A Multiscale View on Bikeability of Urban Networks

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TRAIL

Summary

Knowledge on how to evaluate the bikeability of an urban infrastructure network is scarce and ambivalent. This dissertation provides systematic knowledge on bicycle infrastructure networks and develops methodological tools to assess infrastructure-related bikeability. The findings can be used by urban planners and policy makers to develop more bicycle-friendly cities.

About the Author

Giulia Reggiani conducted her PhD at the Transport & Planning department of Delft University of Technology. She holds a Master's degree in Management Engineering. Her current interests lie in the broad domains of smart mobility, data analysis, and sustainability.

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This research is part of the Allegro project (Unravelling active mode traveling and traffic: with innovative data to a new transportation and traffic theory for pedestrians and bicycles), which is financed by the European Research Council and Amsterdam Institute for Advanced Metropolitan Solutions (no. 669792).

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A Multiscale View on Bikeability of Urban Networks

Dissertation

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by

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Master of Science in Management Engineering
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This dissertation has been approved by the promotors.

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To all those who struggle(d) to get cycling taken seriously as a mode of transport.

Acknowledgements

Doing a PhD is very similar to running a start-up. While profoundly different in their outcome, they do share many commonalities in the execution (Kirchherr, 2018). Both are self-driven processes moved by a desire to uncover new understandings and solutions to problems. The start-up entrepreneur and the PhD candidate share tremendous uncertainties along their way and high individual responsibility. Both journeys offer profoundly rich learning experiences, where adaptability is key to getting through tough challenges. I have enjoyed the past years, sometimes trying to apply ‘lean start-up’ approaches to PhD life, other times endeavoring into deep speculation and feeling like the first and only person to be facing specific research problems. Here, I would like to express my gratitude to all those who have contributed along my journey.

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Within the incubator, a start-up entrepreneur may have the opportunity to share the co-working environment with a like-minded community of people. Dear Allegri, you have been for me the most incredible co-working community! You have made my PhD special in many ways. Danique, Lara, Tim, Alph, Florian, Vincent, Marie-Jette, Alexandra, Martijn, Yan, Yufei, Dorine thanks for the friendly environment, for sharing useful tips and experiences and for always being there when in need of a talk or critical feedback. A special thanks to my office mates who made our office a playful environment with the basketball hoop and an everlasting tournament. Alph, I very much appreciated our out-of-the-box discussions and thought experiments. Your relaxed, yet very ambitious, attitude towards research has been of great inspiration to me. Tim, thanks for always being enthusiastic about my work, your positivity always made me smile. I am really glad that our many discussions and your coding expertise have led to writing a paper together! Last but not least, Lara and Danique I will never be able to thank you enough for voicing out my inner thoughts and for understanding me better than myself. Danique, thanks for the brainstorming sessions on my research and for making me see the connections between projects. I love our early morning breakfasts at Michelle's and hope to keep this nice habit. Lara, I adore your creativity and willingness to go 'all-in' as soon as there is an opportunity to collaborate on cool projects. If it weren't for you many projects would have never come to life - Happy Streets is one of these.

As start-ups need feedback to improve their minimum viable products, PhDs search feedback from scholarly peers to improve the impact and robustness of their research. In my search for feedback, I was honoured to take part in many conferences and to spend a visiting period in Monash University in Melbourne, Australia. I am grateful to Hai Vu for hosting me and financially supporting my stay. I'm deeply indebted to Homayoun and Nora for making my stay in Melbourne a memorable one. Finally, I would like to extend my sincere thanks to the committee members. I am honoured to receive your feedback and to have you as external members in my doctoral defence.

Both launching a start-up and a PhD can be isolating and lonely experiences. Girls – Bea, Verdi and Giò – thanks for making this journey much more enjoyable and less lonely. Our yearly trips around Europe were a vital distraction along the way. Thanks for trying to understand the complexities of academia (and the publishing process) and for always asking how the PhD was going. Benni, I am happy to have you and to know that, despite the distance, I can always rely on you. Lauri, your humor has brightened my darkest days. To all the housemates I have had in the past years, you have been a fundamental part of who I am today thanks to the many scientific debates during our meals. Finally, I can't help but think how grateful I am to Giulia and Mario. It was thanks to your generous invite to spend a summer in Cambridge (Boston) that it all started. The people you introduced me to and the conversations I had during that summer sparked in me an unknown desire to pursue a PhD. Thanks for all the helpful advice you gave me along the way.

Doing a PhD can put a strain on your private life and the relationship with your partner is no exception. Dear Ruggi, love of my life, without your immense patience this PhD would not have been possible. Thanks for the late nights spent discussing PhD choices and also coding together, or worse, fixing bugs in my untidy python scripts. Your encouragement and hard working mind-set have truly fuelled this journey. This PhD meant a long distance relationship for us but you were ready to take the challenge and always spurred me to go for my call. Happily enough covid-19 was the opportunity for you to join me and start appreciating life in the Netherlands. Thanks for the happiness you bring, I look forward to the next challenges in our life!

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Giulia Reggiani
April 2022

Contents

Chapter 1

Introduction

"But if thought corrupts language, language can also corrupt thought."

— George Orwell

It is now a well-known fact that the use of bicycles can help alleviate some of the ever-increasing urban transport and public health problems that afflict life in contemporary cities. According to ECF Eropean Cyclistis' Federation (2015) the increased use of bicycles can contribute to solving 11 of the 17 United Nations global sustainable goals. While everyone agrees that bicycles are a solution, in practice, we see bicycles as a disadvantaged transport mode in cities with a limited amount of space (Szell, 2018; Gössling et al., 2016), fragmented infrastructure (Orozco et al., 2020), and often marginalised in urban transport planning (Koglin & Rye, 2014).

Planning for bicycle infrastructure has been slow, piece-wise and location-specific (Koglin & Rye, 2014; CROW, 2017) and literature has mainly focused on best practices and case studies without providing theoretical guidance (Koglin & Rye, 2014). Moreover, infrastructure alone does not always lead to bike use; bicycle use relates to bikeability aspects of a city (Pucher, J. and Buehler, 2007). Due to the aforementioned characteristics, planning for (increasing) bicycle use is still more an art than a science (Koglin & Rye, 2014). What makes one city more bikeable than another? What kind of data is needed to measure and improve bikeability? How is bikeability of a city perceived by the different user groups? These are just some of the questions that need to be answered in order to develop systematic strategies for bicycle infrastructure planning to support urban planners that aim to increase bicycle use in cities.

To introduce a systematic approach to bicycle planning, we first need to understand the key determinants of bicycle use and their interconnections. In this sense, in recent years, the concept of bikeability has been proposed and developed which goes in the direction of providing a holistic perspective of bicycle use determinants and methods to assess them. After providing an overview of bikeability, this thesis will focus on infrastructure-related bikeability aspects (necessary but not sufficient conditions for cycling in a city) and how to assess them.

In the remainder of this introductory chapter, we first give a more rigorous definition of the bikeability concept (section 1.1) by developing a conceptual model on factors that impact the bikeability of a city. Then, the research objective is articulated into research questions (section 1.2) and the research approach is outlined (section 1.3). Finally, the main contributions of this PhD project (section 1.4) and the structure of this thesis (section 1.5) are presented.

1.1 Notion of bikeability

Efforts in the domain of bikeability have been diverse in topic, scale and data (Kellstedt et al., 2021): some studies considered infrastructure quality, others safety, and still others accessibility. Attempts have been made to define and classify bikeability. However, many studies show that it is an ambiguous non universally defined term (Arellana et al., 2020; Kellstedt et al., 2021; Castañon & Ribeiro, 2021) and that a consensus document should be elaborated on how to define and assess bikeability (Kellstedt et al., 2021). Combining and expanding the definitions used in previous works, in this thesis we propose to define bikeability as follows: *bikeability is the extent to which the actual and perceived, physical and cultural, environment is adequate for the use of bicycles*. With this definition, we show that bikeability is a multifaceted concept, which includes not only the physical but also the cultural and social environment influencing the attractiveness of cycling in a city. As a consequence of this broad definition, bikeability relates to the study of many components and their relations that change the attractiveness of cycling (i.e. bikeability). In the following paragraphs, we explain the relation between the components of bikeability according to the conceptual model in Figure 1.1.

Bicycle use in a city is the result of people's *activity needs and desires* to reach certain destinations combined with good *bikeability* conditions (i.e. low transport resistance). Bikeability is influenced by the physical and cultural environment, the former relates to the spatial and physical characteristics of a city the letter is shaped by human activity, behaviour and social norms.

Concerning the physical environment, the use of bicycles is attractive if the transport system (*bike system*) of a city allows it; most studies show a positive relation between bicycle network infrastructure (its safety, convenience and comfort) and the use of bicycles (Pucher, J. and Buehler, 2007; Buehler & Dill, 2016). The bike system component also reflects bicycle ownership (Oke et al., 2015) and the availability of bike sharing systems (Ma et al., 2020), the bicycle technology itself and the price of owning or renting a bike. The physical component also includes the *land-use system* which consists of the spatial distribution of activity locations and facilities. There is a direct and indirect impact of the land-use system on bikeability since studies have identified a relation between environments conducive for cycling and land-use features like density and spatial distribution of amenities (van de Coevering, 2021). The last physical factors to have a direct influence on bicycle attractiveness are the *climate and geography of the place* and the weather resilience of its residents (Goldmann & Wessel, 2021).

Concerning the cultural environment, *attitudes and social norms* have an impact on the attractiveness of bicycle use (Heinen et al., 2010). Social normative pressures and beliefs play a role as theorised by the theory of planned behaviour (Lois et al., 2015). Conse-

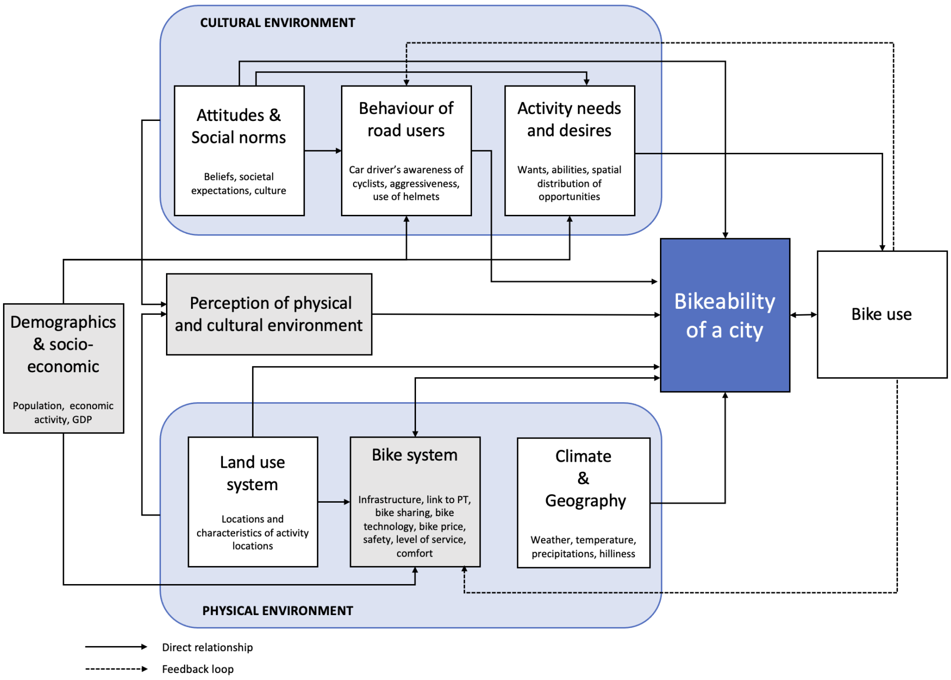

Figure 1.1: Conceptual model on the relationship between components of Bikeability. The gray components are object of study in this thesis.

quently, they can influence how attractive it is to cycle. Culture and social norms influence one's *activity needs and wants*; for example, in some countries, it is socially accepted that a politician goes around by bike in others it needs to move with a car escort. In turn, *activity needs and desires* combined with good bikeability trigger the use of the bike. *The behaviour of road users* is the result of the attitudes and norms component, the bike usage, demographics and road laws of a city. Road users (both cars and other cyclists) impact how safe and confident other cyclists perceive cycling. In some cities cyclists are wearing high-end sporty gear, this makes cycling appealing for sports fanatics but less attractive for commute purposes. Moreover, the share of *bike use* in a place can motivate others to cycle (changing their behaviour), and, based on the visible bicycle demand, policymakers are more inclined to invest in bicycle network infrastructure.

Demographic and socio-economic changes in a city are external components that indirectly have an impact on bikeability by shaping the activity needs of its residents as well as the development of the bicycle infrastructure system. To the author's knowledge, the relation between the city's demographic factors (like population size) and the development of the bicycle system has not been investigated in literature and will be among the topics of research in this thesis. Traffic laws and policies are other external components that influence the land use and bike system as well as the behaviour of road users and the social norms. The conceptual model does not include the policy factor for simplification and readability reasons.

Finally, the conceptual model considers how perceptions of individuals mediate the relation between all the aforementioned components. Perceptions introduce subjectivity of how the physical and cultural environment is sensed, as opposed to objectively measurable components described in the previous paragraphs. Note that bikeability should not be measured by mere bike use because there could be a city with an objectively poor bicycle environment but where many residents perceive it as safe and convenient for cycling (see vehicular cycling movements). This would result in high bike use although, according to the conceptual model in Fig 1, it is not a very bikeable city. There need to be other objective factors (together with subjective perceptions) that make the place truly bikeable.

In conclusion, bikeability is a concept that depends on many diverse factors. To evaluate bikeability one needs to evaluate and understand the connections between all these other factors. So, bikeability is an interesting but difficult concept because the factors that make bicycles attractive (or not) are numerous, unrelated, difficult to measure and may give different results, but this does not mean that bikeability is not a fundamental concept.

Critiques to the concept of bikeability

The allegations against the concept of bikeability are mainly of two types. 1) That it's redundant because there already exists the well-studied concept of accessibility. 2) That it's ambiguous and ill-defined, this is because the literature shows several and diverse definitions. The definition of bikeability is a broad but fundamental one, as described by the conceptual model in Figure 1.1. Therefore, the allegations don't hold because 1) who says it is redundant confuses a necessary with a sufficient condition. If we define accessibility as: 'the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)' (Geurs & van Wee, 2004) we see that bicycle accessibility relates to the *land use* and *bike system* components of the conceptual model (in Figure 1.1). Consequently, accessibility is non-sufficient prerequisite for a place to be bikeable. 2) Whoever says it is ambiguous, thus useless, fails to understand that to define this concept one has to consider a vast number of relationships with complex factors that need to be evaluated and measured. However, the complexity of the evaluation does not mean that the concept is not important. The concept of democracy, in the same way, is very vague but very important to have. Thus there is no ambiguity of the term, it is simply a term that covers a vast topic.

1.2 Research objective and questions

Given the limited and diverse knowledge on how to assess infrastructure-related bikeability of urban areas, this thesis aims:

To gain empirical knowledge on bicycle infrastructure networks and develop methodological tools to assess infrastructure related bikeability.

In order to achieve this objective, this thesis approaches infrastructure-related bikeability from two perspectives: network level and link level. The thesis starts investigating infrastructure at a city scale to gain empirical knowledge on network characteristics and city-wide patterns. Later, given that a network is the sum of its components, we narrow the focus to the street scale. The street scale perspective investigates methods to extract level of service information at a street level, to gain a more detailed and refined picture of the city-wide bikeability. Following this framework, the research objective is divided into six research questions, three questions pertain to network-level bikeability, and the other three to link-level bikeability. In the following, we explain these research questions and the relation between them.

1. To develop knowledge on bicycle networks we first need to understand what is a bicycle network. Bicycle networks are made of different infrastructure types for car-, bicycle- or mixed-use which leads to the fact that different definitions have been used to define a bicycle network. However, it is crucial to bring together the definitions of bicycle networks and understand the structural differences among them to know the consequences of the choices and investments made in bike infrastructure networks. For this reason, we pose the following research question: *As different definitions of bicycle networks exist, how does the bicycle network scale for different definitions of the bicycle network with the population (growth) and what are their structural differences worldwide for these different definitions?* **[Chapter 2]**

2. Having identified different types of bicycle network definitions in the previous step, it is necessary to address the improvements of the bicycle network performance. To do so we need to identify, in the literature, network solutions to improve bicycle network performance. Then we should combine the network solutions to the bicycle maturity of a city, so as to understand at what maturity stage a city should make use of these solutions. Finally, the network solutions need to be combined with the data collection technique required to implement the solution. In order to develop such a theoretical framework, linking the bicycle network needs of cities to network solution and data collection techniques we need to answer: *What type of bicycle network needs do cities have and which network development solution, in combination with data collection systems, can satisfy the different needs?* **[Chapter 3]**

3. Investigating on the previous research questions, it was clear that some cities have strategically invested in segregated bicycle paths, whereas others rely more on bicycle lanes with no physical separation from vehicular traffic. Thus, cycling in most countries entails switching among streets with different characteristics (e.g. length, safety, convenience, and comfort levels). As a consequence, the quality of bicycle networks should be evaluated based not on one but on multiple characteristics and not focusing on the "average" cyclist but considering the whole spectrum of user groups with their diverse needs. However, none of the existing studies attempts to measure network bikeability taking these two fundamental aspects into consideration, this leads to the third question: *How should a bicycle network be assessed in order to take into consideration multiple infrastructure characteristics and the diversity of user preferences?* **[Chapter 4]**

4. To assess the quality of a bicycle network information on the quality of its components (links) is needed. Thus, there is a need to focus on data and methods to assess quality of a network link. One way to measure the quality of a bicycle street is to use bicycle level of service (BLoS) rankings. Much has been developed to assess BLoS

in low volume bicycle contexts. Efforts in this regard have mainly been related to the quality of paving, the width of the bicycle lane, speed and volume of vehicular side traffic. However, since the cycling conditions change throughout the day depending on the number of users on the streets, to have a more dynamic picture of the BLoS, one should incorporate variables (such as travel time) that describe the bicycle traffic conditions based on the presence of other cyclists. The most common technology deployed on cycle paths to measure the presence of cyclists, at least for the Netherlands, is inductive loop sensors. In order to exploit this broadly deployed data collection system, we study: *To what extent can Artificial Neural Networks (ANNs) exploit loop sensor data to estimate bike travel times in proximity to signalised intersections?* **[Chapter 5]**

5. By answering the previous research question, it was clear that arrival signals of cyclists, from loop sensors, are not enough to estimate travel times. In order to have accurate travel times, it is necessary to have information on the accumulation of cyclists at the traffic light (queue). As a consequence, this encourages the development of queue estimation algorithms (based on loop sensor data) that can improve overall travel time estimation. As we deepen our exploration on bicycle level of service based on the presence of other cyclists we need to investigate: *To what extent can loop sensors be used to estimate queue accumulation in front of traffic lights, which ultimately measures bicycle level of service?* **[Chapter 6]**

6. Not only objective and measurable features influence the perceived BLoS, but also subjective variables take part in influencing the overall BLoS. However, so far, studies have not investigated how these two variables are related in influencing perceived BLoS. To analyse perceived BLoS, we conduct a preliminary study (during the coronavirus outbreak) to analyse: *What type of relation exists between perceived bicycle level of service and presence of other users on the cycle path?* **[Chapter 7]**

1.3 Research approach

This section outlines how we intend to study bikeability. Hereafter we delineate the focus, data and methods used in this thesis.

Due to the broad concept of bikeability, the focus can be on a variety of domains. This thesis focuses on infrastructure-based bikeability, which is a major prerequisite to stimulate bicycle use in a city. We focus our explorations on network and link-level scale, going from the city level and narrowing down to the street level component. The city-level perspective needs to consider the complexity of interconnected systems and the diversity of infrastructure types. The street-level perspective studies characteristics of one network component, which summed up with other components result in the network performance.

Most of the analysis carried out in this work exploits quantitative methods which are based on real-world data. Thus having reliable data plays an important role in this thesis. Spatial data of networks is retrieved from the Open Street Map (OSM) project an open-source data set built by 'a community of mappers that contribute and maintain data about roads, trails, cafes, railway stations, and much more, all over the world' (Open Street Map, 2021). Such crowd-sourced and open access platforms provide an attractive and often up-to-date source of detailed data (Ferster et al., 2019). Although we are aware of tagging inconsistency, Ferster et al. (2019) reports that OSM can be more updated than municipality records, given the higher frequency with which 'the crowd' contributes to updating the OSM compared to the city releasing updated data. Data on the presence of cyclists at a link is retrieved from inductive loop sensors and smart cameras. The former is widely adopted at intersections in the Netherlands, the latter is a recent data collection system that is rapidly gaining ground.

To answer research questions 1, 4, and 5 different types of statistical analysis and quantitative techniques are employed. The applied methods mostly rely on statistical tools, such as regression techniques and supervised and unsupervised learning algorithms. To analyse bicycle network characteristics related to research questions 1 and 3 network science theory concepts and algorithms are applied. Research questions 2 and 6 are addressed by making use of a survey and interview methods. For the survey (research question 2) the respondents are experts of traffic control and management in major dutch municipalities whereas the structured interviews (research question 6) address bicycle users of a bicycle path in the city of Delft, the Netherlands.

1.4 Scientific and societal contributions

The overarching contribution of this thesis is to increase the understanding of factors influencing bikeability and how to assess them. Findings from this thesis contribute to science by expanding the understanding of bikeability and developing bikeability assessment methods. Results developed in this thesis have implications for transportation practice, by providing insights for policy, planning and management of bicycle attractive places.

1.4.1 Scientific contribution

Hereafter we outline the most relevant scientific contributions developed in this thesis.

Identifying scaling relation between active mode infrastructure and population size, also in relation to scaling of other infrastructure networks

We relate kilometres of infrastructure with the city population to reveal scaling relations of active and non-active mode types of infrastructure. With this analysis, we add new insight on the scaling relations between infrastructure types and city size which unravels how demographic changes in cities, resulting from increasing urbanization, may impact the transport system and ultimately the travel behaviour of residents.

Identifying bicycle network types and their structural differences

We systematically define types of bicycle networks and investigate the structural differences between them. This expands the knowledge on the hierarchy and functions of bicycle networks types. We carry out a novel bicycle network analysis over multiple cities and multiple network definitions. Our findings on network connectivity, fragmentation, and density help researchers understand the different structural properties of bicycle network definitions and their impact on network evaluation methods.

Providing a theoretical framework and empirical evidence on data collection systems for bicycle networks
We review data collection systems for urban bicycle networks and combine them to bicycle network needs of cities. In doing so, we propose a framework (supported by empirical data) that informs on international best practices and relates them to the level of bicycle culture of a city. We develop empirical evidence on bicycle data collection systems deployed in major dutch cities, which makes clear the potential availability of bicycle data that there is in the Netherlands and that could be used for future research on bicycle traffic solutions.

Developing a methodology to assess infrastructure-based bikeability
We propose a multi-objective methodology to evaluate the infrastructure bikeability of a city based on multiple factors. The methodology extends the literature on bicycle network evaluation techniques by quantitatively comparing the quality of bicycle connections for the different user groups. As a visual instrument, we develop 'the bikeability curve' to analyse the trade-offs that users need to make between different characteristics of a bicycle route.

Defining a methodology to measure the level of service of one bicycle street segment
We investigate how loop sensor data, widely available in major Dutch cities, can be employed to evaluate BLoS based on travel time and queue length) at a signalised intersection. First, via a simulation based analysis, we provide quantitative insights on the limitations of estimating travel times of cyclists on a street segment based on loop sensor data alone. Secondly, we develop a methodology to estimate the bicycle accumulation levels on a signalized link by using an unsupervised learning technique. We explain and provide empirical evidence on the difference between a purely data-driven approach and one with domain knowledge. We draw conclusions on which approach has a superior performance.

Analysing the relation between the objective and subjective level of service at a bicycle street segment
We measure and analyse the relation between perceived BLoS on a street segment and the presence of other cyclists on the path. The relation we find enriches the interpretation of objective (simpler to measure) indicators. Moreover, it suggests that future research should design level of service measures based on the presence of other cyclists.

1.4.2 Practical implications

The broader implications of this thesis relate to policies, urban plans and traffic management solutions that can make bicycle use more attractive in a city.

Policy
The analysis of the different bicycle network types and the methodology to assess bikeability guides policymakers in their decision on where to invest to improve bicycle infrastructure. Many factors affect bikeability such as comfort and safety and convenience, however, every user has a different trade-off between these factors. Therefore, when prioritising projects, the whole variety of user groups should be considered. In addition, the international comparison between cities in the Netherlands and Melbourne provides some signals about how

context may change and redefine the bicycle network needs of a city. Thus, it is important to have a strategic long term vision on bicycle needs and data collection plans.

Urban design

More attention and resources are being allocated to bicycle infrastructure. However, where to build it and what type of bicycle path to use is still an open question. Based on our taxonomy of bicycle networks, it is clear that there exist different bicycle networks in a city, with different functions, hierarchies and structures. Urban planners are advised to recognise and develop the different bike networks to cater for the needs of different user groups and activities. Moreover, it is not the extension of the network per se, but the structural characteristics like density and connectivity that make the network more bikeable.

Multi-modal traffic management

As some cities succeed in attracting more bicycle use, some parts of the network may become congested and decrease their perceived level of service and safety. Novel traffic management solutions can mitigate this and the implications from this thesis bear relevance for both traffic management planning and operational traffic management. Multi-model traffic management planning relies on historical data and assessment models to understand the functioning of roads and plan a network management system. Whereas operational multi-modal traffic management systems are based on real-time data to take operational decisions. To this end, accurate real-time estimates of bicycle travel times, queues and perceived level of service are developed for traffic control systems and re-routing advice.

1.5 Thesis outline

The thesis is divided into two parts, one that investigates aspects of bikebility at a network level and a second part that zooms in to explore bikeability at the link level. The thesis is composed of a collection of eight chapters; an overview of the outline is illustrated in Figure 1.2.

