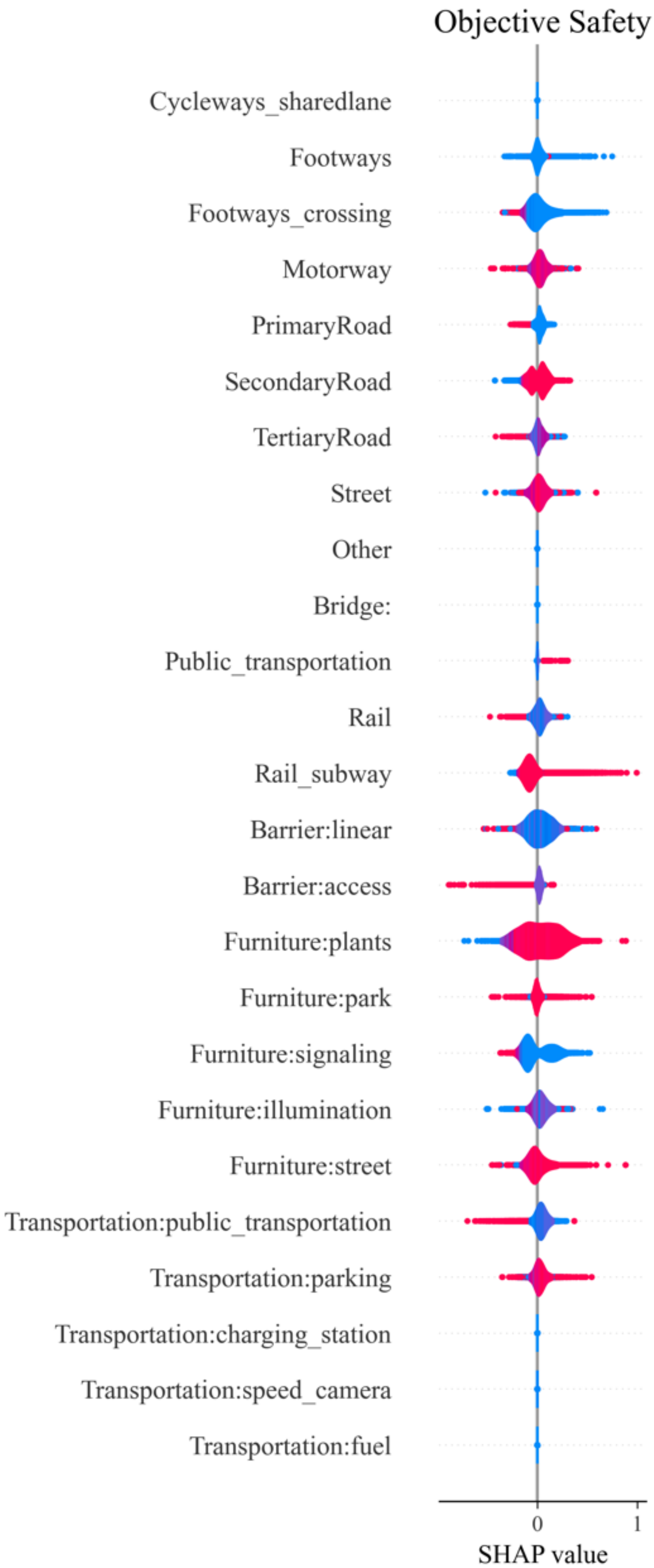


Figure I.2: *Figure continued.*