The network-level part of the thesis starts with Chapter 2 containing a multi-city analysis to empirically identify similarities and differences between different bicycle network types worldwide. Chapter 3 follows by providing a theoretical framework on how to select bicycle data collection systems. The study links the theory to practice by providing evidence on the deployed data collection systems in Melbourne and in dutch cities. The network-level part of the thesis concludes with Chapter 4 in which we propose a methodology to evaluate infrastructure-based bikeability. The methodology is based on the concept (defined in this thesis) of bikeability curves.

The link-level part of this book explores different methods to estimate bikeability based on the presence of other cyclists. Chapter 5 investigates a neural network-based model that estimates cyclists travel times, as a proxy for bike level of service at intersections. Chapter 6 follows by adopting a clustering-based method to estimate the queue level of cyclists upstream of a signalised intersection. The link-level section ends with chapter 7 which carries out a survey and regression analysis on the relation between perceived bicycle level of service and objective variables of density and flow.

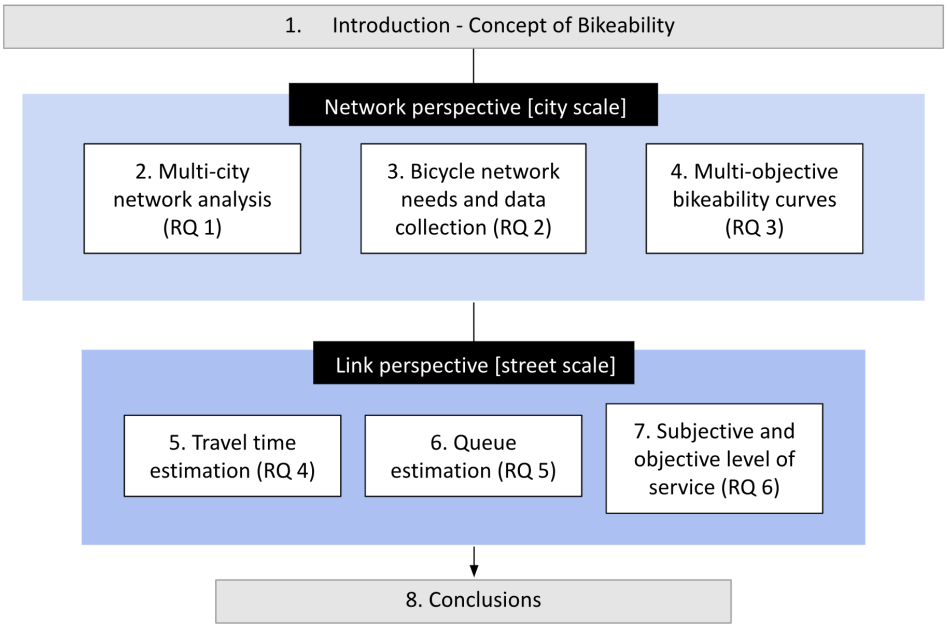

Figure 1.2: Outline of the thesis.

Chapter 8 draws conclusions based on the main findings by answering the research questions. Then it discusses implications for practice and directions for future research.

Part I

City scale

Chapter 2

Empirical analysis of bicycle networks worldwide

"Cities have the capability of providing something for everybody, only because, and only when, they are created by everybody."

— Jane Jacobs, The Death and Life of Great American Cities

First, this chapter investigates, using empirical data of 47 cities, how the urban infrastructure is distributed among different modes (bike, cars, pedestrians, metro). Then it investigates what infrastructure types are part of a bicycle network and proposes four bicycle network definitions to facilitate analysis and comparison of bicycle network characteristics.

As more infrastructure is included in the bicycle network definition, it is unknown how the structural characteristics of networks change. Therefore, this chapter systematically defines and analyses different types of bicycle networks to understand how the selected bicycle network definition affects the structural characteristics of the network. Understanding this can unravel how demographic changes in cities can impact the transport system and contributes to the body of knowledge necessary for design interventions by policymakers.

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2.1 Introduction

Biking is looked upon as an efficient and sustainable means of transportation. It has a huge impact on reducing congestion, and various forms of pollution, and is a major driver in promoting active and healthy lifestyles. Yet, in practise, we often see that bicycle infrastructure is disadvantaged by providing a limited amount of space for it (Szell, 2018; Gössling et al., 2016), and a highly fragmented street network (Orozco et al., 2020). Based on the spatial structure of a city and the activity patterns of its inhabitants, policymakers have to decide how limited and contested space is distributed between the different transport modes. It is challenging to allocate dedicated space to bicycle infrastructure, as traditionally street networks are designed for car-use and can often be substituted for informal biking.

Traditional street networks are made of different infrastructure types for car-use, bicycles or mixed-use (OSM, 2021b). Street networks used for cars are efficient and well-connected: the amount of street infrastructure per capita decreases as population increases (Bettencourt, 2013). To promote other active forms of transportation (example, biking) policymakers require a fundamental understanding of how these infrastructure types scale with the size of a city population, and how can they be expanded or developed.

Multiple scholars have advanced our understanding of bicycle networks (Mekuria et al., 2012; Schoner & Levinson, 2014; Buehler & Dill, 2016; Orozco et al., 2020). But some studies attempting to define bicycle networks have done so in an ad-hoc manner, which makes results difficult to replicate and generalise, and provide tailored evidence to policymakers for targeted interventions in the expansion and design of bicycle infrastructure. This ultimately impedes building upon previous findings and slows the epistemological advances in the domain of active mode infrastructure. Bicycle networks can be defined by considering the aggregation of different infrastructure types. Identifying which infrastructure types make-up a bicycle network is not easy, yet it highly impacts the results of space allocation studies by making a city seem more bike-friendly than it is if one considers a bike network made of all streets where it is possible (instead of safe or comfortable) to cycle on. As summarised in Figure 2.1, studies on space allocation and network characteristics have adopted very different bicycle networks definitions (Murphy & Owen, 2019; Wu et al., 2021; Szell, 2018; Nello-Deakin, 2019), which inevitably affect the result of the analysis and hinders any type of comparison between studies.

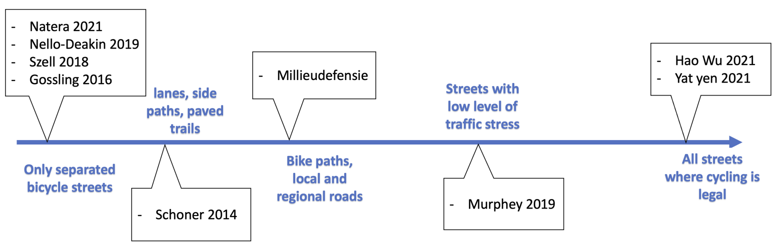


Figure 2.1: Previous studies on space allocation and network analysis have used different definitions of bicycle networks.

Moreover, previous research suggests that, adding bike infrastructure (dedicated or shared) may not be enough to stimulate bicycle use, if it does not reinforce the network structure (e.g. density, connectivity) (Schoner & Levinson, 2014). Thus, it is crucial to bring together the definitions of bicycle networks and compare structural differences among them to understand consequences of the choices and investments made in bike infrastructure networks. A comparison between bicycle network definitions would identify the positive or negative structural characteristics of different bicycle network definitions, which ultimately influence bicycle attractiveness (Kamel & Sayed, 2021). A multi-city comparison with common definitions of bicycle networks would bridge this gap by systematically analysing the same networks over multiple cities to identify worldwide relations, thus contributing to the body of knowledge necessary for design interventions by policymakers.

In this article, we systematically define and analyse different types of bicycle networks to understand how the city size affects infrastructure development per mode and if the selected bicycle network definition affect characteristics of the network. We apply the analysis to 47 cities to provide empirical evidence and facilitate comparison in structural properties of the networks. We structure the analysis by asking two questions:

1. As larger cities build less infrastructure per capita, how do the different infrastructure types scale with city size and how is the scaling relation of the different bicycle network definitions affected?

2. As different definitions of bicycle network exist, how can we provide evidence-based knowledge on the structural differences and similarities of bicycle networks worldwide?

Understanding the scaling relations between infrastructure types and city size can unravel how demographic changes in cities, resulting from increasing urbanization, will impact the transport system and ultimately the travel behaviour of residents. We carry out a novel bicycle network analysis over multiple cities and multiple network definitions. Our findings will help researchers understand the different structural properties of bicycle network definitions, and their impact on network evaluation methods. Policymakers will be able to identify the bike network that meets their policy objectives. This analysis is particularly relevant now given the ‘window of opportunity’ that the Covid-19 pandemic has created for many policymakers to convert car dominated streets into bike lanes. Our analysis for example, shows the changes in structural properties if a city makes all its residential streets truly bikeable. Moreover our numerical analysis will provide unique benchmark values that urban planners can use to set their network objectives against the average or best performing cities.

This manuscript is structured as follows. In the Methodology section we present the network data and methods used. Then the Empirical Analysis and Results section illustrates the outcome of the analysis for 47 cities. The Implications for practice section discusses practical relevance. Finally, the Discussion and Conclusions section follows.

2.2 Methodology

The goal of this study is to understand how the city size affects infrastructure availability per mode and to systematically define and analyse different types of bicycle networks to observe if the selected bicycle network definition affects characteristics of the network. The methodology consists of 5 steps as shown in figure 2.2 and the following sections describe each step.

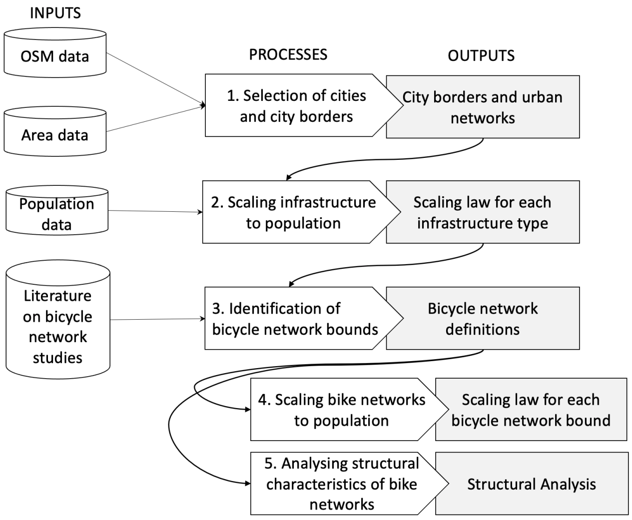


Figure 2.2: Overview of the research methodology.

2.2.1 1. Selected Cities and City Boundaries

We analyse bicycle networks in different cities. The sample composition is built in such a way to include cities from as many different continents, with small to large population scale and with all ranges of bicycle mode share (from 1 to 46%). We decide to use Open Street Map (OSM) data due to its open accessibility, while being aware of the potential data quality issues. In fact, (Ferster et al., 2019) report observing inconsistent tagging of bicycle infrastructure types. On the other hand, they also report that OSM can be more updated than municipality records, given the higher frequency with which ‘the crowd’ contributes to updating the OSM compared to the city releasing updated data.

The sample selection was constrained to the availability of OSM data; we only selected countries with OSM network data exceeding 80% completeness (Barrington-Leigh & Millard-Ball, 2017) and with medium to high levels of bicycle ownership (Oke et al., 2015). This choice inevitably biases the city sample towards more developed countries for which these data are digitally available, leading to more similar typologies of street patterns among cities (Louf & Barthelemy, 2014). Moreover, in order to have a representative sample of cities with high bicycle mode share, the sample has an over-representation of the dutch cities, which are typically of small size (population of maximum 1 million inhabitants). To address this concern, we included a sufficient amount of small-sized cities that have lower cycling rates than in the Netherlands, in order to not bias the sample with small-sized cities that only represent a high cycling mode share level. The list of cities under analysis is reported, for lack of space, in Table 2.2 in the Supplementary material.

Defining the city boundaries is a non trivial task. Cities are not well-defined entities that can be described by administrative boundaries, functional economic areas, urban form, and presence and movement of people (Rybski et al., 2019). Cities, differently to urban centres, have an administrative and cultural identity that influences bicycle network investments and travel behaviour. Instead, urban centres are made of dense territories which may be composed of different local political administrations. We selected city boundaries based on Nominatim (OSM, 2021a) (a tool to search OSM data by name) administrative boundaries. If more than one boundary is available for a city we always avoid city metropolitan boundaries which, in most cases, incorporate scarcely populated areas and more than one local administration. After extracting municipality borders we use https://www.citypopulation.de/ website as a visual reference to extract the corresponding population and area information. This ensures that the population matches the selected city boundaries. Area, population and bicycle mode share information per city is reported in the Supplementary material (see section City Data).

2.2.2 2. Scaling infrastructure to population

We extract urban network, of the selected city boundaries, from the OpenStreetMap (OSM) project via OSMnx (Boeing, 2017) we compute the respective kilometer length of each infrastructure type (e.g primary roada, secondary road, pedestrian street) for each city. Then, we use the least-square linear regression method to fit a power-law distribution to the kilometers of infrastructure and the population and analyse the scaling exponents. In general, three methods are commonly used to define a best fit line for bivariate variables; least-square linear regression , major axis, and standardized major axis. The fitting method used differs depending on whether a measurement error is considered. For simplicity we do not consider measurement error in the X variable, thus, we use least-square linear regression method. Future studies can test out the alternative methods.

2.2.3 3. Identification of bicycle network bounds

Combining the results of the scaling laws to best practices identified in the literature we define four bicycle network definitions (bounds). To define bicycle networks,we use infrastructure types used in OSM. In Table 2.1 we report the keys, values and definitions of the main infrastructure types, as defined on OSM. The remainder of the paper refers to these definitions when describing types of street infrastructure.

Since there is no universally accepted definition of a bicycle network, we systematically estimate upper and lower bound definitions and use them as candidate definitions for our network analysis. Driven by previous studies and the ability of employing these definitions to any city worldwide, we identify four definitions of bicycle networks. The network definitions are step-wise incremental, thus the lower bound is the smallest in size and the upper bound network is the largest, as it includes all the streets included in the previous definitions. Going from the most physically separated from vehicular traffic (widely considered as the safest) to the least segregated (also considered the least safe[1] to cycle on) we label them lower bound, medium-lower bound, medium-upper bound and upper bound.

[1] Note that this attribute of safety is based on expert advice used to tag the streets and literature. In reality perceived safety of cyclists might differ.

Table 2.1: Description of the main urban street tags from Open Street Map (OSM, 2021b).

Key	**Value**	**Description**
Highway	motorway	Restricted access major divided highway, with 2 or more running lanes plus emergency hard shoulder.
	trunk	The most important roads in a country's system that aren't motorways.
	primary	The next most important roads in a country's system.
	secondary	The next most important roads in a country's system.
	tertiary	The next most important roads in a country's system.
	residential	Roads which serve as an access to housing, without function of connecting settlements. Often lined with housing.
	living_street	Residential streets where pedestrians have legal priority over cars, speeds are kept very low and where children are allowed to play on the street.
	pedestrian	Roads used mainly for pedestrians, in shopping and some residential areas which may allow access by motorised vehicles only for very limited periods of the day.
	footway	For designated footpaths; i.e., mainly/exclusively for pedestrians. This includes walking tracks and gravel paths.
	path	A generic path open to all non-motorized vehicles and not intended for motorized vehicles unless tagged so separately. This includes walking and hiking trails, bike trails and paths, and horse trails.
	cycleway	Indicates a separate way for the use of cyclists
	bridleway	For horse riders. Pedestrians are usually also permitted, cyclists may be permitted depending on local rules/laws. Motor vehicles are forbidden.
	track	Roads for mostly agricultural or forestry uses.
Cycleway	lane	A lane is a route that lies within the roadway

- The lower bound network is made of bicycle tracks that are physically separated from vehicular traffic, living streets with very low speed limits, and recreational paths. Studies of (Szell, 2018; Orozco et al., 2020; Nello-Deakin, 2019) use only bicycle streets that are physically separated (protected) from vehicular traffic, because of their higher safety levels. In our definition of lower bound, in addition to the separated bicycle streets, we also include living streets and paths which can be considered equally safe and comfortable because active modes have priority over cars (OSM, 2021b). Thus, the lower-bound definition consists of only protected bicycle streets.

- We define the medium-lower bound network as a combination of protected and unprotected bicycle streets, because unprotected bicycle lanes (considered less safe) are mostly present in Western countries with the strongest car culture (Szell, 2018). Note that bike lanes are visually (not necessarily physically) separated form vehicular traffic.

- The medium-upper bound extends the previous definition by adding residential streets. These are streets for local traffic which typically have low volumes of through movement. During the covid-19 pandemic, some cities have transformed these into slow streets (WHO, 2020). This motivates the definition of a bicycle network that assumes all residential streets to be suitable for cycling.

- Finally, the upper-bound network includes all streets where cycling is not prohibited by law, which encapsulates the broad definitions of bicycle networks used in literature (Wu et al., 2021; Yen et al., 2021).

For reproducibility purposes, the OSM queries used to define the four bicycle networks are reported in Table 2.4 in the Supplementary material.

Note that the bikeability[2] and safety of all bicycle streets is generally dependent on the city and its culture. This is especially true for non bicycle separated streets e.g. residential streets, bike lanes (with no physical separation), and all vehicular roads where cycling is allowed. However, it is reasonable to assume that the lower bound network is the safest bicycle network in all countries, whereas the upper bound also includes the least safe streets.

The taxonomy of bicycle networks is schematically visualised and explained in Figure 2.3. The four networks are step-wise incremental since all streets included in the lower bound network are also present in the upper bound networks. To illustrate how the bicycle network bounds are different in structure and extension, in Figure 2.9 in the Supplementary material we visualise the four bicycle networks for a small (Delft) and large (Rome) city.

2.2.4 4. Scaling bike networks to population

Similarly to step 2, we use the least-square linear regression method to fit a power-law distribution. In this step we analyse how the kilometers of the bicycle network bounds scale to population.

[2] We refer to bikeability as the the extent to which the actual and perceived, physical and cultural, cycling environment is adequate for the use of bicycles

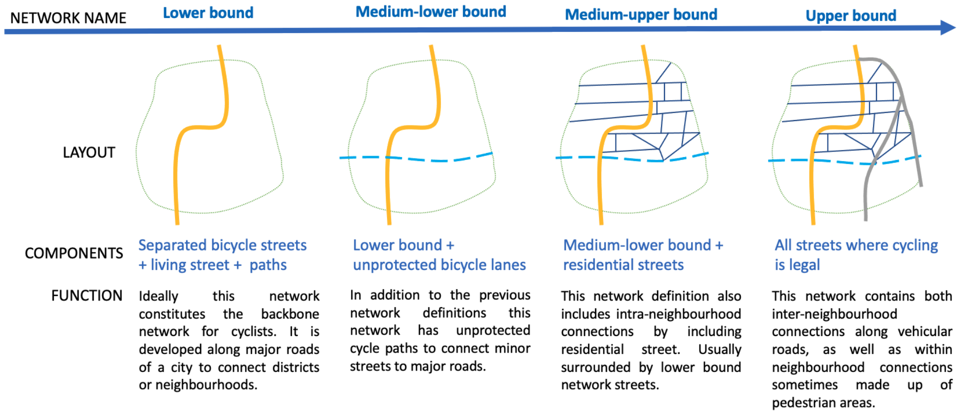


Figure 2.3: Taxonomy of bicycle network types.

2.2.5 5. Structural Analysis and Network Measures

As illustrated in Figure 2.3, there are disparities in the extent to which a bicycle network spans a city. To provide an information basis for policymakers to direct infrastructure investments, it is imperative to study network structural characteristics more systematically. Most structural characteristics are correlated to travel behaviour and can be influenced by policymakers to incentivise bicycle use. A pioneering study on bicycle network analysis identified size, fragmentation, directness, density, and connectivity as macroscopic factors to measure bicycle network quality (Schoner & Levinson, 2014). Besides these characteristics, we also include granularity - measured as average street length - due to its wide adoption in urban street network analysis studies (Boeing, 2021; Yen et al., 2021). These network measures are a good proxy for information about land use and transportation system (i.e. cost of travel) of the city (van Wee et al., 2013; Schoner & Levinson, 2014; Kamel & Sayed, 2021). The measurements are computed with standard (python) libraries in the network community such as NetworkX and OSMnx. A definition of each measurement is reported hereafter.

Size, or extension, of urban bicycle networks measures the total kilometre length of the network. To measure a specific infrastructure type (e.g. residential streets) the relative size is measured as the ratio of that infrastructure type over the extension of the whole network. The extension, in absolute and relative terms, shows investment decisions of cities and allows to analyse space distribution between transport modes. Previous studies have found positive relationships between the size of a city's bicycle facility network and its bicycle commute share (Dill & Carr, 2003; Buehler & Pucher, 2011; Parkin et al., 2007).

Fragmentation, as defined in this work, measures the number of the connected components of a network and their size distribution. A network made of only one connected component, implies that there is a path between every pair of nodes in the network. Whereas, networks made of many connected components result in more isolated parts which do not connect to all nodes of the network. The size of a connected component is computed as ratio of the kilometer extension of the connected component over the total extension of the network. Most cities have one giant connected component that makes up the car, pedestrian, and rail network, whereas the bicycle street network is often fragmented into many connected components (Orozco et al., 2020). Having either a few medium sized components or one dominant component facilitates bicycling, but excessive fragmentation with small fragments should be avoided (Schoner & Levinson, 2014). Moreover, fragmentation of the network can constitute a resistance to cycling by reducing safety and comfort.

Granularity of an urban street network measures block size which is the elementary component of an urban map. The average street length is a proxy to measure city granularity. Previous empirical results have shown that this indicator has positive relationship with levels of economic vitality for cities (Long & Huang, 2019). Fine-grained urban areas are also naturally more attractive for active modes because there are more locations to stop along the way, than in coarse-grained urban areas. We study how network granularity changes over the bicycle network definitions. Note that the underlying street network stays the same, so the physical street layer has always the same granularity, however the bicycle networks have different granularity depending on which components of the street network are included in the definition. Cyclists experience higher or lower granularity depending on the streets they deem bikeable.

Directness, the inverse of circuity, measures the ratio of euclidean (straight line) to street distance. This network characteristic describes the directness and the efficiency of transportation networks. Cyclists are affected from the directness of their routes, so policies that make bicycle trips more direct and efficient will increase adoption of cycling as a mode of transportation (Rietveld & Daniel, 2004).

Network density provides information on the land use of a city and can be measured in a number of ways. We measure it as intersection density (intersections/km2). Density has been identified as the most influential factor for bicycle commuting among network characteristics in a study across US cities (Schoner & Levinson, 2014). That study concluded that: "cities hoping to maximize the impacts of their bicycle infrastructure investments should first densify their bicycle network before expanding its breadth". Studies on the relationship between the built environment and travel have identified that residents of high-density neighbourhoods use the bicycle more often (van de Coevering, 2021) and that a change in the density factor score of *one* standard deviation corresponds to a 77% increase in rates of bicycle commuting (Schoner & Levinson, 2014).

Connectivity describes how well locations (nodes) are connected via network links and can be measured in a variety of ways. In this work, similar to previous urban studies (Boeing, 2017, 2021; Schoner & Levinson, 2014), connectivity is measured in terms of streets[3] per node, proportion of streets per node, and clustering coefficient of nodes. These characteristics respectively shed light on the average node level connectivity, distribution of node level connectivity, and neighbourhood level connectivity. The average streets per node measures the average number of physical streets that emanate from each node (i.e. intersection or dead-end). It is the street equivalent of the network's average node degree. The

[3] Streets are edges of an undirected representation of a street network. The bicycle networks to some extent can be directed. It can however be complicated to determine whether a given segment in the network is directed or not (Viero, 2020). Cities can have many configurations: two-way streets which only have one bike lane on one side; one way streets with one (or two) bike lane in the same/or opposite (both) direction as the car traffic; mixed use streets where both directions are allowed. Given that it is in many places common for cyclists to bike against the allowed direction (even though it is illegal), and the available data from the city do not describe whether a given segment represent bike lanes on both sides or only one side/direction (Viero, 2020), the following analysis will therefore assume that the network is undirected.

clustering coefficient of a node is the ratio of the number of edges between its neighbors to the maximum possible number of edges that could exist between these neighbors. The average clustering coefficient is the mean over all nodes of the network and expresses how robustly the neighborhood of some node is linked together (Kamel & Sayed, 2021). The proportion of streets per node describes the type and distribution of node level connectivity. Empirical results in previous studies have shown a positive and significant relation between connectivity and bicycle commute share (Schoner & Levinson, 2014).

To test if the network measures are statistically different over the four bicycle network bounds (statistically speaking these are groups) we need a repeated measures non-parametric test, because the groups are dependent and not normally distributed. We use the non-parametric Friedman test, similar to the parametric repeated measures ANOVA, used to detect differences in treatments across multiple test attempts. If the H_0 hypothesis of the Friedman's test is rejected, we conduct a post hoc analysis to identify among which bike network bound there is a statistical difference. The post hoc analysis in this case requires a Wilcoxon test with Bonferroni adjustment because we are making multiple comparisons, which makes it more likely that Type I error appears.

Finally, to assess the different types of network definitions, we calculate relative change in network measurements as

$$I_i = \frac{|C_i - C_{i+1}|}{C_i} \times 100, \tag{2.1}$$

where C_i is the characteristic (for example, density) in $i-th$ network (for example the medium-upper bound network) and C_{i+1} is the same characteristic computed for the following network definition (so in this case the upper bound network).

2.3 Empirical Analysis and Results

This section presents results of the scaling analysis and of the structural analysis of the bicycle networks. In particular, sections Scaling infrastructure type to population and Scaling bicycle network kilometers to population investigate on research *question 1* and the subsequent sections investigate on research *question 2*.

2.3.1 Scaling infrastructure type to population

Our data confirms that the size of all road infrastructure scales sub linearly with population, meaning that cities are economies of scale and are efficient in providing road infrastructure. This is in line with the findings from urban scaling law studies (Bettencourt, 2013). Zooming into the specific infrastructure types, Figure 2.4 shows that, the metro infrastructure scales linearly ($\beta \simeq 1$), the car infrastructure scales sub linearly with an exponent ($\beta \in [0.6-0.8]$), and the cycling and pedestrian infrastructure scales sub linearly but more slowly ($\beta \in [0.2-0.6]$). All relations are statistically significant with p-value smaller than 0.01. R^2 is lower for active mode infrastructure[4] than for non-active ones, thus population size does not explain much variance of kilometers of active mode infrastructure. However, there is a clear distinction between active and non-active mode infrastructure scaling exponent; larger cities provide overall less active mode infrastructure per capita.

[4] cycleway, path, living street, footway, pedestrian

	Beta	95% C.I.	R^2	p_value
all	0.70	[0.61,0.78]	0.86	0.000
metro	1.02	[0.75,1.3]	0.68	0.000
cycleway	0.26	[0.09,0.43]	0.16	0.004
path	0.53	[0.32,0.74]	0.36	0.000
living_street	0.45	[0.15,0.75]	0.16	0.005
footway	0.57	[0.42,0.71]	0.59	0.000
pedestrian	0.44	[0.29,0.6]	0.42	0.000
bridleway	0.17	[-0.2,0.54]	0.03	0.360
service	0.70	[0.58,0.81]	0.77	0.000
motorway	0.59	[0.32,0.87]	0.30	0.000
trunk	0.84	[0.61,1.07]	0.56	0.000
primary	0.81	[0.68,0.94]	0.78	0.000
secondary	0.80	[0.66,0.93]	0.75	0.000
tertiary	0.81	[0.71,0.92]	0.83	0.000
residential	0.78	[0.66,0.9]	0.78	0.000
track	0.69	[0.39,1.0]	0.31	0.000

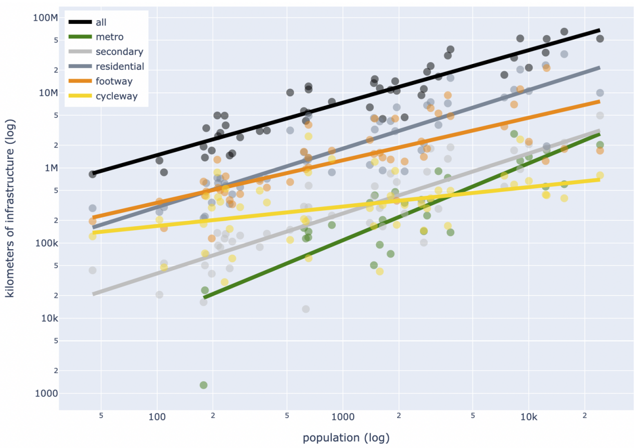


Figure 2.4: ***Scaling of urban infrastructure types.*** *Relation between total kilometers of infrastructure and population of the corresponding 47 cities. β is the slope of the linear fit to the log transformation of the data. The table groups beta values into public transport (green), active mode (orange), and vehicular infrastructure (gray). The plot on the right uses shades of those three colors to visualise some relations. Lines represent the closest fit to a scaling relation $Y = Y_0 N^{\beta}$ with β , p-value , and R^2 reported in the table.*

We underline that the aforementioned scaling relation may incorporate a comparison issue. In fact, there is a risk of not only comparing cities of different sizes but also of comparing networks at different development stages (e.g. cities with different bicycle cultures). Looking at the kilometres of cycleway infrastructure it is clear that some cities supply larger amounts than others. Thus, the realisation that cities may be at different development stages. This confirms the importance of defining different network bounds in order to compare cities at different bicycle network levels.

2.3.2 Scaling bicycle network kilometers to population

In absolute terms, the size of the bicycle network increases as the definition includes more infrastructure types *by definition*. All bicycle network types have statistically different sizes in terms of kilometers of network. In particular adding unprotected bike lanes increases the average network size by 1.75 %, adding residential streets and streets where cycling is not prohibited respectively increases the network size by 228.12 % and 134.04 %.

The four types of bicycle networks scale at a different rate to population size. The lower and medium-lower bound in Figure 2.5 scale half as slower than the medium-upper and upper bound. The inclusion of non-dedicated bicycle street (as in the definition of medium-upper and upper bound networks) increases the scaling rate, between kilometers of bicycle infrastructure and city size, from $\beta \simeq 0.4$ to $\beta \simeq 0.7$. So, the fastest way for a city to increase kilometers of bike network per person is to increase safety of residential streets and streets where cycling is not prohibited (if they are not bicycle friendly already), for instance by reducing speed limits. The R^2 values require some attention. The values differ a lot between the networks; the lower and medium-lower bound networks have an R^2 around 0.4, which is considered a weak relation, whereas the medium-upper and upper bound have R^2 of moderate and high. This entails that population size does not have a strong explanation power about the growth of the most segregated bicycle infrastructure. We also see in Figure 2.5 that the medium-lower bound network is very similar to the lower bound in terms of infrastructure extension, meaning that the dedicated but unprotected streets (based on OSM tags) are not that common in cities.

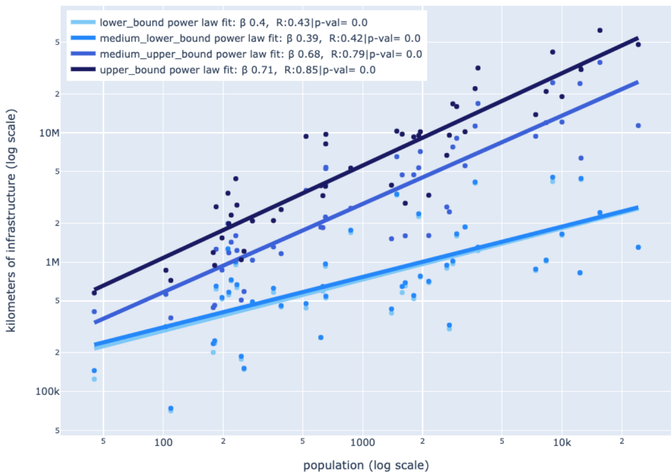


Figure 2.5: ***Size of the bicycle networks.*** *Scaling of the four types of bicycle network kilometers to population. Data for 47 cities extracted from OSM in 2020. Lines relate to the closest fit to a scaling relation* $Y = Y_0 N^{\beta}$.

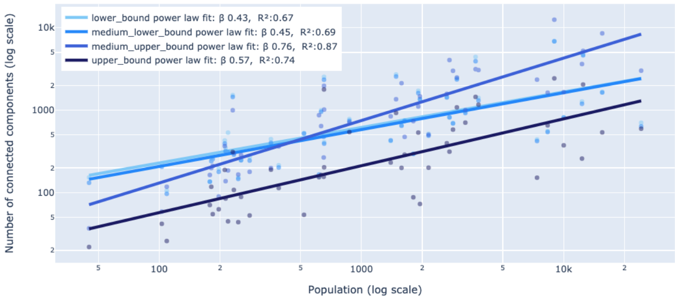
In conclusion, we see that different bike network bounds scale differently with population. It all depends on the infrastructure types included in the bicycle network definitions. In the next sections we study the aggregated structural characteristics of the four candidate definitions of bicycle networks.

2.3.3 Fragmentation

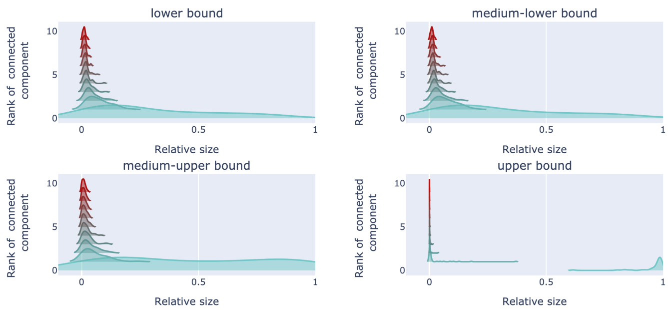
The number of connected components is significantly different depending on the type of bicycle network, as is shown by applying a Friedman test. A post hoc analysis with Wilcoxon signed-rank tests, with a Bonferroni correction applied ($pvalue = 0.083$), showed significant differences between all networks except between the lower bound and the medium-upper bound and between the medium-lower bound and medium-upper bound. Thus each network definition has on average a different number of connected components, except for the medium-upper bound which has a similar distribution to the other lower bound networks.

By analysing the number of connected components of the four bicycle network types, we see in Figure 2.6(a) that as the bike network definition includes more infrastructure types (different shades of blue in Figure 2.6(a)) the number of connected components decreases.

Exception to this is the addition of residential streets (medium-upper bound). Namely, the slope of the fitted line in the medium upper bound is larger than the slope of the lower bound, meaning that for cities with small population the residential streets behave as a ‘connector’ (since the number of connected components is less than the connected component in the lower bound), and for big cities they behave as ’connectors’ (since the number of connected components is higher than the connected component in the lower bound).



(a)



(b)

Figure 2.6: ***Connected components of the bicycle networks.*** *(a) Number of connected components in relation to bicycle network definition and city size. (b) The connected component size distribution of 47 cities over lower, medium-lower, medium-upper, and upper bound bicycle network types. The abscissa is constrained to 10 connected components; connected component of rank 1 is the largest connected component, of rank 2 is the second largest connected component and so on. The ordinate shows the relative size of each connected component with respect to the total network kilometers. For a given city, the sum of all relative size over all connected components is equal to one.*

Figure 2.6(b) shows the difference in the connected component size distribution of the four bicycle networks. In the lower bound network the largest connected components (i.e. rank of connected component = 1) are small (average relative size is below 0.5), and the following components are of medium size (relative size of 0.2 to 0.1). Moving towards the upper bound network the networks have the largest connected components of relative size close to 1 and the other components of negligible small size. From Figure 2.6(b) we note that the addition of residential streets does not change the component size distribution, though Figure 2.6(a) shows that residential streets do change the total number of connected components. The real difference in component size distribution is given by adding all streets where cycling is not forbidden. This results in the upper-bound network being the least fragmented network.

2.3.4 Granularity

Figure 2.7(a) shows that city granularity significantly decreases in value and dispersion as the bicycle network definition broadens to include non dedicated bicycle streets. This indicates that the broader bicycle network definition has more homogeneous street segment lengths between cities compared to the lower bound bicycle network. The average street length of the lower bound network varies from maximum of 311m in Bogota to a minimum of 57m in Helsinki. Whereas the average street length of the upper bound network varies from maximum of 223m in Shanghai to a minimum of 47m in Helsinki. This empirically confirms that the lower bound bicycle network can be considered as the safe backbone network for cycling, with a few long and direct streets (with not many branches), and the other networks as an expansion to it, with more branches and intersections.

The Friedman test showed a significant difference in granularity depending on the type of bicycle network. The median average street length for the lower, medium-lower, medium-upper and upper bound network are 109, 87, 76, and 74 respectively. A post hoc analysis with Wilcoxon signed-rank tests, with a Bonferroni correction applied ($pvalue = 0.083$), showed significant differences between all networks.

2.3.5 Directness

The average street circuity decreases in value and dispersion as the bicycle network definition broadens as shown in Figure 2.7(b). The Friedman test showed a significant difference in the average circuity depending on the type of bicycle network. The median circuity for the lower, medium-lower, medium-upper and upper bound network are 1.098, 1.077, 1.054, and 1.068 respectively. The Wilcoxon signed-rank tests (with a Bonferroni correction) showed significant differences between all networks except between the medium-lower and the upper bound.

The average street circuity of the bicycle networks are higher than the circuity of street networks of many world sub regions (Boeing, 2021). For example Europe has a street circuity between 1.065 and 1.059 according to (Boeing, 2021). Our analysis, instead, shows that Fukuoka, Boston and Rome have the circuity of 1.20 and Rotterdam of 1.04; these are the highest and lowest circuity values for the lower bound network.

The network with lowest circuity is the medium-upper bound, which shows the convenience of adding residential roads to the bicycle network definition. Residential streets create within neighbourhood connections. For this reason by including them in the bike network definition they result in more direct routes that do not meander around residential areas but cut through them. We notice that circuity increases from the medium-upper to the upper bound network, one explanation is that the upper bound network does not only add within neighbourhood connections, it adds all streets where cycling is allowed. The latter results to be more circuitous than the residential streets.

2.3.6 Density

Figure 2.7(c) reports intersection density values for the different bicycle network definitions across 47 cities. Data shows that the lower bound network has significantly lower densities, in terms of number of intersections over square km, compared to the other networks. The Friedman test showed a significant difference in average intersection density among the different bicycle networks. The median density for the lower, medium-lower, medium-upper and upper bound network are 6.1, 14.7, 49.8, and 61.8 respectively. These densities are much higher than the vertex densities (average 1.55 $vertex/km^2$) of bicycle networks reported in (Schoner & Levinson, 2014). The reason could be linked to the choice of the cities in the two studies. Our study selected cities over four continents but still has a large representation of European cities, while the other study was entirely focused on US cities.

The Wilcoxon signed-rank tests (with a Bonferroni correction) showed significant differences between all networks. This confirms that the network becomes more dense of intersections as more infrastructure types are added to the network. The biggest increase in density is between the medium-lower bound and the medium-upper bound. This is interesting because it highlights the crucial role of residential streets in densifying the network.

2.3.7 Connectivity

Empirical results in Figure 2.7(d) show that the lower bound network has a significantly lower number of streets per node. The Friedman test showed a significant difference in values and the Wilcoxon signed-rank tests (with a Bonferroni correction) showed significant differences between all networks except medium-lower and medium-upper bound. The medium bound networks have a similar amount of streets per network, showing that residential streets do not increase the average node connectivity. Interestingly it is not the upper bound network that has the highest number of streets per node. Our interpretation is that the upper bound network, although it has the largest network in size, it does not connect the streets to existing nodes. It most likely adds new nodes, as well as street, components to the network.

Figure 2.7(e) shows that the bicycle network with the highest clustering coefficient is the upper bound meaning that that network is the most clustered and connected at the neighbourhood level. The Friedman test showed a significant difference in values. The post hoc Wilcoxon signed-rank tests did not show significant difference between the lower and medium-upper bound and the medium-lower and the medium-upper bound network, indicating that residential streets do not play a crucial role on the neighbourhood level connectivity. For the upper bound, instead, the clustering coefficient significantly increased with the addition of all streets where cycling is allowed.

Results in Figure 2.7(f) highlight a big difference between the lower bound network and the others. The lower bound network is characterised by a very big share of dead-ends (64%), lower share of 3-way intersections (33%) and an even lower share of 4-way intersections (6%). The large proportion of dead-ends in the lower bound bicycle network makes clear that this type of bicycle network has many loose ends, resulting in a less connected network. This is very different from the average vehicular street network. (Boeing, 2017) has shown that the average USA urban agglomeration is characterized by a preponderance of three-way intersections. The typical urbanized area has many three-way inter-

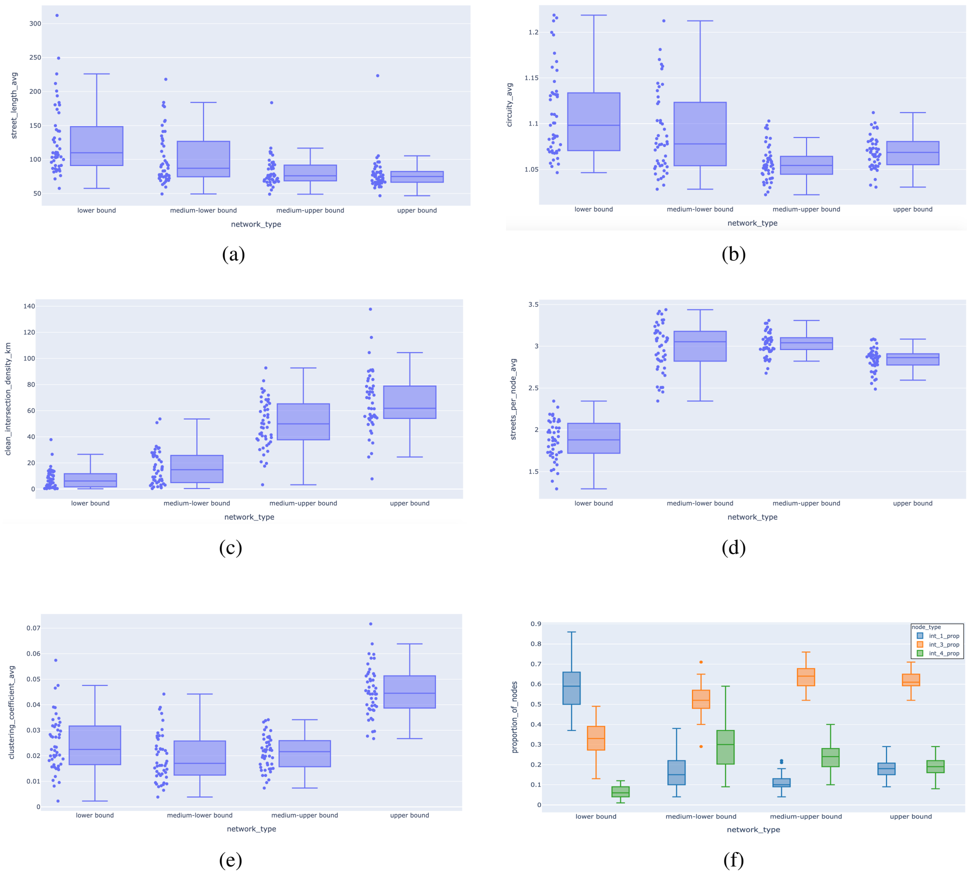


Figure 2.7: ***Structural characteristics of bicycle networks.*** *(a) Average street length, (b) Average street circuity, (c) Average intersection density, (d)Average streets per node, (e) Clustering coefficient, (f) Proportion of streets per nodes*

sections (59%), fewer dead-ends (21%), and even fewer four-way intersections (18%). The medium-upper bound bicycle network, instead, has very few dead ends (10%), many 3-way intersections (64%), and a few four-way intersections(24%). Thus adding residential streets to the bicycle network results in more 3- and 4-way intersections.

2.3.8 Relation between indicators

This section explains how the previous indicators are related and how they support or contradict different findings. This will be discussed through the example of Delft and Rome. The summary of network indicators for these two cities (across the four bicycle networks) is reported in Figure 2.10, which for lack of space is in the Supplementary material.

As the total street length increases also intersection density seems to increase. However, the relation is dependent on how the new streets are added. If streets are added as disconnected components they will increase the node density but not the intersection density. Whereas if the new streets are linked to the existing network their addition increases the intersection density. Thus the increase in total street length has a higher impact on intersection density if the number of network components does not increase. This is visible in Figure 2.10 between the medium-lower and medium-higher bound networks. Rome has a bigger increase in total street length than Delft, however it also has a much higher increase in number of components. The result is that Delft's medium-upper bound network has a much higher intersection density.

As we go from the lower to the upper bound network the average street length decreases. Previous researches have shown that longer links are safer to travel given that there are less discontinuities and hindrances (Kamel & Sayed, 2021). This reinforces our definition of lower bound network being the safest, and upper bound network being the least safe, not only for the infrastructure type but because of the higher exposure to road discontinuities. The advantage of lower average street length is the lower average circuity of an edge, which leads to more direct routes.

Finally, the clustering coefficient indicator and the average street per node show two different aspects of network connectivity. In fact, the clustering coefficient relates to the average node degree and not so much to streets per node indicator. The average streets per node is based on the number of physical streets and not the network edges (in practice there can be one physical street but two network edges, one for each riding direction). By using the average street per node indicator, we look at the connectivity of an undirected representation of the network; reasonable if we assume that it is common that cyclists use a bike lane in both directions (Viero, 2020). To measure connectivity and robustness of the directed network the clustering coefficient (or the average node degree) are more suitable.

2.4 Implications for practice

The findings of this paper are of interest for researchers and policymakers. The type of bicycle network a researcher analyses in her study has implications on the study results; for example, the lower bound network turned out to be the most fragmented whereas the upper bound network is significantly more connected. Policymakers can use the average structural performance of bicycle networks as benchmark values to assess existing urban networks or plan urban development elsewhere. Moreover, policymakers can identify the type of bicycle network that meets their policy objective and determine the traffic calming measures needed to make the network suitable for different user groups. In the following, we illustrate a simplified framework of how policymakers can use the outcome of our analysis.

1. A city sets its objectives regarding the bicycle network based on the desired network characteristics. Network requirements are defined in terms of size, fragmentation, granularity, directness, density, and connectivity according to the city context.

2. Once the objectives have been set, the network structural indicators should be computed over the four bicycle network definitions.

3. Then, the city can proceed to identify which (or a combination) of the four bicycle networks fits all the determined structural requirements[5] (as defined in step 1.).

4. Finally, the city determines what needs to be done to make all roads (e.g., in terms of traffic regulations) included in the identified (at step 3) network definition truly bikeable. This analysis can be carried out per user group, referring to the four user groups proposed by (Geller, 2009).

In reality the decision process of developing a bike network is more complex, as planners do not only consider the structural characteristics, but also dynamic variables like traffic volume.

2.5 Discussion and Conclusions

In this study, we regressed kilometre of infrastructure with the city population to reveal scaling relations of the different types of infrastructure. In addition, we systematically defined four types of bicycle networks and conducted statistical tests to investigate the structural characteristics of bicycle network worldwide. The following sections elaborate on the results and draw conclusions by answering the questions stated in the introduction.

As larger cities build less infrastructure per capita, how do the different infrastructure types scale with city size and how is the scaling relation of bicycle networks affected?

Empirical results show that all types of infrastructure scale sublinearly, with the exception of subway infrastructure, which scales linearly. Although the types of infrastructure dedicated to active modes (cycleway, footway, pedestrian) scale sublinearly, they scale slower than non active mode infrastructure. Namely, we observed that cities that have double the population appear to have 26% more kilometers of bicycle dedicated infrastructure but 80% more primary, secondary, and tertiary car road infrastructure. This provides a striking insight on cities' investment decisions. Cities have been defined as efficient places due to their economies of scale in infrastructure. Our results confirm this efficiency but point out at the less liveable and sustainable side of large cities. Larger cities systematically invest less in bicycle dedicated infrastructure.

We observe that cities that have better biking conditions also have traffic norms that make car roads also bikeable. Since car roads can be used by bikes, but not vice versa, cities can compensate for the difference in bicycle infrastructure per capita by making multi-modal use of the streets safe for both modes, and across user groups. This is supported by our results showing that the scaling relation between kilometers of bicycle network and population is faster if the bike network includes multi-modal streets.

Following the logic of the built environment influencing attitude and ultimately travel behaviour, there is a risk that larger cities provide less bicycle friendly environment which

[5] Note that it could happen that the requirements are too stringent for the current street network so none of the defined bicycle networks meets all the defined conditions. This suggests that either the city needs to re-define the structural characteristics based on the existing street network of the city or it should consider a network growth strategy to build new streets (Orozco et al., 2020).

may results in less positive attitude towards the bike. This risk is smaller if the bicycle network (used by most user groups) is made of more than just the separated bicycle tracks. We note that, among urban areas, large cities are places with larger disparity between active and non-active mode infrastructure supply. Sustainable and active mode challenges in urban mobility seem to lie in the large cities.

As different definitions of bicycle network exist, how can we provide evidence-based knowledge on the structural differences and similarities of bicycle networks worldwide?

We have designed a multi-city and multi-definition analysis on bicycle networks. This allowed us to numerically analyse the structural differences between bicycle networks and build evidence-based knowledge on unified definitions of bicycle networks. Our results show that network characteristics significantly change between different bicycle network definitions. Almost all characteristics are significantly different over the four network definitions. The lower bound network is significantly less extended, dense and connected and more coarse grained and circuitous. This confirms that the four bicycle networks identified in this study are structurally different. It also implies that the choice of the bicycle network definition is a fundamental one and has consequences on accessibility, equity, and safety evaluations of a city. For example, it can result in opposite accessibility evaluations if one were to compare accessibility per mode based on the upper instead of the lower bound network.

Studies have shown the fragmented and underdeveloped nature of many bicycle networks worldwide and advise on significantly extending the protected bicycle lanes to create complete bicycle networks. Although we are in favour of spatial equity and justice between modes, and in reducing barriers to cycling, we challenge this type of notion based on the idea that a fully separated bicycle network is often not a feasible outcome. As an example, in cities that prioritise cycling, there are many segregated bike paths but also many shared streets where bikes go together with pedestrians and cars (think of historical city centre areas or residential areas). Driven by the question: “What type of streets make up a bicycle network" we propose four definitions of bicycle networks, from the fully separated to the least (which includes also car streets where cycling is allowed) and systematically analyse their structural characteristics. This enables to evidence that the lower bound network is much more fragmented than the upper bound, both in number of connected components and size distribution of the components. This means that a policymaker aiming to reduce fragmentation of the bicycle street network can focus its efforts on making the infrastructure of the upper bound network (which is not dedicated exclusively to bicycles) truly bikeable, instead of expanding the size of the lower bound network.

Our empirical multi-city analysis showed the importance of residential streets which, by creating within-neighbourhood connections, increase the network density, directness, connectivity, and significantly extend its size. Including residential streets expands the total kilometers extension of more than 200%, reduces circuity of 4% and increases density of intersection more than 700%. These are streets that already exist in the urban texture and are less expensive to transform into bicycle streets. In most city context, the physically-separated-from-traffic cycle tracks are not sufficient for people to reach their daily activity destinations by bicycle. However, the hierarchical combination of separated cycle tracks and residential streets (used by multiple modes) improves the network structure allowing cyclists to reach many more destinations within their neighbourhood.

Summary and final remarks

In conclusion, this analysis unravelled a disparity in supply of active mode infrastructure, especially in big cities which systematically invest less in bicycle dedicated infrastructure. Moreover, our findings suggests that city authorities could focus more on improving residential streets that already exist (with bicycle ad-hoc measures such as speed limit) rather than predominantly focusing on developing new separated or semi-separated bicycle streets. Depending on the legislation and the street design these can be very safe or unsafe roads for cyclists. Once a city has identified the definition of bicycle network it wants to refer to, it should take action to make it bikeable for its target user group. By doing so, planners can design cities not only to be exciting and efficient but also apt for sustainable mobility.

2.6 Supplementary material

2.6.1 City Data

In Table 2.2 we report the cities included in this study grouped by continent.

Table 2.2: List of 47 cities under analysis, divided by continent.

America(9)	Asia(6)	Europe(30)		Oceania(2)
Boston (USA)	Fukuoka (JP)	Almere (NL)	Houten (NL)	Melbourne (AU)
Bogota (CO)	Osaka (JP)	Amsterdam (NL)	Istanbul (TR)	Sydney (AU)
Curitiba (BR)	Seoul (KR)	Antwerp (BE)	London (UK)	
LosAngeles (USA)	Shanghai (CH)	Barcelona (ES)	Madrid (ES)	
Montreal (CA)	Taipei (TW)	Berlin (DE)	Milan (IT)	
NewYork (USA)	Utsunomiya (JP)	Bologna (IT)	Moscow (RU)	
Portland (USA)		Bordeaux (FR)	Mulhouse (FR)	
Sao Paolo (BR)		Breda (NL)	Munich (DE)	
Toronto (CA)		Brussels (BE)	Paris (FR)	
		Copenhagen (DA)	Rome (IT)	
		Delft (NL)	Rotterdam (NL)	
		Eindhoven (NL)	Strasbourg (FR)	
		Freiburg (DE)	Tilburg (NL)	
		Groningen (NL)	Utrecht (NL)	
		Helsinki (FN)	Vienna (AT)	

Table 2.3 presents information on area, population and bicycle mode share of the selected cities. For Sydney and Melbourne the study areas is the central district because the only alternative to metropolitan area boundaries, available on Nominatim API, was city centre boundaries. This means we focus on a smaller portion of the city. For Freiburg, instead, the only boundaries available on Nominatim AP were county-level city borders. The sources of the bicycle mode share reported as apex in table 2.3 are reported hereafter.

1. http://tems.epomm.eu/index.phtml
2. https://www.fietsberaad.nl/Kennisbank/Cijfers-over-fietsgebruik-per-gemeente
3. https://www.bloomberg.com/news/articles/2020-08-10/to-tame-traffic-bogot-bets-big-on-bike-lanes
4. https://censusreporter.org/profiles/40000US09271-boston-ma-nh-ri-urbanized-area/
5. https://sustainablemobility.iclei.org/ecomobility-alliance/curitiba-brazil/
6. Barbosa et al. (2016)
7. https://www2.deloitte.com/content/dam/Deloitte/tr/Documents/public-sector/Istanbul_GlobalCityMobility_EN.pdf
8. https://censusreporter.org/profiles/40000US51445-los-angeles-long-beach-anaheim-ca-urbanized-area/

9. https://s3.ap-southeast-2.amazonaws.com/hdp.au.prod.app.com-participate.files/7015/2412/3934/Transport_Strategy_refresh_-__Public_Transport.PDF
10. https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/Moscow_GlobalCityMobility_WEB.pdf
11. https://www.nyc.gov/html/dot/downloads/pdf/mobility-report-2018-print.pdf
12. https://censusreporter.org/profiles/40000US71317-portland-or-wa-urbanized-area/
13. https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/SaoPaulo_GlobalCityMobility_WEB.pdf
14. https://bicycleinfrastructuremanuals.com/manuals4/The%20Korea%20Transport%20Institute_Bicycle%20Transport%20Policy%20in%20Korea_2013.pdf
15. https://www2.deloitte.com/content/dam/insights/us/articles/4331_Deloitte-City-Mobility-Index/Shanghai_GlobalCityMobility_WEB.pdf
16. https://www.smh.com.au/national/nsw/more-people-using-public-transport-in-sydney-but-car-still-wins-the-day-20121030-28h3b.html
17. https://ecf.com/news-and-events/news/velo-city-global-series-taipei-rise
18. Koike (2014)

Table 2.3: Measures of the forty seven cities included in the analysis. For each city we report the area, population and bicycle mode share of the selected city boundaries.

City	Area (km^2)	Population (1e3)	Bike share (%)	City	Area (km^2)	Population (1e3)	Bike share (%)
Almere[2]	129	211	31	Madrid[1]	604.46	3266	0
Amsterdam[2]	219.42	872	33	Melbourne[9]	37.71	178	4
Antwerp[1]	82.83	197	23	Milan[1]	181.75	1396	6
Barcelona[1]	101.18	1636	1	Montreal[1]	442.61	1806	2
Berlin[1]	890.69	3669	13	Moscow[10]	1250	12480	1
Bogota[3]	392.29	7387	7	Mulhouse[1]	22.38	109	0
Bologna[1]	140.71	390	7	Munich[1]	310.73	1484	14
Bordeaux[1]	49.85	254	3	NewYork[11]	778	8336	3
Boston[4]	125	617	1	Osaka[6]	223	2725	27
Breda[2]	128.64	184	32	Paris[1]	105.31	2148	3
Brussels[1]	33.05	181	3	Portland[12]	374.63	654	2
Copenhagen[1]	91.52	632	30	Rome[1]	1285.97	2837	1
Curitiba[5]	434.3	1948	5	Rotterdam[2]	128.77	651	16
Delft[2]	24.05	103	39	Sao Paolo[1]3	1523.2	12325	0
Eindhoven[2]	88.92	234	32	Seoul[1]4	606.58	10010	2
Freiburg[1]	152.91	231	34	Shanghai[15]	6340	24183	16
Fukuoka[6]	343	1579	15	Strasbourg[1]	78.24	280	8
Groningen[2]	83.76	213	45	Sydney[16]	26.6	246	1
Helsinki[1]	215	653	11	Taipei[17]	269.44	2645	6
Houten[2]	19.81	45	37	Tilburg[2]	88.6	219	32
Istanbul[7]	5343	15519	1	Toronto[1]	664.69	2965	1
Kyoto[6]	827.26	1468	18	Utrecht[2]	75.01	357	36
London[1]	1295	8992	2	Utsunomiya[18]	416.57	520	20
LosAngeles[8]	1361.38	3792	1	Vienna[1]	414.64	1911	7

2.6.2 Bicycle network types

For reproducibility purposes, Table 2.4 reports the OSM queries used to define the four bicycle networks.

Table 2.4: Bike network definitions in terms of OSMnx queries.

Bike network label	**OSM query**
lower bound	highway=cycleway OR highway=path OR highway=living_street AND bicycle!=no
medium-lower bound	highway=cycleway OR highway=path OR highway=living_street OR cycleway!=no AND bicycle!=no
medium-upper bound	highway=cycleway OR highway=path OR highway=living_street OR cycleway=lane OR highway=residential AND bicycle!=no
upper bound	bicycle!=no

Figure 2.8 illustrates the function of lower and upper bound networks in real city examples. For example, in Delft the lower bound network is the backbone along major multi-lane roads, and also living streets inside neighbourhoods. In Rome, some parts of the lower bound network are built along major roads, other parts are in parks and along the river for more recreational use.

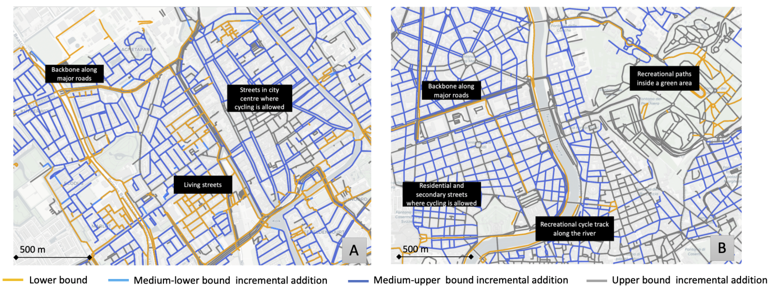


Figure 2.8: The function of the lower and upper bound networks in the city of Rome and Delft.

Figure 2.9 shows the bicycle network definitions applied to a small (Delft, the Netherlands) and a large (Rome, Italy) city. The lower bound network in Delft appears to be a connected backbone of the network, whereas in Rome it seems more fragmented.

Note that OSM has a much larger number of tags or tag combinations that could catch specific (un)protected bicycle infrastructure. The inconsistency and non frequent use made us not include other more detailed tags such as: cycleway:left = shared_lane or cycleway = opposite_lane.

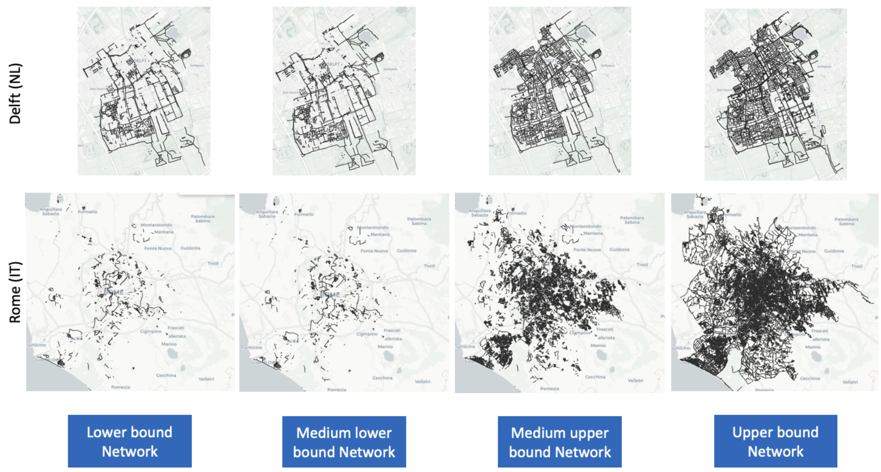


Figure 2.9: Bike network definitions in a small (Delft) and large (Rome) city.

2.6.3 Relation between indices

Figure 2.10 reports the network structural indicators for the cities of Rome(IT) and Delft(NL) and across the four bicycle network definitions.

city	network_type	street_length_total	components	street_length_avg	circuity_avg
Rome	lower bound	490862.50	698.00	183.77	1.21
Rome	medium-lower bound	514315.46	690.00	150.30	1.17
Rome	medium-upper bound	4612586.14	2999.00	96.06	1.08
Rome	upper bound	9945674.43	581.00	96.29	1.10
Delft	lower bound	158656.00	221.00	81.66	1.07
Delft	medium-lower bound	166670.39	206.00	65.26	1.06
Delft	medium-upper bound	301995.90	59.00	62.64	1.05
Delft	upper bound	473213.92	42.00	59.84	1.06

city	network_type	intersection_density	streets_per_node_avg	clustering_coefficient_avg	avg_node_degree
Rome	lower bound	0.86	1.80	0.03	3.57
Rome	medium-lower bound	2.36	2.90	0.03	3.63
Rome	medium-upper bound	28.72	2.86	0.03	3.51
Rome	upper bound	46.90	2.70	0.06	4.32
Delft	lower bound	39.25	2.03	0.02	3.81
Delft	medium-lower bound	94.26	3.12	0.02	3.78
Delft	medium-upper bound	146.20	3.08	0.02	4.60
Delft	upper bound	189.52	2.86	0.05	5.11

Figure 2.10: Network measures of Rome and Delft over the four bicycle network definitions. The blue bar in each cell is a visual representation of the value of the indicator. Each indicator (column) has a fully colored bar for the highest value.

Chapter 3

Bicycle network needs and data collection techniques

“To the man who only has a hammer, everything he encounters begins to look like a nail."

— Abraham Maslow

Chapter 2 has empirically depicted the bicycle network reality by defining their space allocation compared to other modes and structural characteristics. In the current chapter, we focus on the potential improvements (*bicycle network needs*) of the bicycle network performance. We do so by proposing a framework to evaluate and improve the convenience, safety, and comfort of urban bicycle networks. This chapter defines a framework that relates the bicycle network needs (potential improvement) of cities with data collection systems. We showcase the need-driven framework through a case study of Melbourne, Australia, a bicycle emerging city, and surveying 15 municipalities (and their consultancies) of the Netherlands. By using the proposed need-driven framework policy-makers can understand how to fully exploit bicycle data collection systems and make a systematic plan for the bicycle infrastructure network.

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3.1 Introduction

As an increasing number of data sources emerge for bicycle data (Lee & Sener, 2020), transport authorities face the challenge of understanding how to use the data and which data sources can be fit for their network needs. Some recent studies discuss how bicycle data is produced, shared and analysed in smart cities (Behrendt, 2016; Nikolaeva et al., 2019). However, the availability of data collection technologies does not automatically translate into collected data sets and use in practice. For example, research has shown that while many cities consider safety of major importance for bicycle interventions many do not collect data to assess risk (Grossman et al., 2019). This opens the discussion about which type of bicycle data a city should collect given its policy objective.

Despite the accumulation of literature pointing at the importance of bicycle data, so far, no study has proposed a framework to determine what type of data cities should collect, conditional on their level of bicycle culture (LoBC) and network needs. Cities have different LoBC (as described in section 3.2): some have never focused on stimulating cycling whereas others were so successful in doing so that are now struggling to deal with rush hour flows. For this reason, we argue that each city has different *bicycle network needs* (BNNs) - the set of requirements that a street network should meet in order to improve its bicycle operating functions given their LoBC. To understand which functions a bicycle network should meet, we refer to the basic principles of safety, directness, coherence, attractiveness, and comfort defined by the traffic and transport knowledge platform CROW (CROW, 2017). Examples of BNNs are the initial development of a network, expansion of the network, maintenance of the network, capacity management, parking facilities at destinations, and ITS (intelligent transport systems). To fulfil their BNNs cities require different policies; some cities need to first focus on bicycle safety to encourage cycling as a means of transport, whereas others need to collect real-time data on bicycle flows for advanced route guidance systems that mitigate congestion. Developing cycling plans requires data, however, too often there is a lack of knowledge on which type of data is available and is needed to meet the city's BNNs.

In this paper, we tackle the relation between BNNs and data collection systems by developing a framework - denominated the “journey to bicycle data collection"- which relates the BNNs of cities to data collection systems. Figure 3.1 reports a visualization of the proposed framework that can be described in a need-driven fashion as five sequential steps that city experts can carry out:

1. identify the main BNNs of a city
2. define solutions that fulfil those BNNs
3. understand the information needed as inputs for the solution
4. define the data requirements to derive the required information
5. establish which data collection systems satisfy the data requirements.

Although we believe that a need-driven approach is the most effective way to design and deploy a bicycle data collection system, it is often the case that municipalities go through the framework in a “technology push" approach (reversed order). Starting from the technology

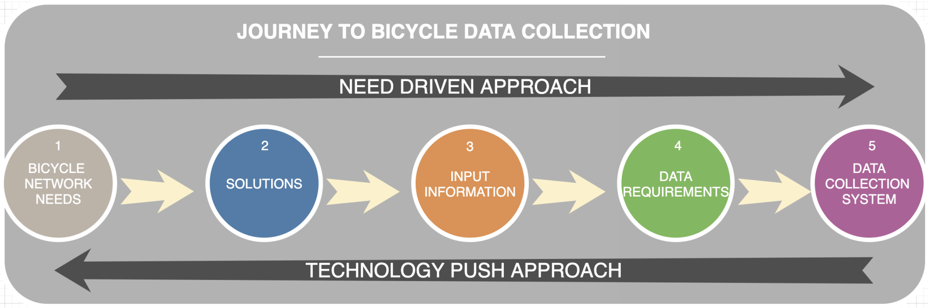

Figure 3.1: Journey to bicycle data collection - conceptual framework.

(to be) deployed they look for applications of the data and the BNNs that can be fulfilled. The limitation of a technology push approach is that the technology deployed may never fulfil the BNNs, which implies inefficient use of resources. Also, a combination of the two approaches is possible, thus once sensors are installed, municipalities search for further options to use the data.

This article aims to summarise the BNNs, solutions, and data collection systems of urban bicycle networks to support practitioners to identify the sensors or data collection systems that best match their BNNs. In doing so we delineate a framework that shows international best practices and relates them to BNNs and level of bicycle culture (LoBC). Such a framework guides how and when practitioners should implement data collection systems for bicycles. The Netherlands, with its mature bicycle culture, was chosen as a study area to understand the framework. Empirical evidence, from a survey with 15 municipalities, illustrates the framework logic; the Dutch cities have bicycle sensors that meet the BNNs of bicycle-friendly places. The result of the survey is an unprecedented inventory of the deployed sensors, extracted information and ICT (information and communication technology) solutions used for bicycle detection and data collection at a major intersection in the Netherlands. As a consequence the survey sheds light on the potential availability of bicycle data that there is in the Netherlands and inspires more research on possibilities of how to apply it, thus linking data availability with BNNs. Second, using the developed framework a case study in Melbourne, Australia, was undertaken to assess the alignment of the framework with a bicycle ignorant/emerging city.

The paper is structured into two main parts: a theoretical framework and empirical case studies. The theoretical section follows the structure of the framework presented in Figure 3.1. Section 3.2 identifies BNNs of cities, section 3.3 presents macro-classes of possible solutions, and section 3.4, 3.5, and 3.6 describe respectively the input information, data requirements and data collection systems (or sensors) needed for the functioning of each solution. The article follows in section 3.7 and 3.8 with empirical evidence, collected via a survey, on bicycle data collection systems of bike networks in the Netherlands and a case study in Melbourne, Australia. After discussing the outcome of the survey and case study in section 3.9, conclusions are drawn in section 3.10.

3.2 Bicycle network needs (BNNs)

While some studies have attempted to rank cities' bicycle friendliness, to the best of our knowledge, no study has yet identified classes of cities based on similarities in their needs. Grouping cities based on their BNNs can help in identifying solutions. We propose a classification of cities inspired by Maslow's pyramid of needs (Maslow, 1943). The *hierarchy of needs* theory argues that humans have a pyramid of needs in which lower layers of the pyramid represent the basic physiological (e.g. food, water, sleep, etc.) and safety needs, that must be met before focusing on other (secondary) needs like social, self-esteem, and self-actualization. Needs lower in the hierarchy must be satisfied before individuals can focus on higher needs.

Similarly to Maslow's needs, we hypothesize that cities have a pyramid of needs. With respect to cycling, we argue that cities have different BNNs depending on their *Level of Bicycle Culture* (LoBC) (which defines the levels of the pyramid). As mentioned by Pelzer (Pelzer, 2010) bicycle culture consists of the social environment as well as material and physical circumstances. Based on the bicycle culture, a city has specific BNNs (needs relating to the physical environment). The bicycle culture of a city can be established by comparison of bike traffic volumes (Oosterhuis, 2013). In addition to this, the criteria we use to characterize the LoBC are bike modal split, bike traffic volumes (referring to crowdedness), safety, and comfort. An indicative characterization of the levels is reported in Figure 3.2. We define five LoBC: 'bike-hostile', 'bike-ignorant', 'bike-emerging', 'bike friendly', and 'bike-dominant' to identify the main classes of BNNs, as shown in Figure 3.3. Bike-emerging cities should strive to become bike-friendly, however, bike-friendly cities may need to avoid becoming bike-dominant if local volumes of cyclists exceed network capacity. During the development of our framework, a study about levels of bicycle maturity was published (McLeod et al., 2020), showing the relevance of the topic. While the research by Mcleod et al. (McLeod et al., 2020) does not focus on BNNs nor data collection systems for bicycles, it does classify best practices related to policy consistency, advocacy, integration with public transport and planning tools into levels of bicycle maturity[1].

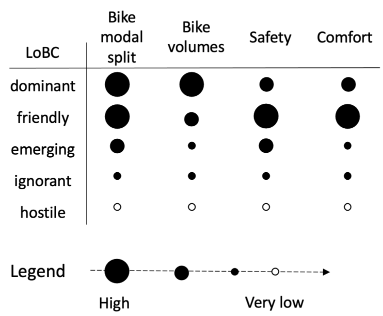

Figure 3.2: Levels of bike culture and the criteria that hold for the corresponding level.

The levels of bicycle culture defined by us are:

[1]For an equivalence between our LoBC and the maturity stage identified by McLeod el al. (McLeod et al., 2020), 'bike friendly' level matches both 'tactic' and 'practice' maturity stage.

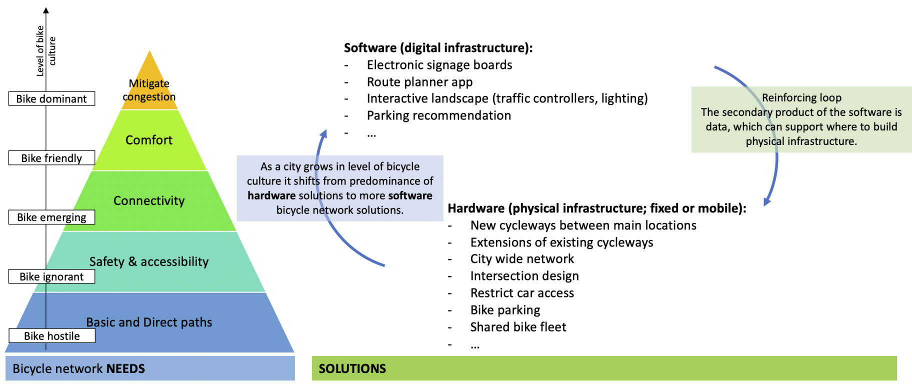

Figure 3.3: Pyramid of bicycle network needs associated to the Level of Bicycle Culture (LoBC) and the related classes of network solutions.

- **Bike-hostile:** is a city that is mainly focused on car infrastructure development. This type of city needs a starting point made of **basic bicycle infrastructure streets**. Its street network requires **convenient (direct and well-known) bike connections** between important areas of the city. At this stage, it is more important for a city to redistribute road space among modes with fast-to-build and inexpensive bike lanes rather than constructing more expensive segregated bike tracks. This basic infrastructure will enable some people to cycle. Bike modal split, volumes, safety and comfort are absent or very low in this type of city.

- **Bike-ignorant:** is a city that starts having an interest but has never made plans to develop cycling as a mode of transport. This type of city does not have a connected bike network, just a few sparse links that are not part of a coherent plan. It may (or may not) have a few separated bike paths. If such a city has an interest in starting a bike culture it should first-and-foremost look at **safety** (Winters et al., 2011) and **accessibility** of its streets. By accessibility, we mean the ability to access important destinations by travelling along the bike network. Thus, it relates to the user's access to the network, and also to the connection of the network to important areas of the city. It can do so by extending the existing bike streets and converting the bike lanes along the major vehicular roads into segregated bike tracks to create safe access to main destinations in the city. Cycling conditions are poor resulting in low bike modal split, volumes, safety and comfort (Silva et al., 2019).

- **Bike-emerging:** is a city which has started to plan for cycling mobility but does not have a well connected bikeable network yet. This type of city is interested in understanding latent cycling demand (Lovelace et al., 2017), cyclists' use of the network in order to identify weak points of the infrastructure (Rupi et al., 2019) to improve the **networks overall connectivity**. The requirement is to increase connectivity of the network beyond the main destinations. Bicycle modal split is at a medium level as well as safety, whereas comfort and bicycle volumes are low.

- **Bike friendly:** is a city that has successfully attracted people to cycle and has a well-connected bicycle network. Bicycle modal split, safety and comfort are higher than bike-emerging cities. This type of city may want to increase mode share even more, by making multi-modal trips easier. The aim is to make the existing bike network even more **efficient** and **comfortable** to cycle on, by focusing on travel times, comfort, and integration with public transport (Pucher, J. and Buehler, 2007; Buehler & Dill, 2016; Centre for Public Impact, 2016).

- **Bike-dominant:** is a city where cyclists rule the streets. These places are so successful in attracting cyclists that they start to experience unforeseen problems in the bicycle world. The few cities that have reached this stage, like Amsterdam and other Dutch cities, are proof of a new type of urban cycling problem (city of Delft, 2019; De Groot-Mesken et al., 2015). The bicycle volumes and density levels, at some points of the network, are beyond the capacity of the bike paths resulting in a reduction in perceived safety and comfort. Cycle lanes are already in place, but more is needed to improve cycle flow, especially during rush hours. This situation relates to the vehicular world, where congestion and capacity problems have been an issue much earlier. New solutions are needed to **mitigate congestion** in the bicycle domain.

Our framework does not have the ambition to classify cities bases on their performance; it rather identifies clusters of BNNs and guides cities to find solutions and data collection methods that fulfil these BNNs. Note that each level of the pyramid presents the main BNN, meaning that a city may (and in fact should) also focus on other minor BNNs at the same time. For example, if one focuses exclusively on safety, a city may end up with a very safe cycle path between areas for which there is no demand. People will be stimulated in using the bike network only if they can go from their home to where they want to, by bike, that is to say, they also require higher-order needs of a well-connected network.

As a final remark, let us note that next to network-wide identification of needs, also more local identification of network pinch-points is possible. To breakdown the network-wide needs into link-level (i.e. road) needs a priority map is used; this map shows which links have the largest impact on the performance of a city network. To this end, a couple of intermediate steps should be taken, as illustrated in (Hiddink et al., 2017).

The local network needs can be identified via link specific set of functions and priority criteria (which lead to function maps and priority maps of a city). Three network link functions are defined:

1. Fast bicycle path: bundling connection of (commuter) traffic from external areas to specific prime locations, where a low travel time (or high speed) is decisive,

2. Main bicycle path: bundling connection between all prime locations, where facilitation of large traffic flows is decisive,

3. Bicycle paths: cycle paths where access to residential areas is the main feature.

The priorities are determined based on three criteria:

1. The number of preferred[2] routes on a link,

[2] Preferred routes are based on policy and route choice criteria. An example of policy statements could be “no main cycle routes through the city centre”.

2. The importance of the routes on a link (depending on trip purpose),
3. The magnitude of traffic flow on a link.

Per link, these three criteria are counted and combined to a priority ranging from one to six. The magnitude of actual traffic flows can be estimated or substantiated by data or models. For cyclists, public transport (with respect to the number of travellers) and pedestrians this is not always trivial due to lack of data and adequate models. Finally, policymakers may use a combination of priority maps and function maps to show where essential connections are located and prioritize network improvements. We refer to (Hiddink et al., 2017) for details and implications for monitoring.

3.3 Solutions for BNNs

This is the second step of the framework, which focuses on solutions that can help in reaching BNNs. We identify two macro-classes of solutions: *hardware* and *software* solutions (see Fig. 3.3). With *hardware* solutions we indicate physical infrastructure interventions such as construction or redesign of cycleways, whereas with *software* solutions we indicate digital infrastructure solutions such as mobile phone applications for route planning applications and demand-responsive traffic signal controllers. As a city grows in level of bicycle culture it shifts from predominantly *hardware* solutions to more *software* solutions, although the hardware still needs to be in place and maintained. As an example, a non-physically connected bicycle network will not achieve connectivity only by means of ICT solutions (route guidance apps can suggest more connected routes than the shortest route that one has in mind, but they will only tackle the BNNs to a small extent). On the other hand, software solutions like interactive landscapes do provide a solution to the need for more comfort in networks that have fulfilled the primary BNNs of basic and direct paths, safety-accessibility and connectivity.

In general, the distinction between hardware and software solutions is not so clear-cut, since most software solutions may require also hardware. Thus, our classification of the solutions in the following sections should not be seen as a rigid truth but as a hint to understand the distinctions.

This section provides a first attempt to inventory bicycle network solutions, found in the literature, based on the BNNs. The focus is on the infrastructure network solutions (expansion or improvement of bicycle streets). Other solutions from the land-use domain (such as urban density and mixed land-use to increase the number of different amenities found around each location) can also improve bikeability but are beyond the scope of this article. The following is by no means an exhaustive list of solutions but it is indicative of the range of options. Each sub-section introduces solutions from a level of the pyramid of needs (from bottom to top).

3.3.1 Solutions for basic and direct needs

Solutions at this stage of BNNs are mainly focused on identifying where new basic infrastructure should be located and building it. This will attract some people to cycle within the city. The main solution types are:

- **Build bike lanes and bike paths between main locations**: in order to cycle the pre-requisite is to have some well-marked streets for cyclists, possibly segregated from vehicles (*hardware* solution). The debate on where to start building bicycle infrastructure has developed the concept of potential for cycling, i.e. where cities have higher or lower potential demand so to encourage cycling (Silva et al., 2019). Good connections to universities and schools are known to attract students considered as forerunners for cycling in cities (Pogačar et al., 2020). Cycling potential demand is the required information (discussed in section 3.4) for the implementation of this and other solutions.

- **Bike sharing fleet**: provides access to bicycles with a pay per use system. This *hardware* solution enables people without a personal bike to cycle in a city and thus to use the infrastructure (Song et al., 2020). In addition, bike-sharing systems make large amounts of data available that can guide decisions on where to extend the bicycle network (Lee & Sener, 2020). Whether the data is owned by the municipality itself or by private bike-sharing companies makes the difference in how the information can be exploited.

3.3.2 Solutions for safety and accessibility needs

Increasing safety can be achieved by reducing the chance of a crash or the impact of the crash. The main interventions to improve safety and accessibility are:

- **Infrastructure re-design or car restrictions:** *hardware* solutions that reduce the chance of a crash while cycling are road, intersection, or public space redesign that allocate space for cyclists. Other solutions for residential areas and shared spaces are to limit the speed of cars or restrict their access.

- **Traffic signal:** A separate traffic signal for cyclists is a *software* solution that increases safety (as well as comfort) because cyclists have their own signal phase which reduces the conflicts between cars and cyclists or makes conflicts less severe.

- **Lighting:** Intelligent bicycle lights that increase visibility at night when a cyclist is approaching are another *software* solution to increase perceived safety.

- **Extension of existing links:** this *hardware* intervention aims at increasing accessibility to the existing bicycle network. Ultimately, more residents of a city will have access to more locations by bicycle.

- **Safe journey planner:** a *software* tool to plan a safe and comfortable route, avoiding roads perceived as dangerous for cyclists such as busy roads without appropriate bike infrastructure, tram tracks or cobblestones (an example is the route planner app of Ghent (BE)[3]).

- **Cooperative systems**: these are *software* solutions to allow communication between cyclists to vehicle (B2V)[4] or between a cyclist and roadside infrastructure (B2I)

[3] https://fietsrouteplanner.stad.gent/index.html?language=en_US

[4] various projects are ongoingly related to collaborative bicycle to vehicle (B2V) safety. Tome is an example of this: https://www.tomesoftware.com/b2v/#About

(Nikolaeva et al., 2019). This would reduce the risk of a crash by having the road users share location information among themselves and also gather data on crashes, and close collisions that can be used to redesign infrastructure.

3.3.3 Solutions for network connectivity needs

On one side cities should seek for overall connectivity of a network (i.e. all locations connected to all others), on the other they should not build superfluous infrastructure, between areas with little or no latent demand. The main solution types for connectivity needs are:

- **Increase network-connected components:** this *hardware* solution aims at connecting the incomplete and separate bicycle network. There is ongoing research on which network growth strategies to follow (Orozco et al., 2020); connecting the closest connected components, connecting the largest connected components, connecting areas with the highest demand, and connecting areas with wider streets are all possible solutions that urban planners chose depending on the city context.

- **City-wide network matching the latent bicycle demand:** Planning the network as a whole is another valid *hardware* solution, rather than as independent and disconnected projects. A systematic review of infrastructural interventions to promote cycling is presented in (Mölenberg et al., 2019), where the city of London is presented as an example of city-wide network extension.

3.3.4 Solutions for comfort needs

In order to achieve increased levels of comfort along a bicycle network, here are some solutions found in the literature as well as some common practices implemented by Dutch and Danish municipalities:

- **Route guidance app:** are a *software* solution that recommends comfortable bicycle routes to users. Many cities start to offer such applications that recommend routes based on distance and some other criteria that attempt to measure bicycle-friendliness or comfort. For example, one can select the quietest, fastest or a balanced route when cycling in the UK thanks to its journey planner[5]. How to measure the comfort of a bicycle route is an ongoing challenge. In section 3.4 we discuss the information needed for this type of solution. Let us note that, while it is acknowledged that cyclists choose their route differently to drivers of vehicles, also considering contrasting objectives (Ehrgott et al., 2012) it is not trivial to identify which is the most comfortable route when considering more than one objective.

- **Vehicle-actuated traffic control:** this is a *software* solution that activates traffic controllers based on bicycle and vehicular demand (Muller & De Leeuw, 2006). This is a well-established solution in many Dutch cities (as results show from our survey in section 3.7). A further improvement of this application could measure the bicycle and vehicular demand based on the number of people waiting by bike versus by car and prioritize the direction with the highest amount of people queuing.

[5] https://www.cyclinguk.org/journey-planner

- **Dynamic green wave adaptation:** green waves are common practice in some bike-friendly cities. The aim of this *software* solution is to synchronise consecutive traffic lights so cyclists do not need to stop at intersections, which increases comfort and decreases waiting times. Dynamic green waves can adapt the green wave to the cyclists' current travel speed (De Angelis et al., 2019).

- **Connection to Public Transport**: public transport agencies play a major role in facilitating cycling (McLeod et al., 2020). Efforts should start with a *hardware* type of solution of secure bicycle parking at major train stations and aim at integrating bicycle and public transport consistently across the network also with *software* type of solutions.

3.3.5 Solutions for congestion needs

As cities become bike-dominant, new solutions are needed to tackle the new (sometimes unforeseen) problems however there are not many implemented examples of these types of solutions. Bike-dominant cities are facing problems such as congestion and bike parking shortages that require new solutions for the bicycle mobility world. Hereafter we provide exploratory solutions tested in some bicycle dominant cities and ongoing research ideas. Since the bike-dominant type of BNNs are fairly recent and not spread worldwide, the solutions implemented are limited.

- **Intersection re-design:** intersections are points where flows from different directions meet and partition over the network. Both *hardware* and *software* solutions can be implemented. The city of Amsterdam, has developed a cone-shaped crossing for cyclists, which aims to avoid queue spillback effects by shortening and widening the shape of the queued cyclists[6]. Delay at intersections can also be reduced by guiding cyclists to queue closer together, as shown in the empirical study by Wierbos el al. (Wierbos et al., 2021). A *software* solution is to allow longer green phases at the traffic controller to discharge queued cyclists.

- **Parking advisory:** are digital signs used to guide cyclists to free parking spaces. This can help cyclists when parking is crowded to find a spot and keep the parking lot tidy. Some solutions guide cyclists (through digital signs on the street and applications) in finding a parking space for their bike [7].

- **Route guidance based on real-time bicycle level of service (BLoS):** for cities experiencing congestion problems route guidance apps should recommend non-congested routes, in contrast to guidance apps for emerging cities that focus on safe and comfortable routes (sometimes also the most popular among cyclists). To have a realistic picture of the quality level of a bicycle street BLoS is used. BLoS in bike-dominant cities should incorporate variables that describe the (real-time) bicycle traffic conditions based on factors such as flow, travel time and speeds (Kazemzadeh et al., 2020).

[6] https://bicycledutch.wordpress.com/2018/04/10/intersection-upgrade-a-banana-and-a-chips-cone/
[7] https://www.europeandataportal.eu/en/news/discover-p-route-dutch-bike-parking-application

3.4 Input information

Once a city identifies the solutions to fulfil its BNNs, the next step is to understand all types of information required before, during, and after implementing a specific solution. Information can be related to the current situation or a future scenario depending on the planning stage. In general, first observations of the current situation are used to assess the state of the bicycle infrastructure and network operation characteristics. Secondly, future demand or bike crashes can be predicted to decide on a network expansion (or change). The solutions we describe in the following subsection can be seen as observed information; however, it is also possible to predict many of these types of input information. In later stages, during the data requirement and data collection, some information may be discarded due to difficulty in measuring it with the currently available technology.

This section is divided into five subsections, containing the main information required as input for each level of bike network solution (from bottom to top in the pyramid of needs).

3.4.1 Information for basic and direct paths

A first step is to map the current routes cyclists can take. The following step identifies current and potential cycling trips. Based on the results of the two previous phases planners can identify important origins and destinations and use the map to see where links are missing. Hereafter we report the input information to execute this type of solution:

- **Origin – destination (OD) of trips**: this information enables the identification of cycling desire lines and the neighbourhoods of a city which have high potential to start cycling (Lovelace et al., 2017). This provides geographical information for the city from which planners can infer which locations need a convenient bicycle connection.
- **Cycling potential demand:** potential demand identifies where future bicycle trips may occur in a city, which may, or not, be observable yet. Cycling potential tools exist to extract bicycle desire lines (potential demand) information. Cycling potential tools use OD information or mobility data to explore the geographical distribution of cycling potential, at point, area, origin-destination, route or individual levels (the reader may refer to (Lovelace et al., 2017; Olmos et al., 2020; Silva et al., 2019), and reference therein).
- **Age and gender**: this demographic information can provide useful statistics on who are the potential cyclists of specific areas. By knowing such information a municipality can define long term strategic solutions to attract cyclists of specific user groups.

3.4.2 Information for safety and accessibility

Safety is measured by the chance of a crash (bike exposure) in combination with the impact of the crash. Accessibility is measured by the number of amenities that are reachable by bike. Hereafter we report the input information needed to improve safety and accessibility:

- **Bike-car collisions**: this information is needed in order to redesign and improve the safety of bicycle infrastructure. Bike-car collision records are usually a highly incomplete source of data due to the under-reporting of bicycle collisions especially when collisions are minor (Watson et al., 2015). Thus, this data points out major crash locations which may not always be the locations where cyclists feel most unsafe.

- **Bike-car conflicts**: conflicts are events that would result in a collision unless one of the involved parties changes behaviour (i.e. near misses). Using traffic conflicts as a proxy for safety diagnosis is becoming more popular since they are more frequent than collisions and they identify the preconditions that lead to collisions. Computer vision can detect such collisions as shown in (Sayed et al., 2013).

- **Bike only crashes**: or bicycle-bicycle crashes happen especially when there are large speed differences. Crashes can happen also with cyclists alone, when cyclists fall, because of poles or curbs, or uneven cycle paths. This information is crucial for infrastructure redesign.

- **Exposure data - volumes**: Bicycle (and vehicle) counts are necessary to measure exposure levels in order to assess risk. New cycleways can alter risk exposure by encouraging or discouraging travel via bicycle. Measuring exposure levels is fundamental especially in before-after studies. However, still many bicycle emerging cities do not collect bicycle counts, despite stating the importance of safety in bicycle planning (Grossman et al., 2019).

- **Residential, employment and activity locations**: geographical information on resident's household location, employment locations, and main activities in a city is needed to measure accessibility, and plan how to improve it. Besides accessibility to the network, information on residents' accessibility to a bicycle is important (Song et al., 2020).

3.4.3 Information for connectivity

The necessary information for network connectivity improvements are:

- **Trips**: more detailed demand data is needed, than just origin-destination to consider connectivity of all relevant destinations in a city. Knowing the trips of cyclists allows for the mapping of their movements over a network allowing for an understanding of route preferences. This information is essential in network growth decisions.

- **Physical network data**: is important to have an updated visualization of the bicycle network so to identify network growth strategies. Strategies can aim to increase the connectivity of subcomponents or the whole network.

- **Placement of new bike links**: this information is fundamental for extending connections of a bicycle network. It can be extrapolated based on diverse bike growth strategies available (Orozco et al., 2020) in combination with bicycle potential demand.

3.4.4 Information for comfort

To implement solutions for bicycle network comfort this information is worth collecting:

- **State of the infrastructure:** information on the infrastructure conditions (e.g. potholes) enables timely maintenance and repair of the infrastructure.

- **Position of cyclist**: having this information enables a wide variety of solutions. For example, knowing the position of an anonymous user approaching the intersection allows for the implementation of bicycle responsive traffic controllers.

- **Speed of cyclist**: in order to have more sophisticated traffic controllers, extra information about the speed of the approaching cyclists could be measured. The advantage for a cyclist would be to keep their current speed without the need to decelerate. For example, in (Dabiri et al., 2019) a speed advice system for cyclists is modelled so that the traffic controller learns the reaction behaviour of cyclists and adapts its future advice.

- **Queue of cyclists**: this information would be an improvement to dynamic traffic controllers willing to minimise the waiting time of the overall system. By incorporating the queue information they could weigh the incoming flows based on the number of users in the queue.

- **Bike density**: this information is extremely relevant for bike-dominant contexts. The Covid-19 pandemic urged for physical distancing, also while cycling and additional measures at intersections (Salomons, 2020). Thus density information has become extremely relevant during the Covid-19 pandemic as a measure of safety and comfort of users.

- **Emotions** this information can provide insight regarding the mood characteristics of cyclists at different places. To the author's knowledge, this information is currently not being collected by any municipality. However, by knowing such information a municipality can have an even more detailed level of service measure. By looking at low emotions planers may define and know when to trigger custom strategies to re-route, in space and time, bicycle flows so to ultimately mitigate congestion.

3.4.5 Information for congestion-free lanes

Some bicycle information that could be useful for congestion-free solutions are:

- **Queue of cyclists**: this information is useful to understand when there are spillover effects, and dynamically allocate longer green light phases to mitigate them.

- **Parking occupancy**: occupancy information of big parking lots is useful to guide users quickly to a free spot. This way a city makes better use of existing parking by distributing users where there is more available capacity.

- **Flow**: this information is useful for users to plan their routes. Real-time flow information is needed to develop apps that function similarly to Google Maps, Waze and other vehicular route guidance apps.

- **Bicycle level of service (BLoS)**: is a measure of on-road bicyclist comfort level as a function of a roadway's geometry and traffic conditions. This measure is used in bike-emerging cities to assess bicycle path conditions based on static street parameters (such as number of lanes per direction and path width) and the neighbouring vehicular traffic flow characteristics. However, for bike-dominant cities, BLoS can also incorporate information that describes the (real-time) bicycle traffic conditions based on factors such as flow, travel time and densities (Kazemzadeh et al., 2020).

3.5 Data requirements

This step of the framework translates the input information, needed for the solution, into specific data requirements. This phase determines the quality of the solution application. In general, the higher the quality of the data (in terms of accuracy, reliability, latency), the more costly the data collection will be, but also the higher the performance of the application. However, some applications may require lower quality data than others to perform adequately. For example, one may need travel times as input information. Depending on the data requirements travel time can be estimated daily, hourly, or per minute. If a city wants to re-route cyclists depending on current travel times on the network, having only daily data is not useful. In that case, per minute travel time information may be needed to have a realistic (close to real-time) description of road conditions. Another application is speed advice near intersections (Dabiri et al., 2019). Such a system requires detailed information on queue lengths at intersections and position information of the cyclists (as well as connectivity to inform the cyclist). Limited accuracy or too large latency would incapacitate the efficient functioning of the application.

This section describes the main data requirements to consider to translate the input information (step 3 in figure 3.1) into a data collection system (step 5 in figure 3.1). These data requirements can apply to different input information from the previous step. The choice of the data collection system (step 6) is bound to the data requirements identified in this step. We point out how the choice of the data collection system is not defined by the input information required but by the information combined with the data requirements (frequency, accuracy etc.).

- **Microscopic or macroscopic data**: depending on the information needed the data requirements will be per individual or aggregated.
- **Frequency of the measurements**: the closer to real-time the information needed the more frequent the measurement intervals
- **Data quality**: refers to the accuracy of the data (e.g. expressed as the relative error in the position, speed, etc.), the reliability of the data (the % of sufficiently accurate measurements), and the latency of deployment (how long does it take for the data to become available[8])
- **Representative of user population**: the more the information needs to be representative of the cycling population, the more the data needs to be collected from the total

[8]Note that latency also depends on the way the data is stored and made available to the application: while an intersection controller may have 'direct access' to the sensors, many applications involving travel time data will poll the information from a server.

amount of cyclists and not just by a sample. Fixed location sensors have the potential to detect all users in contrast to mobile phone apps or GPS systems which will realistically be downloaded only by part of the population. There is evidence that cyclists who use smartphone apps to record their bike rides have different riding and socio-demographic attributes compared to those who do not (Garber et al., 2019).

- **Privacy sensitivity**: when deciding to collect personal data, authorities involved need to consider the amount of privacy-sensitive data they can - and want to - collect. In some countries, organizations are compelled to protect these data and to have control over the protection. Meaning that one may decide to not store personal data, or process it (or aggregate it) in ways that make it less privacy-sensitive. If on one side cycling should not be excluded from the "smart" and digital innovation context of cities (Behrendt, 2016), we should not collect privacy-sensitive data without a real need.

3.6 Sensors and data collection systems

This last step of the framework translates the data requirements into sensors or data collection systems. Based on data requirements (step 4 in figure 3.1) and the input information (step 3 in figure 3.1) planners decide the data collection system. At this stage also the techniques for state estimation are decided so to extract the required information.

Table 3.1 provides an overview of the sensor technologies and methods in relation to the information they can derive. The optimal combination of sensors is highly dependent on the context, the data requirements defined in section 3.5, and the cost of the technology. As a fact, the choice of the sensing system highly depends on the cost of the technology. Municipalities have reported that specific radar systems are too costly and prefer induction loop sensors for permanent use. More expensive systems are typically used for temporary counts, however, it is less common for these technologies to be installed permanently. When accounting for costs a policymaker considers implementation costs, technology costs, maintenance and operation costs. Manual counts have a low technological cost but, in the long run, also may lead to high operational and data processing costs depending on the frequency and quantity of the data collection.

Depending on the application, the data can be used and not stored or stored for future assessments. If the storage is needed we have a data collection system if storage is not required we have a sensing system (strictly speaking). For example, a sensor for traffic control at the intersection collects data that is used directly, to give a cyclist green immediately if no conflicting traffic is present. The same data could be stored to see whether an intersection needs maintenance or improvement to the control systems. Some data collection techniques, like manual counts or surveys, are by default storing the data whereas others use digital sensors that do not necessarily store data. The type of data that are stored makes the systems more or less sensitive to privacy issues.

This section describes bicycle data collection systems contained in Table 3.1. The description of each data source will highlight the data requirements met (or not) by each sensor type and their limitations. For more details on emerging data sources for cyclists we refer the reader to (Lee & Sener, 2020; Willberg et al., 2021), which are the most updated review at the time of writing this article.

Table 3.1: Relation between main information type and data collection system. [a] two closely located sensors are needed to infer speeds. [b] occlusion errors have a negative influence on the estimation accuracy of this variable. [c] sensor can be placed at fixed location or on moving vehicles/bikes. [d] depends on the penetration of the technology in the population.

Data collection \ Information	Collisions	Conflicts	ODs	Trips	Position	Speed	Queue	Density	Flow	Age, Gender, Emotion
Travel surveys	□	□	■	■	□	□	□	□	□	■
Manual counts	■	■	□	□	■	□	■	□	■	■
Push button	□	□	□	□	■	□	□	□	□	□
Inductive loop sensor	□	□	□	□	■	■[a]	■[b]	■	■	□
Infrared sensor	□	□	□	□	■	■[a]	■[b]	■	■	□
Radar	□	□	□	□	■	□	■	■	□[d]	□
WiFi/Bluetooth sensor	□	□	□	□	■	■[a]	■[d]	■[d]	■[d]	□
GPS	□	□	□	□	■	■[a]	□	■[d]	■[d]	□
CDR mobile phones	□	□	■	■	□	□	□	□	□	□
Smart Camera	■	■[c]	□	□	■	■	■	■	■	■
Crowd sourced records	■	■	■	■	□	□	□	□	□	□

- **Travel surveys:** are a traditional way of collecting travel data for transport demand modelling. They are still widely used when other contextual information (i.e. household demographics, trip purpose etc.) needs to be revealed, besides the trip itself. The purpose and way these surveys are conducted have evolved in recent years as described in (Stopher & Greaves, 2007; Hoogendoorn-Lanser et al., 2015) and determines the frequency, accuracy, and representatives of this data collection system.

- **Manual counts:** are easy to implement and do not require expensive equipment. This is still the primary data collection technique in many places and is a good starting point to monitor cycling activity at specific locations for short durations of time (FHWA Federal Highway Administration, 2016). In bicycle emerging cities manual counts are of great value because they can spot anomalies and attributes of cyclists that the most advanced sensor can not detect. The downside is reliability, quality, and the labour cost of the observer. This data collection system has relatively cheap set-up costs, but in the long term can become labour-intensive and not salable for other software solutions such as demand-responsive intersections control. Therefore, manual counts can be a valid starting point for bicycle ignorant and emerging cities, but, once a city starts having higher flows or needs to have more long term counts it should consider automatic data sources - especially if there are plans to implement dynamic traffic controllers for bicycles.

- **Push buttons** are sensors that cyclists need to push to activate. Once activated, the presence of a cyclist is detected. This can be used to activate the green light for their direction. The push-button can also estimate the waiting time of the first cyclist that presses the button, if a log of the timing of the traffic light is stored. The data it collects is not representative of the waiting time of all cyclists that pass the intersection, but only of the first cyclist that approaches the intersection.

- **Inductive loops** detect metal objects (bikes) passing on top of it. A bicycle passing over an inductive loop temporarily 'occupies' it, by changing the magnetic field of a loop, approximately from the moment the front of the bicycle is on the loop until when the rear wheel is out of the loop. This is the individual occupancy. If one uses two loops it is possible to calculate density from the flow and the mean of the local speeds. The level of the queue in front of a red light can also be estimated with two loops and some estimation techniques (Reggiani et al., 2019). The data collected by the loop sensors is potentially representative of all the cyclists passing the intersection (since it is not an in-vehicle device which would inevitably have a selection bias), however, occlusion errors, which appear when two or more cyclists pass on the sensor at the same time, affect the quality of the measurements.

- **Infrared sensors** can detect the presence of a cyclist and estimate speed, flow, and densities similarly to inductive loops. The disadvantage is that they are sensitive to bad weather and do not distinguish between cyclists and pedestrians.

- **Radar technology** can be used for different applications, including presence, density and queue length estimation. The quality of the data may be affected if there are multi-modal users (e.g. pedestrians, cyclists, cars).

- **Wi-Fi and Bluetooth technology** works depending on how many cyclists have an active Bluetooth or Wi-Fi connection on their personal devices. With these sensors, it is possible to identify the flow. Depending on the number of fixed sensors located in the city it is also possible to infer trips of travellers through the network. The network occupancy (approximation of densities) can be estimated via the total number of detections at each moment in time. Furthermore, queues and speeds can be derived based on signals from two closely located sensors. A limitation of these systems is that if it is an area with cyclists and pedestrians it is not trivial to identify mode-specific signals, this has consequences on the data quality.

- **GPS** data collection techniques, can track people with a longer range of travel time and distance. GPS can be collected via mobile phone apps or by specific GPS sensors installed on bikes (bike-sharing companies usually install them on their fleet). This is considered more intrusive since cyclists have to be equipped with sensors and give away privacy-sensitive data. When using this data source one must consider the representativity of the data, given the bias of who uses GPS systems.

- **Call Dial Records (CDR)** is location data collected by cellular carriers when a mobile phone connects to the cellular network. From call records in a city, there is the possibility, depending on the accuracy, to reconstruct trips and OD demand (Olmos et al., 2020). Privacy issues and frequency of the measurements should be considered when comparing this data collection system to others.

- **Smart cameras** work as normal cameras combined with data processing algorithms. They can estimate traditional traffic flow variables such as the waiting time for cyclists, speed, flow and queue length. More sophisticated systems can estimate demographics such as gender or age as well as perform facial recognition which can indicate emotion. The limitations of this technology are related to privacy issues, which make it challenging to implement and non-attractive to users, who often have a negative perception of cameras and surveillance-related sensors.
- **Crowd sourced records** can collect a wide amount and variety of data. Depending on the platform functionality, a wide variety of community needs can be detected. There are platforms to report obstacles and barriers, collisions or near misses, as well as the perceived safety of cyclists. For example in the city of Utrecht, there is a website where one can indicate dangerous places or malfunctioning traffic lights [9].

3.7 Empirical evidence from bicycle friendly and dominant cities

In this section, we investigate the data collection and sensor systems deployed by Dutch municipalities and identify the uses of the systems. In the Netherlands, more than 25% of all trips is made by bicycle (National Institute for Public Health and the Environment, 2018). Based on the bicycle share of trips, kilometres cycled per inhabitant per day, and the fatality rates and non-fatal injury rates by distance travelled we can safely say that most of the cities in the Netherlands are bicycle-friendly (Pucher, J. and Buehler, 2007). However, even among the Dutch cities, some are more friendly and others more bike dominant (i.e. with higher congestion and high flow issues). More information on the respondent cities is provided in section 3.7.2.

The investigation shows common practices in bicycle-friendly and dominant cities. We focus on network intersections since these are the locations that predominantly affect network bikeability and where the Dutch municipalities have focused efforts in terms of data collection systems. The steps in the investigation were: 1) identify what data collection systems are deployed at intersections 2) what type of information is extracted from the data, and what software solutions are implemented based on the gained information. This empirical evidence, linked to the theoretical framework allows for an understanding of which levels of BNNs are being fulfilled. Moreover, by looking at the deployed sensors and solutions implemented we can identify if the sensors are used to their full capacity.

The secondary aim of this survey is to shed light on the deployed bicycle sensors in bicycle-friendly and dominant cities. The survey provides an unprecedented inventory of bicycle sensors used at major intersections. As a fact, it is not well known if the Dutch municipalities pose considerable attention to their bicycle sensor infrastructure, besides the well-integrated bicycle network infrastructure. Given the limited information that is available on best practices for monitoring non-motorized traffic (FHWA Federal Highway Administration, 2016), this empirical evidence also serves as knowledge (and best-practices) sharing between bike-friendly/ dominant cities, researchers, and city planners worldwide.

[9] https://www.utrecht.nl/wonen-en-leven/verkeer/verkeersprojecten/verkeerslichten/

3.7.1 Survey design

The survey was intended for experts that have knowledge on the use of bicycle sensors by Dutch municipalities. That constrained the respondent selection to Dutch municipality employees and consultants who work with and advise Dutch municipalities. The survey was directly sent to the members of Contact group Traffic Control Technicians Netherlands (Contactgroep Verkeersregeltechnici Nederland) and Traffic Control Technicians initiative (Initiatiefgroep Verkeersregeltechnici) and to some employees of SWECO, an engineering consultancy with experience in bicycle traffic control in the Netherlands, on the 19th of May, 2020. Next to this, the survey was posted on LinkedIn (a professional networking social media platform).

To keep the survey short and straightforward (so that respondents answer all questions) the study investigated six specific sensing technologies: push buttons, loop sensors, infrared sensors, Wi-Fi/Bluetooth sensors, smart cameras and mobile applications that can track cyclists. The first three sensors were chosen because they are considered to be the most common bicycle sensors in the Netherlands. The last three sensors were chosen as they belong to the group of new and innovative sensors, that have the potential to become more common in the future.

3.7.2 Survey respondents

The survey was closed on the 9th of June, 2020, having collected fifteen responses in 21 days. We linked individual respondents to the city or consultancy in which they worked (the survey explicitly asked to which city their answers related to). The municipality or consultants that responded to the survey are: *Eindhoven, Delft, Haarlemmermeer, Leiden, Almere, 's-Hertogenbosch, Den Haag, Utrecht, Amsterdam, Enschede, Haarlem, Overijssel (province), Zuid-West x(Rijkswaterstaat), Vialis, Witteveen+Bos*.

Information about the respondent municipalities/regions can be found in Table 3.2, including their number of inhabitants, surface area, bike share and cycling score. Clearly distinguishing which cities are bike dominant or friendly cannot be achieved easily without in-depth investigation on bicycle mobility citywide. However, a useful tool to have a rough indication of the bike culture within a city in the Netherlands is provided by the annual bicycle score assigned by the cycling union of the Netherlands (Fietsersbond, 2020), to which we refer the reader. We finally underline how other classifications of cities are possible and may differ based on the context, time of day, and the data collection method.

Together, the municipalities that responded are 3.7% of all Dutch municipalities yet they represent 17.8% (3 006 375 residents) of total Dutch inhabitants. All responding cities are considered large municipalities (with over 100 000 inhabitants) the cities that responded make up 11 out of 24 of the larger municipalities in the Netherlands. All the municipalities are considered to be *bike-friendly or -dominant* cities, with the distinction in classification dependent on the street and time of day.

The respondents are considered to be representative of the major municipalities not of the whole Netherlands. The two types of bias we identify are: 1) larger cities responded more than smaller ones and 2) inevitably cities that have a wide deployment of sensors are more inclined to respond than ones that don't have any sensors. Some respondents answered on behalf of the province of Overijssel and the South-West region of the Netherlands

(Rijkswaterstaat VCZWN). Within these areas, there are smaller municipalities, yet those responses are too generic to attribute these results to smaller municipalities. Conclusions based on the survey therefore should be drawn with caution. Meaning that the results may refer to the best-equipped cities in terms of bicycle sensors and data collection systems.

Table 3.2: Information about municipalities or areas that participated in the survey. Mode share was gathered from the Fietsberaad (Fietsberaad, 2010). The cycling score was retrieved from the cycling union of the Netherlands (Fietsersbond, 2020).

Municipality or area	Number of inhabitants	Surface area [km^2]	Bike trip share [%]	Cycling score [1 to 5]
Eindhoven	231 469	88.84	22	3.4
Delft	103 163	24.06	26	3.4
Haarlemmermeer	154 235	206.31	15	3.2
Leiden	124 899	23.27	31	3.4
Almere	207 904	248.77	19	3.4
’s-Hertogenbosch	110 790	39.98	18	3.7
Den Haag	537 833	98.13	18	3.3
Utrecht	352 866	99.21	20	3.4
Amsterdam	862 965	219.49	21	2.9
Enschede	158 986	142.72	25	4.1
Haarlem	161 265	32.09	24	3.2
Overijssel (province)	1 156 431	3 420.74	-	-
Zuid-West (Rijkswaterstaat)	-	-	-	-

3.7.3 Survey results

This section reports the main results from the survey and reflects on the extent to which the framework is implemented in practice.

Deployed sensors and data collection systems

Figure 3.4 shows that all responding municipalities stated that 80%-100% of all their signalised intersections are equipped with inductive loop sensors and push buttons. Two respondents, out of fifteen, stated that 80%-100% of all their signalised intersections are equipped with mobile phone-Bluetooth technology. Whereas, two cities reported between 1%-40% of all their signalised intersections to be similarly equipped. Three cities, out of fifteen, stated that between 1%-20% of all their signalised intersections are equipped with smart camera technology. Infrared and WiFi/Bluetooth technology has a lower adoption rate. Answers from the survey made clear that the most popular inductive loop sensor configuration is 2 or 3 sensors per direction. Having two or more sensors allows for the extraction of speed information, whereas one sensor can only measure flow. Only four cities out of fifteen reported having one sensor per direction as the most popular configuration.

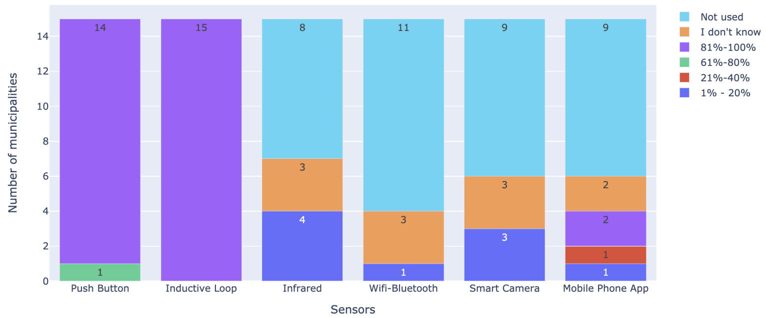

Figure 3.4: Percentage of intersections equipped with the various kinds of bicycle sensors.

Derived information and applications

Figure 3.5 summarises the information being extracted from the deployed sensors. The main action being taken upon bicycle detection systems in the Netherlands is automatic traffic control. All cities reported using vehicle-actuated traffic control but only one reported storing the data. Loop sensors, similarly to push buttons, are predominantly used for vehicle-actuated traffic control. Half of the respondents stated that they use loop sensors for flow, queue and waiting time estimation. Only two respondents, out of fifteen, reported estimating speeds. Mobile applications are mainly used for traffic control purposes, and to a lesser extent for flow, speed, waiting time and queue estimation. Smart cameras are used by one city for traffic control, as well as flow, queue, speed, and waiting time estimation. When asked if the municipalities are aware of being able to estimate certain variables, with the raw data they currently collect, yet not using them, two-thirds of the respondents said they were aware. However, when asked what additional variables they could collect, not all variables were always listed, indicating that there is some knowledge lacking.

	Push Button	Inductive Loop	Infrared	Wifi-Bluetooth	Smart Camera	Mobile Phone App
Used for traffic control	14	14	4	0	1	5
Measuring cyclist presence or absence	10	13	2	1	2	5
Waiting time (s)	4	6	0	0	1	2
Bicycle flow (# cyclists / time unit)	0	7	1	1	1	3
Queue (# cyclists between locations)	0	4	1	0	1	1
Speed (m/s)	0	2	1	0	1	2

Figure 3.5: Current information derived from deployed sensors at intersections. Mobile phone apps mainly work with GPS technology and when connected to traffic lights can request green as a cyclists is approaching.

How much of the framework logic is implemented?

To close the circle of reasoning, let us go from empirical evidence back to the theorized framework. Based on the results, it is remarkable to notice that almost all signalised intersections in the Netherlands have some kind of detection sensors for bikes, mainly for traffic control purposes. Based on the theorized framework, cities in the Netherlands are facing 'bike-friendly' and 'bike-dominant' needs. The results from the survey give an example of what bicycle-friendly and dominant cities focus on, it turns out that these cities are involved in developing solutions to deal with comfort and congestion. The main implemented solution, is bicycle-actuated traffic control, which addresses bike-friendly and dominant needs, such as travel time, comfort, and to a smaller extent also safety, showcasing cities higher up in the pyramid of bicycle network needs. Although vehicle-actuated traffic control is a well-established reality in the Netherlands, from our understanding, it is not based on speed nor the number of queued cyclists but the presence of one or more cyclists. The additional information could be used to implement more advanced solutions in bike dominant contexts. The survey shows that the sensor technology to estimate speed and number of cyclists is already being deployed (see Table 3.1) and that cities should develop new state estimation and processing techniques to capture this information. The proposed need-driven framework leads to a more systematic approach to identifying needs-solutions-information. Such a systematic approach helps in better exploiting the sensors, by identifying more information to extract in order to implement other solutions.

The results of the survey show that ICT sensing technology is abundant in all signalised intersections of major cities in the Netherlands in contrast to the small amount of derived information. For example, three municipalities are starting to employ smart cameras however, the survey did not show new employment of the data coming out from the cameras. Having a structured framework as we propose, would avoid redundancy in sensors and make sure that all additions to the data collection system enable derivation of novel information. Notwithstanding the importance of the findings, the survey is not without limitations. The survey results should be interpreted with caution because there might be a miss-alignment between the survey designer posing a question and what the respondent understands. Future research could consider semi-structured interviews with municipalities, as this would allow researchers to gain direct feedback on the understanding of the question from the respondents. More qualitative research should be carried out with a broader range of experts (also with experts outside the traffic controller domain), to gain more certainty on what actions are implemented based on the derived data.

3.8 Empirical evidence from bicycle ignorant city

In his section, we report the common practices of cities with lower levels of bicycle culture. As an example of a bicycle ignorant/emerging city, we refer to a case study in Melbourne Australia. Melbourne has bike trip share of 2% which shows some signs of bicycle use (so it is more than a bicycle hostile city) but still, the trip bike share is at low levels compared to other cities (Pucher, J. and Buehler, 2007). Moreover, a study revealed that traffic-related fatality and serious injury rates per kilometre travelled for cyclists in Melbourne are high in comparison with private motor vehicle occupants (Garrard et al., 2010). For these reasons, we consider Melbourne as a bicycle-ignorant city reaching towards a bicycle-emerging culture.

Through the analysis of the strategic cycling plans developed by the City of Melbourne (City of Melbourne, 2015), we can identify the type of data collection systems currently being used and the information derived from these systems to develop network solutions. Through this case study, common practices of a bicycle ignorant city are identified, while the benefits of the proposed BNN framework are highlighted. The focus of data collection in Melbourne and cities with similar LoBC is on infrastructure, parking, safety and facilitating connections to activity locations such as schools and shops (City of Melbourne, 2015). This section presents the data collection systems and information used in such cities to highlight their alignment with the proposed framework.

3.8.1 Data collection systems

Manual records of crashes involving cyclists are among the primary data collection systems in place in Melbourne. Police reported events are manually recorded and stored in an online database (Road Crash Information System (RCIS)). Hospital admissions and Emergency Department presentations are also reported. However, there are well-documented limitations with each of these data collection methods due to under-reporting, particularly of minor crashes and bicycle only cases (Boufous et al., 2013). Melbourne has a well-established household travel survey, which is used to monitor cycling participation and travel behaviour (Victorian Government, 2021). The data collection systems in household travel surveys are not specific to cycling, and collect information on all travel behaviour. While they do indicate mode share and user preferences, there are noted limitations due to sample size which limit data to aggregate analysis. Increasingly, manual counts of bike flow are being initiated across Australian cities (Bicyclenetwork.com, 2021). Events such as the one day "Super Tuesday" count are carried out by volunteers from cycling advocacy groups and provide a snapshot of cycling by collecting data along major cycling corridors and at key intersections (Bicyclenetwork.com, 2021). Inductive loop sensors represent somewhat of a novelty in bicycle ignorant cities. Melbourne has recently installed 12 inductive loops at key locations, increasing the network to 42 off-road and 4 on-road detection sites (Victorian Government, 2021). Bicycle inclusive cities aim to involve the community of cyclists to listen and fulfil their needs. For this reason, it is common to have a crowdsourced platform to report network failures and infrastructure improvement possibilities (Conrow et al., 2018). Finally, phone applications are used by some cities to log cyclist trips. The representatives of these data need to be taken into consideration, as most cyclists may not log all their trips, or only log longer trips more commonly associated with recreational riding (Jestico et al., 2016).

3.8.2 Derived information and use

The information that is captured in the aforementioned data collection systems in Melbourne pertain to safety and network improvements. Namely, the deployed data collection systems aim to identify unsafe locations, travel behaviour and bike use, missing connections in the bicycle network and improve parking needs. This information is used to develop and improve the physical infrastructure network (hardware solutions). This suggests that a city like Melbourne can be classified as an ignorant cycling city (in accordance with the framework presented in section 2), in that it strives to meet ignorant bicycle needs. The case study of Melbourne highlights the large amount of manual data collection which a bicycle ignorant city relies on. Manual counts in particular open debate on the objectivity of measurement. For cities that aim to reach a medium or high bicycle mode share, there is a need to have a long term and comprehensive overview of its bicycle networks, the needs of cyclists and solutions to address these needs. The framework presented in this manuscript aids in planning the data collection system that is required to meet the current and near-future needs of a city. The framework offers insight into the use and benefits of various automated data collection systems that provide objective measurement, which can be used for before and after evaluation of infrastructure and used to measure later stages of bicycle culture.

3.9 Discussion

The results of the survey and case study, linked to the theoretical framework and findings from previous works, allow us to showcase our framework. While bicycle ignorant and emerging city contexts have been widely studied in terms of network growth strategies and data collection systems, it was not known how bike-friendly and dominant cities make use of their sensors and data sources. In this section, we discuss the findings and suggest that the need-driven framework is a useful guide for bicycle network performance improvement.

In bike-ignorant and emerging cities data collection usually is not on the top priority of mobility commissions. These types of cities prioritise building fast and within budget bike lanes and neglect to plan a before and after intervention data collection plan (Mölenberg et al., 2019). However, these cities could highly benefit from data collection on the usage of the infrastructure and travel behaviour to prove the need for such space reallocation and investments. In Melbourne, this could involve investment in detection technology when new bicycle lanes are constructed, or intersections are upgraded. Bicycle ignorant cities focus on safety, origin-destination and trip data in order to create a strategic starting point for their cycling network (Silva et al., 2019; Lovelace et al., 2017). Only a few started to monitor flows, but not with automated sensors.

The survey carried out in the Dutch municipalities showed that in bike-friendly and dominant cities the collected data is mainly the presence of a cyclist. This is easy to measure with loop sensors and is the basic input for vehicle-actuated traffic controllers. Only a few municipalities estimate flows, waiting times, queues, and speeds at intersections. The reason for estimating only presence and not other traffic variables can be related to the higher data processing complexity, inaccuracy of loop sensors (e.g. errors due to occlusion), and a lack of knowledge on how to apply the new information. Although there are new sensing technologies deployed at intersections, as reported from the survey (e.g. mobile phone apps and smart cameras) the information extracted from these systems is the same as what is obtained from more traditional types of sensors, resulting in an underutilization of the new sensors. One limitation to the development of more advanced data applications evolving from smart camera data could be due to privacy issues. Thus more research is needed on privacy-preserving systems to fulfil new BNNs of municipalities.

Finally, the Netherlands is a bike-friendly nation (in certain places bike dominant) that is starting to face congestion problems on the bicycle network (city of Delft, 2019). This may suggest that one day, bicycle ignorant cities, like Melbourne, that are stimulating cycling today, will need to deal with the same issues the Netherlands is currently facing. Moreover, the recent Covid-19 pandemic has created a surge in cycling in cities and people transition to cycling rather than take crowded public transport (Kraus & Koch, 2020) and also increasingly engage in cycling as a recreational activity. This has seen cities needing to fulfil bike network needs faster than expected, particularly through “pop-up" infrastructure. However, this rapid increase in cycling hardware often occurs without planning and implementing the required software for data collection in accordance with the BNNs. The *first-mover disadvantage* theory suggests that other emerging cities can benefit, without necessarily copying, from the Netherlands. To this end, results from the survey should be interpreted with caution and each city should use the need-driven framework to identify its optimal combination of data collection systems as opposed to installing the same sensors deployed in Dutch cities.

3.10 Conclusion

In this paper, we proposed a *need-driven framework* which helps municipalities and research communities in identifying what sensor or data collection systems should be deployed based on the level of bike culture of a city (pyramid of needs). Via the pyramid of needs, cities can identify solutions and bicycle data collection systems that can improve their network performance (e.g. via design adaptation, deployment of traffic management schemes, ICT, mobility service provision such as share bicycles). Rather than using a technology-push approach, in which popular or easy to install technology is deployed, cities should follow a need-driver approach as suggested by the framework so to meet their bicycle network needs and make efficient use of resources.

Empirical evidence from the Netherlands and Australia reflects the logic of the framework, albeit further research is needed to explore hostile and ignorant cities. Previous works have reported that bicycle ignorant and emerging cities focus on origin-destination and trip data in order to develop a strategic starting point for their cycling network (Silva et al., 2019; Lovelace et al., 2017) and this is confirmed when reviewing literature from Melbourne. Whereas the survey to the Dutch cities shows that bicycle-friendly and dominant cities focus on comfort and congestion needs and collect different types of data, related to the real-time use of the network and its intersections. Results from the survey show that the main municipalities in a bike-friendly country use intersection sensing technology mainly for real-time bicycle-actuated traffic control, which we argue is a means to improve comfort - especially when bicycles are prioritized over other modes of transport.

This systematic overview on network needs, solutions, information, data requirements, sensors and data collection systems contributes to 1) identifying a starting point for data collection in bicycle-ignorant cities, 2) improving the synergy between needs and data collection systems, 3) using the deployed technology at its full capacity and 4) developing better traffic management solutions for bike dominant type of cities, based on (potentially) available data.

Chapter 4

Multi-objective bicycle network assessment

"The graphical method has considerable superiority for the exposition of statistical facts over the tabular. A heavy bank of figures is grievously wearisome to the eye, and the popular mind is incapable of drawing any useful lessons from it as of extracting sunbeams from cucumbers."

— Farquhar brothers

Chapters 2 and 3 investigated bicycle networks at the city-level scale, identifying structural trends and global needs, respectively. This chapter investigates and proposes how to evaluate a bicycle network at a city-wide scale, at a neighbourhood level, as well as only evaluating one origin-destination pair. In general, having a bicycle network that is fully separated from vehicular traffic is not realistic, even for top-performing cities. Thus, cycling in most countries entails switching between streets with differing lengths, safety, convenience, and comfort levels. As a consequence, the quality of bicycle networks should be evaluated by examining not one but multiple factors and by considering which factors are most important to the users.

Chapter 4 proposes a multi-layer and multi-objective methodology to assess bikeability per origin-destination pair and for the entire network, a technique that is useful for evaluating and planning bicycle networks. The methodology relies on the novel concept of bikeability curves, which are introduced in this chapter and which make it possible to assess how bikeable a network is for its heterogeneous users. Testing this methodology on two cities with very different bike cultures—Amsterdam and Melbourne—shows the effectiveness of bikeability curves in describing the most distinctive traits of these two networks.

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4.1 Introduction

Few cities have a fully connected network of separated bike tracks. Often, bike networks consist of a heterogeneous set of streets (including car streets) with various comfort and convenience levels. This forces cyclists to switch between networks with different comfort levels during their journey (as if they travel through a multi-layer network). Unlike drivers of private vehicles, cyclists choose their routes by taking multiple contrasting objectives into consideration, for example, they consider the distance and suitability of a bike route (Ehrgott et al., 2012) while also accounting for safety and comfort (Stinson & Bhat, 2003).

Cyclists have heterogeneous route preferences and therefore, one single route that is optimally bikeable for all individuals does generally not exist between an origin-destination (OD). For example, commuter cyclists might prefer a very short bike route with high discomfort while recreational cyclists might prefer a longer route that is more comfortable (Krizek et al., 2007). Many studies have successfully modeled cyclists' route choice behaviour and have reported findings concerning the average cyclists' route preference in terms of detour, facility type, travel time, etc. (Krizek et al., 2007; Menghini et al., 2010; Broach et al., 2012; Zimmermann et al., 2017). While the average behaviour is useful for understanding attractors and deterrents of cyclists in general, it does not provide a comprehensive picture of individual facets (since averagin blurs out the effects of diversity among cyclists). We think that network assessment tools should provide a full picture of what the network supplies means to all users, not only to the average cyclist. Since transparency and understanding of the network quality are key elements to decision makers we aim to provide a tool to evaluate the network free from user preference assumptions. It is then up to the policymaker to slice the analysis for a specific user type she wants to serve.

The heterogeneity of both the street network and of users' preferences motivates the development of a multi-objective methodology to assess the bikeability of a network. Having multiple objectives offers a more comprehensive evaluation (in terms of user heterogeneity) of the network, but also makes the evaluation more complex (Gholamialm & Matisziw, 2018). This work addresses this problem via a network-wide bikeability curve concept we elaborate on. The main contribution is to define an assumption-free methodology for assessing how bikeable specific OD pairs and the networks themselves are, by taking into account the heterogeneity of the streets and users' preferences. To this end, this work provides a multi-objective tool for city planners to study bikeability of specific OD pairs, neighbourhoods or a whole city network.

This article is organized as follows. Section 4.2 presents a literature review on bikeability assessment methodologies. Section 4.3 illustrates the proposed methodology. Implementation of a key component of our methodology (the discomfort function) is discussed in section 4.4. An application of the methodology is presented in section 4.5 via case-studies of Amsterdam, Netherlands and Melbourne, Australia. After discussing the applications of the proposed framework and implications for future research in section 4.6, the conclusions are presented in section 4.7.

4.2 Literature review

Answering the question "how easily can a person get to their destination by riding a bike?" is a non-trivial task in complex urban networks, while it is crucial for measuring the goodness of a bike network. In some previous studies, this question has been mostly answered by focusing on network structural properties and neglecting user preferences. For example, (Dill, 2004) explores a wide range of connectivity measures from various domains such as landscape ecology, geography, and urban planning. Whereas (Schoner & Levinson, 2014) and (Orozco et al., 2020) use network science to measure connectivity via indicators such as network completeness and the number of connected components. However, the comfort and safety of a bicycle network is a crucial component for its assessment, as it reveals to be an important factor affecting cyclists' route choices (Stinson & Bhat, 2003). For this reason, to assess urban bicycle networks, we refer to the concept of 'bikeability'.

Bikeability can be defined as the extent to which an environment is convenient and safe for cycling. However, a recent review of the existing literature shows that bikeability has been defined and assessed in several ways and the study concludes that there is no universally accepted definition (Kellstedt et al., 2021). Bikeability is the combination of objective and subjective factors and it integrates concepts such as bicycle comfort, bicycle suitability, bicycle friendliness, and bicycle accessibility. According to a review published in 2020 (Arellana et al., 2020) comfort and safety were the most common factors to construct bikeability indexes, around 96% of the reviewed studies included at least one of these factors. Lowry et al. (2012) present bikeability in relation to the scale of analysis and distinguish between suitability of a link and bikeability defined as the convenience and comfort of routes over the entire city network. In our work, bikeability focuses on the detour and type (or presence) of physical bicycle infrastructure, which can be regarded both as a comfort and a safety factor (Arellana et al., 2020). The scale of the assessment developed in this study is based on segment level measurements of length and comfort at a city- or neighbourhood-level analysis.

The concept of comfort introduces user preferences and the trade-off between directness versus comfort to the analysis. Cyclists have different route preferences: some may prefer direct routes, while others prefer more comfortable ones. Previous studies have made it clear that cyclists are willing to choose a longer route over the shortest path in order to ride bicycle-designated streets, i.e., more comfortable and safer routes (Sener et al., 2009; Larsen & El-Geneidy, 2011; Broach et al., 2012; Hood et al., 2011; Krizek et al., 2007). Detours depend on trip length (Larsen & El-Geneidy, 2011; Krizek et al., 2007) and cyclists who cycle regularly are less likely to use a bicycle facility (Larsen & El-Geneidy, 2011). On average recreational and afternoon cyclists tend to have larger detours compared to morning commuters (Krizek et al., 2007; Hyodo et al., 2000) thanks to fewer time constraints that allow longer travel times.

The average detour rates of trips range between 8% and 93%. In (Broach et al., 2012; Winters et al., 2010; Boisjoly et al., 2020), 50 to 75 % of observed trips deviate from the shortest route by 10%. Hood et al. (2011) analyse marginal rates of substitution and show that the average cyclist is willing to add a mile on bike lanes in exchange for only half a mile on ordinary roads. Evidence from Minneapolis states that on average cyclists travelled 67% longer in order to include a cycle path facility on their route whereas weekend cyclists are willing to cycle up to 40% more (resulting in 93% detour) (Krizek et al., 2007). Figure 4.1 manifests the variety amongst different cyclists and contexts when it comes to the willingness to make detours, which supports our motivation to define an assumption-free assessment tool.

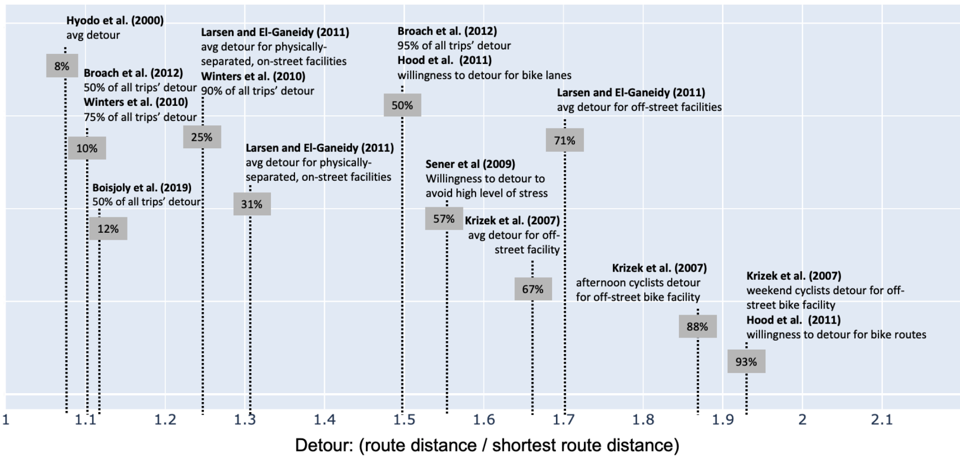


Figure 4.1: Overview of cyclists' detour behaviour and bike facility preference reported in the literature.

A well-known study that has incorporated the interplay between comfort and distance is (Mekuria et al., 2012). Mekuria et al. (2012) and studies following a similar approach (Furth et al., 2016; Lowry & Loh, 2017; Abad & van der Meer, 2018) define the preference of the users as an a priori specification of tolerance level of traffic stress. To analyse low-stress connectivity, these studies assume that a trip is connected at a certain level of stress if all segments of the trip are below that stress level and if the detour is below a fixed rate. These are a priori assumptions that may limit the analysis on specific user types. For example, one may be willing to accept a high-stress level for a small part of the trip to avoid large detours. Moreover, the accepted detour ratio depends on the user (different users may accept different detour ratios) and on the gained comfort. We believe that it is useful to observe how the network performs when assumptions on detour and comfort are not fixed, as fixing preferences a priori may obscure the complete picture of the network bikeability and results in an analysis that is highly dependent on the assumption parameters. In order to not make assumptions on the preferred comfort level of users, our work will not reduce bikeability to one aggregated value. Instead, we represent it as a set of bikeability curves that can be aggregated to analyse the quality of the entire city network. This allows us to analyse the network depending on all possible user preferences without the need to specify their behaviour beforehand.

Instead of using a generalised cost function, which requires a priori assumptions on users, we model route choice as a multi-objective behaviour. This allows us to also assess the network in an assumption-free method. Although a few existing studies (Ehrgott et al., 2012; Kang & Fricker, 2018; Wang et al., 2018) has used multi-objective criteria in route choice modelling no previous study, except (Gholamialm & Matisziw, 2018), has attempted to assess a bicycle network with it. The work of Gholamialm & Matisziw (2018) points out the higher complexity of analysing optimal route alternatives for multiple ODs compared to only one OD and addresses it with aggregated summary metrics which only reflect a partial picture of bikeability. Summary matrices are computed for one criterion at a time, meaning that they do not show the trade-off between the different criteria (see the method section in (Gholamialm & Matisziw, 2018)).

Our methodology extends the multi-objective bikeability assessment literature by providing a more general framework that avoids summary metrics, to observe bikeability depending on all the different user preferences. We tackle the increased complexity of multi-objective analysis by providing a methodology to build an average bikeability curve: an intuitive and visual instrument to evaluate a network. This work develops a methodology for the analysis and visualisation of bikeability that uses the shape of Pareto fronts (Khorram et al., 2014) to extract information. We validate and illustrate the use of our proposed method by assessing and visualising the network-wide bikeability of two cities.

4.3 Multi-layered bikeability assessment methodology

We do not assume that the users will—or in fact, can—always cycle on streets that do not exceed their tolerance of discomfort. For example, one could prefer separated cycle tracks (that have a low level of discomfort) but be willing to take a higher risk or discomfort and cycle along with vehicular traffic for a short part of the trip, if this avoids a very long detour. This is also because only separated cycle tracks will not—at least for many cities—make a pathway from an origin to the desired destination. Thus cyclists go through a multi-objective optimisation process to select their route comprised of cycling tracks and other types of roads.

In general, multiple objectives should be considered simultaneously for assessing a bicycle network. To name just a few we can consider: traveled distance, perceived safety, number of interruptions, and comfort. For a matter of simplicity, we illustrate our methodology for two representative costs: distance and discomfort. Distance is an objective factor whereas discomfort is a subjective, and complex factor to measure (Arellana et al., 2020). The methodology still holds for a wider set of objectives at the cost of less interpretability[1]. In the following paragraphs, we illustrate how the problem of assessing bikeability between a pair of nodes can be seen as a trade-off, between distance and discomfort, on a multi-layer network.

We claim that there is no universally accepted definition of what a bike network is. As (Mekuria et al., 2012) points out, there are two perspectives on bicycle networks: from a municipality point of view, a bike network is made up of any street where cycling is not prohibited, whereas, from a user perspective a bike network is a set of streets and paths that do not exceed the person's tolerance for traffic stress. We do not narrow down a bike network to only the separated bike streets where all users feel comfortable to cycle on. Instead, we include all the different streets, from most to least comfortable ones, by defining the bike network as a multi-layer network (see section 4.3.1 for the formal definition) where each layer represents a sub-network made of all roads with homogeneous discomfort. In a multi-layer representation (Boccaletti et al., 2014; Kivelä et al., 2014) of a bike network, a route

[1] For insight about additional complexity of multi-objective optimisation as more objectives are added we refer the reader to (Jakob & Blume, 2014)

becomes a set of links on a set of layers in addition to a set of links connecting the different layers. Figure 4.2 provides a visual representation of a route as a path on a multi-layered graph. A multi-layer network effectively shows the costs a cyclist incurs when cycling from

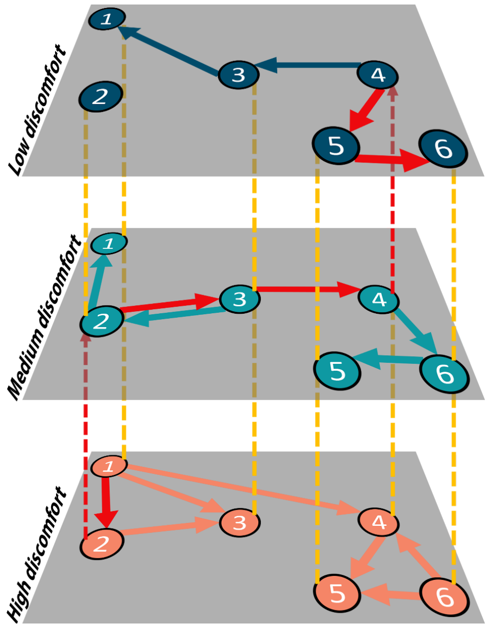


Figure 4.2: Example of a route from node 1 to node 6 using intra-layer links on different layers (solid links) and switching between layers represented by inter-layer links (dashed arrows).

an origin to a destination. This model allows us to generalize the discomfort cost of a route depending on the comfort level of the street segments that define the route and the number of changes between comfort levels. Thus, the discomfort of a trip can be defined as the sum of the discomfort of all the links and nodes in the path.

Hereafter, we first define what is meant by a multi-layer network (section 4.3.1), secondly we present route choice as an optimisation problem based on the concept of disutility (in section 4.3.2). Subsequently, the set of solutions to the route choice problem is identified by the Pareto front (in section 4.3.3). Using a modified Dijkstra algorithm the Pareto optimal (set of) bike routes that connect an OD pair are identified (section 4.3.4). Finally, we define the bikeability curves for one OD pair and for a network (in section 4.3.5 and 4.3.6).

4.3.1 Modelling the multi-layer network

The urban bicycle road network is modelled as a multi-layered directed network denoted by $G = (N, E, L)$, where N is the set of all nodes, E is the set of directed links and L is a set of layers. Each intersection i between the edges is represented by a single node $n_i^\ell \in N$, in each layer $\ell \in L$ of the network. Each link $e \in E$ can be denoted as an ordered pair $e = (n_i^\ell, n_j^{\ell'})$ representing a connection from node i in layer ℓ to node j in layer ℓ'. Intra-layer links $(n_i^\ell, n_j^\ell) \in E$ (i.e. connecting two nodes on the same layer) represent the real connections between different locations by streets of the same facility type. Inter-layer links only connect the corresponding nodes between different layers, i.e. $\forall e = (n_i^{\ell}, n_j^{\ell'})\ \ \ell \neq \ell' \Rightarrow i = j$. These links are used to model the change of facility type while cycling. In order to address the source node of a link, we introduce $\mathcal{S} : E \to N$ as the function that maps a link onto its source node. To address the layer of a link, we introduce $\mathcal{L} : E \to L$ as the function that maps a link onto the layer of its source node. Each link has a length and discomfort attribute which differs across different network layers. The length of an intra-layer link is the physical length of the street segment, whereas the length of inter-layer links represents the length of the "turning manoeuvre", and can be a few tens of meters, for a wide intersection, or set to a small but positive value, for an immediate transition[2]. The discomfort attribute of an intra-layer link models the impedance of cycling on the particular link, which is highly influenced by its facility type, whereas the discomfort of inter-layer link models the inconvenience of changing cycling facility type. Empirical data have shown that such a facility discontinuity implies 1) more diverse motion strategies of users, 2) speed reduction and 3) more maneuvers and braking compared to the control site (Niaki et al., 2018).

We define a directed path through the multi-layered network from node o to node d as an ordered sequence of links $\pi = (e_1, ..., e_{|\pi|})$, with length $|\pi|$, where e_1's source and $e_{|\pi|}$'s target are nodes o and d respectively. The total length of the path π is calculated as

$$D(\pi) = \sum_{e \in \pi} d(e),$$

where $d(e)$ is the length of the edge e. Similarly, the total discomfort of path π is calculated as a sum of path segment discomfort $r(e)$:

$$R(\pi) = \sum_{e \in \pi} r(e).$$

The segment discomfort $r(e)$ is the combination of edge and node discomfort:

$$r(e) = r_e(e) + r_n(\mathcal{S}(e)),$$

where $r_e(e)$ is a discomfort function that maps an edge e to a discomfort value, and $r_n(n)$ is a discomfort function that maps a node n to a discomfort value, which can, for instance, be used to model negative impact on cyclists route choice (due to deceleration, stop, waiting time to traverse an intersection (Ton et al., 2017)). We model $r_n(\mathcal{S}(e))$ to be always zero for the first edge that a person travels.

The methodology presented here is independent of the discomfort function. The only condition is that the discomfort should not be negative, since this could introduce cycles with a positive accumulated utility, which is not supported by our later introduced methodologies. Some examples of discomfort function specifications are reported in section 4.4, where we discuss viable implementations.

[2]Length should always be strictly positive for technical reasons (to prevent infinite looping of the path search algorithm).

4.3.2 Individual route choice model to define bikeability

In this section, we briefly touch upon route choice and utility theory to describe the individual route choice behaviour because bikeability should assess what the network offers, in relation to what the cyclist would choose. Thus, understanding how cyclists choose their routes guides us in defining the bikeability of a network.

Route choice modelers often represent user preferences via so-called (dis-) utility functions (Ben-Akiva et al., 2004). Each route has specific qualities or costs that result in a utility value perceived by the cyclist. Cyclists are assumed to be rational users, thus to be utility maximisers (or disutility minimisers). Without loss of generality, in this work we simplify route choice by assuming that route choice depends only on two major factors such as distance and discomfort[3] factor. The rational cyclist will typically identify the most bikeable route as the one with a distance-discomfort combination associated with the lowest disutility, as defined in (4.1).

The route choice problem can be seen as an optimisation problem where each individual will minimise its total disutility constrained to the set of feasible routes. Let us define Π as the set of all feasible routes from o to d, and let us define $C(D(\pi),R(\pi)) : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ as the cost function that maps a pair of total distance and total discomfort values to a cost value. Now, the individual route choice problem can be formally defined as:

$$\pi^* = \underset{\pi \in \Pi}{\operatorname{argmin}} C(D(\pi),R(\pi)). \tag{4.1}$$

The solution to the optimisation problem of Eq. (4.1) is depicted in Fig. 4.3 where we plot the iso-disutility lines (level sets of $C(D(\pi),R(\pi))$) and the feasible set of routes Π (as points) with respect to a linear utility function. Graphically, the optimal (most bikeable) route corresponds to the route laying on the iso-disutility line closest to the origin. Users might also choose non-optimal routes, we leave the investigation of indifference bands (Vreeswijk et al., 2013) in the field of cycling to future research (see the discussion in section 4.6).

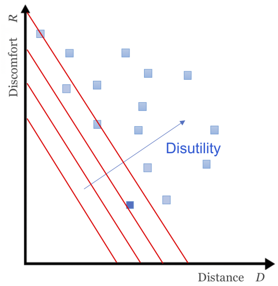


Figure 4.3: Solution to the route choice optimisation problem for one OD pair, in the case of linear cost function $C(D(\pi),R(\pi)) = \beta * D(\pi) + \gamma * R(\pi)$.

[3] Discomfort depends on many factors (both observable and non-observable) (Arellana et al., 2020), here we model discomfort as an ideal impedance value that one can measure to the best of its data availability. Later in the case study we will measure discomfort as presence and type of bicycle infrastructure (which is regarded by some studies as a comfort and others as a safety factor as reported by (Arellana et al., 2020)).

The shape of the iso-utility curves depends on individual preference and is generally not restricted to linear ones. Even if we would expect a linear cost function, the specific slopes of the indifference curves will differ between individuals. Figure 4.4, for example, shows different types of indifference curves reflecting the discomfort acceptance behaviour of cyclists. Depending on the indifference curve being used, the solution to the optimisation problem formulated by Eq. (4.1) is different, and consequently also the most bikeable route. In order to consider the entire set of individual optima, the following section introduces Pareto optimality.

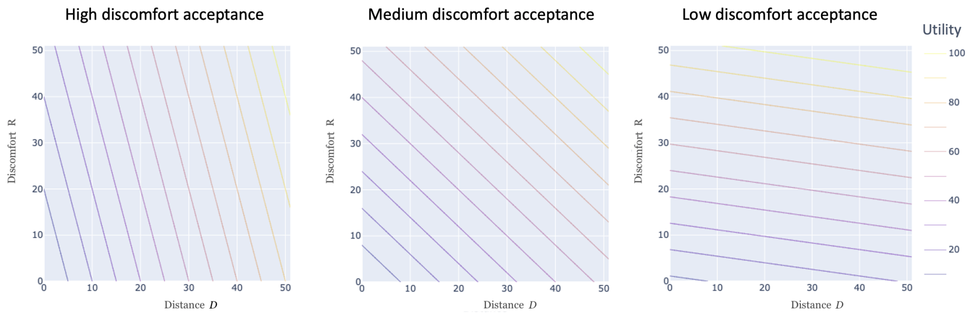


Figure 4.4: Indifference curves reflecting discomfort acceptance attitude of cyclists.

4.3.3 Pareto optimality

In the previous section, we described how the chosen route of a cyclist is assumed to be the solution to an individual optimisation problem, in which the cyclist makes a trade-off between the experienced discomfort and travel distance. The extent to which individuals prefer short trips over comfortable trips defines the shape of their indifference curves and herewith the route that they will select. As a result, one single route that is optimal to all individuals generally does not exist, which makes the definition of a bikeability measure in this context far from trivial. Since a bikeability measure should consider the different users of the system, the measure should somehow incorporate the entire set of individual optimal routes.

Although we cannot identify a global optimal route, we can simplify our analysis by making the assumption that individuals will never prefer a certain route over another one if this route is both longer and more uncomfortable (non-dominant alternatives). Formally, this assumption can be called the “rational cyclist" assumption and can be expressed as:

$$\frac{\partial C(d,r)}{\partial d} > 0 \text{ and } \frac{\partial C(d,r)}{\partial r} > 0. \tag{4.2}$$

This assumption allows us to identify the smallest sub-set of routes which is guaranteed to contain each possible individual-specific optimal route (according to (4.1)). This sub-set is called the Pareto-front and deals with the concept of Pareto optimality. Pareto optimality of a multi-objective optimisation problem is defined as a situation in which it is impossible to score better on one criterion without scoring worse on another criterion. The set of all Pareto optimal choices is called the Pareto front. In the next sub-sections, we briefly discuss

Pareto optimality and how this is applied to the route choice problem to identify the set of optimal routes.

Pareto optimality for route choice problem

In the context of the bicycle route choice problem on multi-layer networks, the concept of Pareto optimality is intertwined with the assumption that people will never prefer a route with a higher distance and discomfort (4.2).

Pareto domination of path $\pi^1 \in \Pi$ over path $\pi^2 \in \Pi$ is now defined as:

$$\pi^1 \leq_P \pi^2 \iff \begin{cases} R(\pi^1) \leq R(\pi^2), \\ D(\pi^1) \leq D(\pi^2), \\ R(\pi^1) < R(\pi^2) \text{ or } D(\pi^1) < D(\pi^2) \end{cases}, \tag{4.3}$$

and the Pareto front Π^* is defined as:

$$\Pi^* = \{\pi^1 \in \Pi \mid \nexists\, \pi^2 \in \Pi, \pi^2 \leq_P \pi^1\}. \tag{4.4}$$

As mentioned before, with assumption (4.2), the optimal route according to (4.1), is guaranteed to be in Π^* for each individual. This makes the assessment of the Pareto front a powerful methodology to study the bikeability of a network in terms of distance and discomfort.

We illustrate the aforementioned concepts in Figure 4.5. As an example, we use a 5x5 2-layer grid network. The two layers represent a very comfortable (green bordered layer) and uncomfortable (orange bordered layer) network. The intra-layer link weights (shown as ordered pairs of values), describe the length and discomfort of the links on the specific layer. The orange layer has a discomfort equals to the length of each link, whereas the green layer has a discomfort value of zero on each link. Thus, the total cost of moving on the orange layer is double the distance, whereas on the green layer the cost is equal to the distance. The only inter-layer links are between the same nodes, and, in this case, have zero length and zero discomfort value.

Finding all possible paths is a hard problem since there is an exponential number of simple paths (with respect to the size of the longest path). The scatter plot on the right shows 100,000 possible routes from the origin to the destination node. The routes were randomly generated excluding cycles (repeated nodes). Each route is a point on the distance-discomfort plane. Among the points, we color-coded the points on the Pareto front in red and joined them with a line. Note that in the example in Figure 4.5 only 7 routes, among the millions of possible routes, are optimal with respect to distance and discomfort.

The shape of the Pareto front, also called “bikeability curve" in the remainder of this paper, will be used as the main tool to assess the bikeability in the multi-layered network. The Pareto front is identified by a modified version of the Dijkstra algorithm presented in section 4.3.4.

4.3.4 Multi-objective shortest path algorithm

Finding the shortest path on a network for a single objective is a well-known problem, solved in an exact way using Dijkstra’s algorithm. In the presented methodology a multi-objective

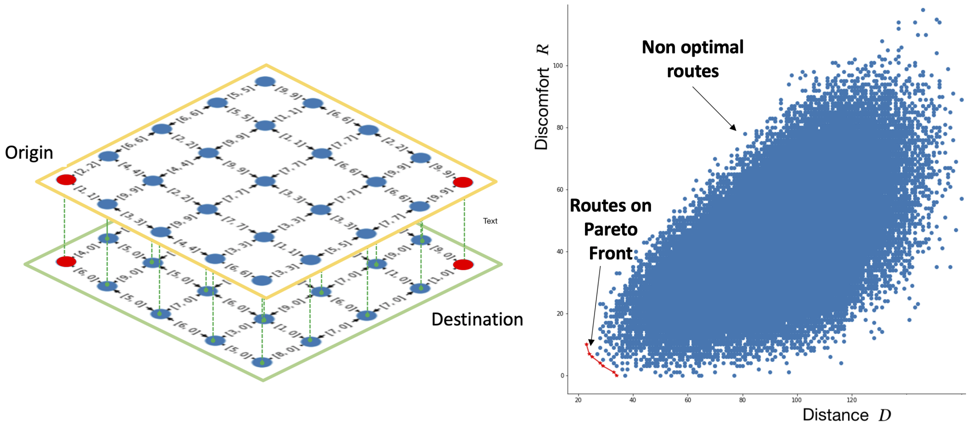


Figure 4.5: Pareto front on 5×5 *2-layer grid network.*

shortest path (MOSP) algorithm is needed since we want to minimise conflicting objectives of detour and discomfort. In literature, there is a wide variety of MOSP algorithms that work on the k-objectives optimal path problem. Algorithms can be classified as an exact, heuristic, approximate and meta-heuristic. In the field of transport, the 2-D problem was already addressed in 1979 in (Dial, 1979). The author describes an exact recursive method to find the Pareto front of a mode choice model in which cost and time are simultaneously being minimised. Another branch of exact methods to solve the MOSP problem is the family of labelling algorithms, in which lists of multi-dimensional labels are assigned to nodes, representing the set of non-dominated path costs (Hansen, 1980; Martins, 1984).

For our study, we implement a labelling algorithm in Python. The algorithm calculates the Pareto front for a given origin to all possible destination nodes. Since we applied our methodology only on small to medium-sized networks, we did not have to consider using more complex methods. For larger networks, the use of MOSP labelling algorithms can become infeasible due to the computation cost. For these cases, some exact methods have been developed, yielding a higher computational efficiency (e.g. (Raith, 2010; Duque et al., 2014)). Also, an approximate method could be adopted, in which approximately non-dominated paths are found, for more insight we refer the reader to (Garroppo et al., 2010). Given that the methodology presented can be generalized to more than two dimensions, for an extension of the multi-objective shortest path algorithm we refer the reader to (Ghariblou et al., 2017; Garroppo et al., 2010).

4.3.5 Definition of the bikeability curve

The bikeability curve, as presented in section 4.3.3, is the Pareto front of routes which minimise two costs imposed on cyclists when choosing a route, in our case those are route distance and route discomfort. For the sake of comparison between routes, we normalise distances and discomfort values as explained in the following paragraphs. This enables us to use this methodology on OD pairs with different distances and to compare the discomfort values across routes.

The relative distance, also referred to as circuity in the remainder of the article, is the route distance (sum of all path links) divided by the Euclidean distance. This measure, used also in (Schoner & Levinson, 2014), allows identifying if there are OD pairs connected by meandering routes, which may suggest the need for new road infrastructure. Note that using Euclidean distance as a denominator can penalise cities whose topography imposes inevitable detours (e.g. cities with canals and bridges) and cities with many short ODs, since the effect of a detour is less for long routes than for short routes. The aforementioned limitations should be considered when comparing different cities. The purpose of this measure is to “identify recreationally oriented routes that meander or circle back on themselves, versus routes that provide an efficient utilitarian connection for commuting" as pointed out in (Schoner & Levinson, 2014).

The relative discomfort is defined as the total discomfort of the route (sum of discomfort on all links of the route) divided by the Euclidean distance (in meters) of the shortest route. The resulting relative discomfort represents the discomfort per meter. This allows for a comparison between discomfort values among the alternative routes.

We use Figure 4.6(a) to explain the bikeability curve on the distance-discomfort space. Point (A), in Figure 4.6(a), represents the shortest route. The ordinate of route (A) shows the highest imposed discomfort on cyclists that seek to cycle the shortest route possible. Point (B) is the shortest route. Its relative discomfort value shows the lowest possible discomfort level to go from origin to destination. Whereas B’s relative distance value measures what is the imposed detour to have the least possible discomfort. Finally, an important measure on the curve is the trade-off rate (ToR) between any two routes on the Pareto front which is defined as $ToR = \Delta\text{discomfort}/\Delta\text{distance}$ between two routes. Ideally, the higher the trade-off rate, the more bikeable the network structure as it means it is easier to go on a more comfortable route with a small increase in path length.

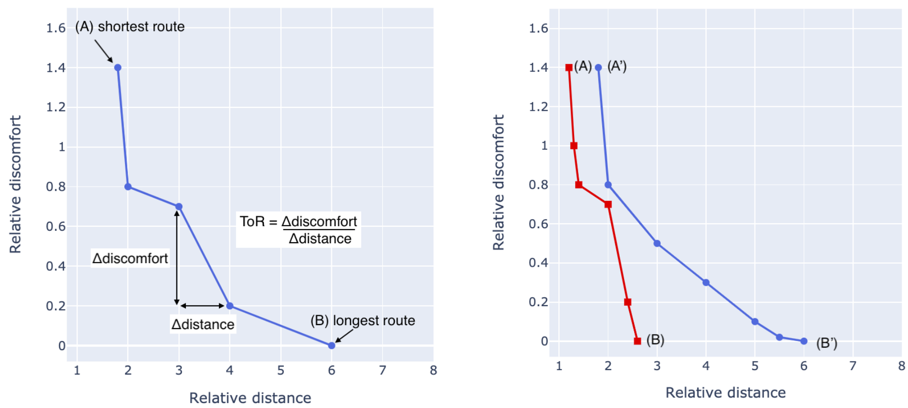


Figure 4.6: Interpretation of bikeability curves. (a) Extreme routes and trade-off rate are shown. (b) Provides an example of comparison between two bikeability curves.

Note that the curves defining Pareto optimal paths can be described by both convex and non-convex functions, where the convexity of the Pareto front depends on the convexity of the feasible set of routes (Brisset & Gillon, 2015). As an instance, in Figure 4.6(b) the blue curve is convex whereas the red is non-convex. If we place stronger assumptions on the utility function such as linearity, instead of assumptions 4.2, some Pareto optima would never be chosen from the users. We prefer not to make strict assumptions on user utility and keep the Pareto front more general.

The ideal bikeability curve, between an OD pair, should resemble a vertical line that reaches the lowest possible discomfort value and with a relative distance close to one. This would guarantee alternative routes that are almost equivalent from the distance aspect, but that offer different discomfort values, including low discomfort values. Moreover, the more routes there are on the bikeability curve, the better because it means that there are many optimally bikeable alternatives. In Figure 4.6(b) the red curve is considered as a better bikeability curve compared to the blue curve because the red curve reaches zero discomfort values with a much smaller distance increase, and has more alternative routes.

The result of the methodology is a curve that, combined with cyclists' route preference, shows what bicycle users' the network serves best. To interpret the bikeability curves the analyst should make use of findings on cyclists' actual behaviour and route choice preferences (see Figure 4.1 for an overview). This way policymakers are informed on which type of users their network is serving and can define improvement strategies to attract new cyclists.

4.3.6 Network-wide bikeability curve

There may be a variety of ways to interpret the bikeability curves and use them to evaluate the network bikeability of the whole city. We present an approach that incorporates all the different individual preferences (thus utility functions) and shows how bikeable the network is according to the different users. There are many ways to combine the Pareto fronts of all different OD-pairs into one single so-called network-wide bikeability curve. We will describe an approach that transforms the set of Pareto fronts into one single network-wide bikeability curve. This curve contains for all possible distance-discomfort trade-off choices, the expected distance, and discomfort of the optimal route for an OD-pair that is sampled from an OD-demand distribution.

For simplicity, let us assume that people have a linear deterministic cost function: $C_\beta(d,r) = d + \beta \cdot r$. Let us now imagine that we have an individual with a certain value of β. We assign this person to an OD-pair that is sampled from a predefined demand distribution w. Precisely, $w(o,d)$ equals the probability that an arbitrary trip in the network has node o as its origin and node d as its destination. We denote d^* and r^* as the distance and discomfort of this person's optimal trip for the selected OD-pair. Using the demand distribution, we can now express the expected distance $\mathbb{E}(d^*|\beta)$ and expected discomfort $\mathbb{E}(r^*|\beta)$, given a certain value of β, as:

$$\mathbb{E}(d^*|\beta) = \sum_{(o,d)\in N\times N} w_{o,d} \cdot D(\pi^*_{o,d}(\beta)) \tag{4.5}$$

$$\mathbb{E}(r^*|\beta) = \sum_{(o,d)\in N\times N} w_{o,d} \cdot R(\pi^*_{o,d}(\beta)), \tag{4.6}$$

where $D(\cdot)$ and $R(\cdot)$ are the distance and discomfort function respectively and $\pi^*_{o,d}(\beta)$ denotes the optimal path from o to d with cost parameter β, which can be calculated according to equation (4.1):

$$\pi^*_{o,d}(\beta) = \underset{\pi \in \Pi_{o,d}}{\operatorname{argmin}} C_\beta(D(\pi), R(\pi)), \tag{4.7}$$

with $\Pi_{o,d}$ the set of all paths between o and d. Similar to the single OD-pair analysis, we notice that it is impossible to express the expected distance and discomfort (i.e. bikeability) as a single point, because of their dependency on the discomfort-distance trade-off parameter β. In a comparable fashion as for the single OD case, we, therefore, define the network-wide bikeability curve B as the set of the unique expected discomfort versus expected distance points, for all possible β:

$$B = \{(\mathbb{E}(d^*|\beta), \mathbb{E}(r^*|\beta)) \,|\beta \in \mathbb{R}_{\geq 0}\}. \tag{4.8}$$

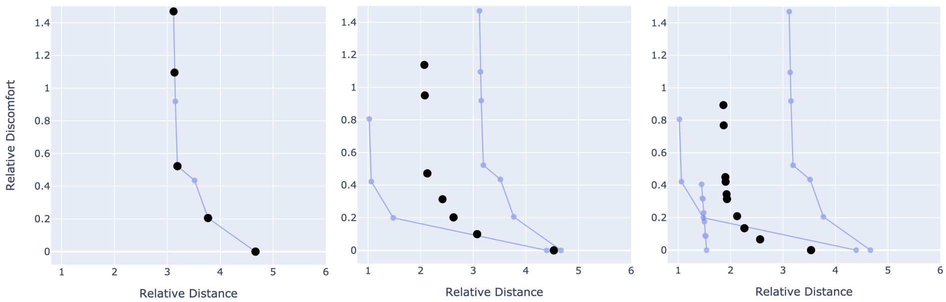


Figure 4.7: Building the network-wide Pareto front, for a generic users with utility: $C_\beta(d,r) = d + \beta \cdot r$. For this example we computed for values of $\beta = 1, 2, \ldots, 10$. In reality β will be computed for a wider range of values.

Figure 4.7 shows how the network-wide bikeability curve builds up starting from one curve and considering one additional curve for each iteration. An interesting property of this network-wide bikeability curve is that it is guaranteed to be convex. This is because we use a linear cost function, which makes that the distance-discomfort point of an optimal route is always in the convex hull of a Pareto front. We will not give the details, but it can be shown that the distance-discomfort aggregation (equations (4.5) and (4.6)) preserves this property.

Calculation of the network-wide bikeability curve

The first thing to realize when calculating the network-wide bikeability curve B is that the parameter space $\Pi_{o,d}$ from which to select the optimal path (equation (4.7)) can be reduced to the Pareto front $\Pi^*_{o,d}$ for origin o and d. To calculate the points in set B (equation (4.8)), we will briefly describe two methods. A simple approach, which is not guaranteed to be 100% correct, iterates over β with a sufficiently small fixed step, such that we expect to not “skip" a point in the curve. Although this simple approach does not guarantee to find all points in B, our case-studies indicate that with a small iteration step this approach is capable in revealing the true “shape" of B.

If networks become large and/or 100% coverage is required, a more advanced approach has to be considered. We realize that there is a limited number of values for β to be tested in order to be sure that we will find all elements of B. The main idea is to first identify the 'critical' values of β for each OD-pair, where a 'critical' value is defined as a value for β at which the optimal route changes. These 'critical' values can easily be determined in an exact way by matching them with the slopes between consecutive points in the Pareto front. Putting the 'critical' β values of all OD-pairs in one large ordered list, we can state that between two consecutive 'critical' β values, the result of (4.7) is guaranteed to be the same in the whole interval between these two values, so it suffices to evaluate only one single point in each interval. This calculation is guaranteed to provide the exact B. The choice between the simple and advanced approach boils down to a trade-off between computational time and accuracy. The advanced approach might become slow for very large networks, where the simple approach could still be computed in a reasonable time at the expense of a reduced resemblance of the true B.

4.4 Implementation of the discomfort function

Discomfort of a path consists of an edge component, expressed by $r_e(\cdot)$, and a node component, expressed by $r_n(\cdot)$. Practitioners aiming to implement this methodology can select the discomfort function specifications depending on the analysis they want to conduct. The only condition is that the discomfort has to be positive. Some examples of discomfort function specifications are presented hereafter.

Possible examples of edge discomfort function $r_e(\cdot)$ are:

- Distance travelled on the bike-unfriendly network:

$$r_e(e) = \begin{cases} d(e), & \text{if } \mathcal{L}(e) \text{ is a bike-unfriendly layer} \\ 0, & \text{otherwise} \end{cases}$$

- Number of facility changes. One could measure discomfort, or express a component of it, by counting the number of facility changes.

$$r_e(e) = \begin{cases} 1, & \text{if edge } e \text{ is an inter-layer link} \\ 0, & \text{otherwise} \end{cases}$$

  Certainly, one could also put specific weights on the different types of facility changes, which demands a deeper empirical insight into the experienced discomfort of all types of maneuvers.

- Accident risk, based on distance and road type. In this case, the discomfort function would be

$$r_e(e) = \alpha_\ell \cdot d(e), \qquad \ell = \mathcal{L}(e),$$

  where α_ℓ is a layer-specific constant that defines the accident risk per distance unit on layer ℓ and $d(e)$ is the exposure to the risk in terms of distance travelled. The accident risk α_ℓ will be different depending on the cities, their road regulation, and bike culture. Both the exposure and the probability of an accident can be functions of the volumes of bikes and cars on the streets.

A similar function can also measure discomfort proportionally to the distance travelled on bike infrastructure of different comfort levels. α_ℓ values will be low (close to or equal to 0) for bike-friendly layers and high for bike-unfriendly layers. This discomfort definition is similar to roadway stress used in (Lowry & Loh, 2017), which is a percentage increase in perceived travel distance.

- The discomfort function can depend on the demand (both at a OD or link-level). As a fact, too many cyclists on the same street segment can slow down the ideal speed of some cyclists and also create queues at intersections that may delay the departure of cyclists at a green light. The challenge to implement such a discomfort function is to obtain real-time estimates of crowdedness on bike streets. Many municipalities in The Netherlands employ inductive loop sensors for traffic signal controllers, through which we can estimate flows or queues in specific locations of the network (Reggiani et al., 2019).

- Bike level of service (BLOS) is an index that attempts to rank bike street segments based on perceived comfort and safety and can be a valid discomfort function for our methodology. For an overview of the methods, we refer to (Zuniga-Garcia et al., 2018) however a comparison on BLOS methodologies showed diverse scores of BLOS for the same street segment (Lowry et al., 2012). This shows that there is no agreement on how to grade a street level of service for bicycles.

Below is a list of possible examples of node discomfort function $r_n(\cdot)$:

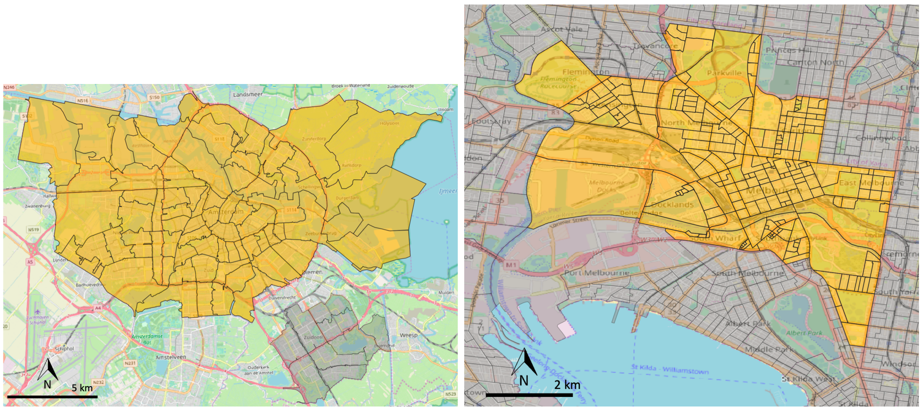
- Presence of a signalized intersections could be modeled as an impedance factor:

$$r_n(n) = \begin{cases} 1, & \text{if node } n \text{ is a signalized intersection} \\ 0, & \text{otherwise} \end{cases}$$

- Expected waiting time at intersections can be a realistic impedance factor of traversing a node.

4.5 Case study: Amsterdam - Melbourne

In this section, we give an example of how the proposed methodology can be implemented on real street networks and analyse bikeability results between two cities, Amsterdam and Melbourne, with very different bike cultures. We explain the data used for the case study in section 4.5.1. The bicycle networks are modeled and coarse-grained in section 4.5.2. The results from the bikeability analysis at city and neighbourhood level are presented in sections 4.5.3 and 4.5.4 respectively.



(a) Amsterdam (b) Melbourne City

Figure 4.8: City areas in analysis, the scale for each city is provided at the bottom-left of each map.

4.5.1 Areas of study and data sets

Melbourne and Amsterdam are selected to show an application of the methodology. These two cities have very different bike cultures, the share of bike trips in Amsterdam and Melbourne is respectively 27% and 2% (Pucher, J. and Buehler, 2007), which allows us to test if the methodology is able to explain the difference in bike culture from a bikeability point of view. For the network of the city of Melbourne, we consider “Melbourne city" area given the higher densities and consequently the higher bike-share compared to other parts of the city. Concerning the network of the city of Amsterdam, we remove from the network the “Amsterdam-Zuidoost" area since it is a disconnected component of the network. The resulting areas of the two cities are shown in Figure 4.8. The size of the two areas is significantly different however, this does not affect the comparison since route distances, in the analysis, are re-scaled according to the shortest distance available.

The case study uses the bike and car street networks made available from Open Street Map project (OSM). Such crowd-sourced and open access platforms provide an attractive and often up-to-date source of detailed data (Ferster et al., 2019). Although we are aware of tagging inconsistency, Ferster et al. (2019) report that OSM can be more updated than municipality records, given the higher frequency with which “the crowd" contributes to updating the OSM compared to the city releasing updated data. Moreover, we are aware of inaccuracies of OSM data such as missing links or disconnected components that in reality are connected. In order to not have bikeability results affected by these inaccuracies, we aggregate the urban bicycle network data (from OSM) to city zone level (described in section 4.5.2). Namely, two locations could be disconnected due to missing links in OSM, but if their respective zones have uninterrupted paths connecting them we assume that also the specific locations are connected. The benefit of using OSM data is evident for reproducibility reasons as well as ease of accessibility.

The travel demand between zones in Amsterdam has been computed based on the outcome of the learning-based transportation oriented simulation system (ALBATROSS) for the base year 2004 (Arentze & Timmermans, 2004). A detailed description of how the modified ALBATROSS data set (calibrated to match Amsterdam's mode split) was derived is available at (Winter & Narayan, 2019). After filtering out all trips that started or ended outside the city, intra-zone trips and trips with a distance larger than 10 km[4], the resulting passenger trips' data set included a total of 52,656 agents performing a total of 139,223 trips.

4.5.2 Modelling the multi-layer networks

We import the networks from Open Street Map (OSM) using OSMNx package available for python (Boeing, 2017). This data is available and easy to retrieve for many cities worldwide, which makes this analysis replicable in other cities as well. We will work with a coarse-grained city network (Hamedmoghadam et al., 2019), rather than the fine-grained urban bicycle network for two reasons: 1) to reduce the computational burden of working with large-scale networks, 2) to be less dependent on OSM inaccuracies, due to crowdsourced nature of the dataset.

Hereafter we explain the meaning of the nodes, links, and layers of the bike network. Given a graph representation of the urban bicycle network $G(N,E,L)$, we build a coarse-grained network $C(N',E',L)$ such that the structure and weights of the coarse network represent the structural characteristics of the urban bicycle network graph. The network is built with a granularity level of zones (statistical areas in Melbourne and postal code areas in Amsterdam). The set of layers remains unchanged when building the coarse-grained network.

Nodes

The coarse-grained network $C(N',E',L)$ has one node per zone per layer, corresponding to the centroid of the zone. This means that a node $n' \in N'$ corresponds to a set of nodes in N. To make this mapping explicit, we introduce $\mathcal{N} : N' \to \mathcal{P}(N)$ as the function that maps a node $n' \in N'$ in the coarse-grained network on the set of corresponding nodes in the original network.

Links

For each origin $o' \in N'$ and destination $d' \in N'$ in the coarse-grained network, and a layer $\ell \in L$, we define an intra-layer edge $e' = ((o')^\ell, (d')^\ell)$ if there exist an origin node $o \in \mathcal{N}(o')$ and destination node $d \in \mathcal{N}(d')$ in the original network that can be connected by a path that only uses nodes in zones o' and d' and edges on layer ℓ.

Each intra-layer edge (i.e. connecting two nodes from the same layer), has a layer-specific length and discomfort associated with the different network-layers. Inter-layer links exist only between the same nodes, and have zero weight associated to them. Thus a user can switch between layers with no discomfort cost via inter-layer links connecting the same nodes on different layers.

[4]We filter based on trip distance and not mode so to do an analysis not on the observed bicycle trips, but on the potential ones. 95% of cycling trips in the Netherlands are within 10 km, thus the exclusion of longer tips from this study (Schneider, 2021)

Layers

We import four network layers, corresponding to different OSM facility types. In particular, the four layers corresponds to the following facility type:

1. bike lanes and bike tracks, denoted as ℓ_1,
2. bike lanes, bike tracks and residential streets, denoted as ℓ_2,
3. all streets where cycling is allowed by city laws, denoted as ℓ_3,
4. car streets, denoted as ℓ_4.

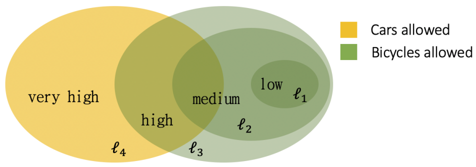


Figure 4.9: Diagram of the four layers and their related level of discomfort. To explain the difference between layers, the queries to retrieve these networks are reported in the Supplementary material.

We assume that the four layers have increasing levels of discomfort [low, medium, high, very-high] although some elements of one layer may be also included in another layer, as shown in the Venn diagram in Figure 4.9. This assumption is made for the sake of simplicity in this case study but can be released (if detailed data on comfort value per network edge is available) without loss of generality. The low discomfort links are contained in the medium discomfort layer and the medium discomfort layers are contained in the high discomfort layer (as green sets show in Figure 4.9), because if one tolerates medium discomfort, they can also tolerate lower discomfort links. The car layer includes both very high levels of discomfort as well as some streets with high and medium discomfort.

Edge Weights

Each intra-layer edge e' on a particular layer $\mathcal{L}(e')$ of the coarse-grained network has a length that corresponds to the average shortest distance, on that layer, between all nodes of the zones it is connecting. The average shortest distance is computed as the mean of all shortest paths between the two zones, without routing through any other zone as in the following formula

$$d(e') = \frac{\sum_{o\in\mathcal{N}(e'_1)}\sum_{d\in\mathcal{N}(e'_2)}\Delta(o,d,\mathcal{L}(e'))}{\sum_{o\in\mathcal{N}(e'_1)}\sum_{d\in\mathcal{N}(e'_2)}\delta_{o,d,\mathcal{L}(e')}}, \tag{4.9}$$

where e'_1 and e'_2 denote the source and target node of edge e', respectively. Reachability $\delta_{o,d,\ell}$ indicates whether or not node d can be reached from node o in the original network G, by using only intra-layer links in layer ℓ of neighbouring zones. It returns 1 if this is the case, 0 otherwise. $\Delta(o,d,\ell)$ represents the length of the shortest path between o and

d, using only links in layer ℓ of neighbouring zones. By the definition of e', this value is always larger than 0, since e' only exists if there is at least one direct path connecting o' and d' on layer $\mathcal{L}(e')$.

Each intra-layer edge e' on layer ℓ' has discomfort value corresponding to a predefined discomfort function. As reported in section 4.4 many discomfort functions can be defined as long as the value is always non-negative, in order to satisfy Dijkstra's algorithm requirements. For the sake of simplicity and interpretability of results, in this case study, we define the discomfort function as a percentage of the distance travelled on a specific layer (Lowry & Loh, 2017). In particular, we assume equally distanced sequence of values, between zero and one, for the percentage of distance to be considered as discomfort. The higher the discomfort on the layer, the higher the percentage of distance that is considered in the discomfort value, as reported hereafter:

$$r_e(e') = \begin{cases} d(e'), & \text{if } \mathcal{L}(e') = \ell_4 \\ 0.66 \cdot d(e'), & \text{if } \mathcal{L}(e') = \ell_3 \\ 0.33 \cdot d(e'), & \text{if } \mathcal{L}(e') = \ell_2 \\ 0, & \text{if } \mathcal{L}(e') = \ell_1. \end{cases} \tag{4.10}$$

Node discomfort attributes $r_n(e')$ are set to zero since it has no relevance to model node attributes for such a coarse-grained network.

4.5.3 City level bikeability assessment

Figure 4.10 shows the individual and network-wide bikeability curves for the two studied cities. The individual curves from the two cities perform quite differently, confirming the idea that in bike-friendly environments, like Amsterdam, the bicycle network provides more direct and comfortable routes. Almost all OD pairs in Amsterdam have a route alternative with zero discomfort, whereas in Melbourne not all ODs have a zero discomfort option and if they do it may require a very large detour. This means that no matter how much detour a cyclist is willing to take in Melbourne it will not always lead to a discomfort value close to zero. Overall, Amsterdam's curves are more vertically shaped, whereas Melbourne curves are more L-shaped, implying that in Amsterdam there is a larger discomfort decrease per distance increase than in Melbourne.

In addition to the individual bikeability curves Figure 4.10 shows the network-wide bikeability curve (in black) as presented in section 4.3.6. In this part, we assume uniform distribution over all selected ODs (note that this assumption may penalize some cities by considering low performing ODs although they have no bicycle demand between them). Note that strictly speaking the relative distance used by the bikeability curves is the route length divided the euclidean distance, whereas most of the results in the literature (as in section 4.2) use the detour which is route length divided the shortest available route. In order to compare these values, we multiply the detour values by the average street circuity of the city, so to compare the observed route circuity with detour values retrieved from the literature. The average street circuity of Amsterdam is 1.06 and it is 1.05 in Melbourne[5].

[5] The average street circuity was computed with OSMNx as the average ratio between an edge length and the straight-line distance between the two nodes it links

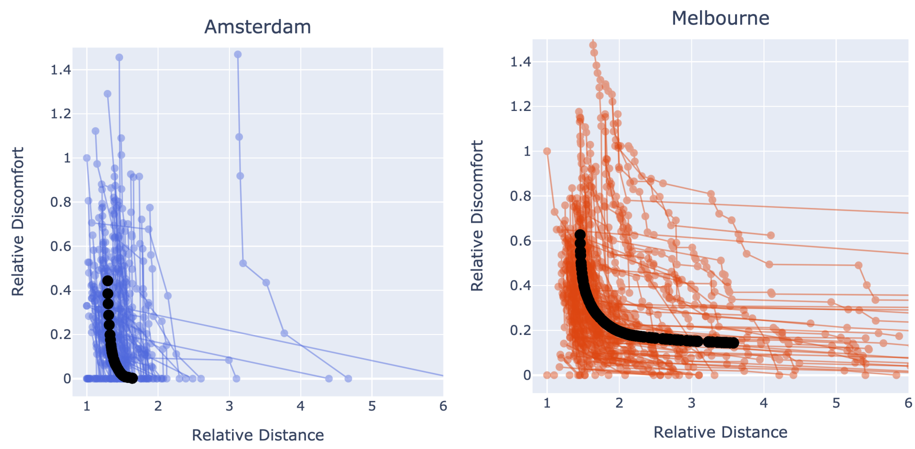


Figure 4.10: The red and blue curves are a subset of all individual bikeability curves for each city (one-hundred randomly selected OD pairs). The black points represent the network-wide bikeability curve computed over all OD pairs.

The average bikeability curve of Amsterdam shows that the average trip requires a circuity value between 1.28 and 1.63, from highest to lowest discomfort. This is in line with findings presented in the literature review in section 4.2, where detour varies between 8 and 93% (which multiplied by the street circuity of Amsterdam's network results in a route circuity of 8 and 98%). Amsterdam's average relative distances, for all discomfort levels, reflect detour preferences of both commuters and leisure type preference, thus it provides a network for a wide range of cyclists types, serving both high and low comfort seekers. Discomfort levels on average reach low (close to zero values) on trips with a circuity of 40 - 60%, given the overview in section 4.2 these are acceptable detour values for low traffic stress seekers and off-street bike facilities. Amsterdam's network-wide bikeability curve has lower values of circuity and discomfort compared to Melbourne.

Melbourne's network-wide bikeability curve, instead, includes trips with circuity up to three and a half times longer and does not reach discomfort values below 0.1. Evidence from revealed and stated preference studies, suggests that detour factors beyond 0.93 (which multiplied by the street circuity of Melbourne's network results in a route circuity of 98%) are not commonly accepted by cyclists (especially not by commuters). Hence, the trips most likely chosen by commuter cyclists in Melbourne are on the left part of the curve; with circuity below 0.9 and discomfort above 0.2. However, those trips do not serve low discomfort acceptance cyclists, since the left part of the curve does not reach zero values (meaning that routes entirely on bike dedicated facilities are not common). The right part of the curve in Melbourne has trips with a large increase of distance (beyond what is acceptable according to the literature (see section 4.2) and only minor reduction of discomfort. These route alternatives, on the right side of the curve, do not meet the needs of sporty cyclists or commuters (high discomfort and low detour acceptance) nor of weekend or afternoon cyclists that seek to cycle on off-street facilities (equivalent to discomfort value of zero) and detour smaller than 93% (Krizek et al., 2007).

Discomfort \ Circuity	1.00	1.20	1.40	1.60	1.80	2.00	2.20	2.40	2.60	2.80	3.00
0.00	0.03	0.13	0.39	0.62	0.76	0.83	0.87	0.89	0.91	0.93	0.94
0.20	0.03	0.21	0.59	0.79	0.88	0.92	0.94	0.96	0.96	0.97	0.97
0.40	0.03	0.31	0.7	0.88	0.94	0.96	0.98	0.98	0.99	0.99	0.99
0.60	0.03	0.36	0.75	0.9	0.95	0.98	0.99	0.99	0.99	0.99	1
0.80	0.03	0.38	0.77	0.91	0.96	0.98	0.99	0.99	1	1	1
1.00	0.04	0.39	0.78	0.92	0.97	0.98	0.99	0.99	1	1	1
1.20	0.04	0.39	0.79	0.93	0.97	0.99	0.99	1	1	1	1
1.40	0.04	0.39	0.79	0.93	0.97	0.99	0.99	1	1	1	1
1.60	0.04	0.39	0.79	0.93	0.97	0.99	0.99	1	1	1	1
1.80	0.04	0.39	0.79	0.93	0.97	0.99	0.99	1	1	1	1
2.00	0.04	0.39	0.79	0.93	0.97	0.99	0.99	1	1	1	1

(a) Amsterdam

Discomfort \ Circuity	1.00	1.20	1.40	1.60	1.80	2.00	2.20	2.40	2.60	2.80	3.00
0.00	0	0.01	0.02	0.04	0.06	0.08	0.09	0.1	0.12	0.13	0.14
0.20	0	0.03	0.16	0.36	0.48	0.55	0.6	0.63	0.65	0.67	0.68
0.40	0	0.06	0.36	0.61	0.72	0.77	0.81	0.83	0.85	0.86	0.87
0.60	0	0.08	0.47	0.72	0.82	0.87	0.89	0.91	0.92	0.93	0.93
0.80	0.01	0.09	0.52	0.79	0.88	0.91	0.93	0.95	0.95	0.96	0.96
1.00	0.01	0.1	0.53	0.81	0.91	0.94	0.96	0.97	0.97	0.98	0.98
1.20	0.01	0.1	0.54	0.82	0.92	0.95	0.97	0.98	0.98	0.98	0.99
1.40	0.01	0.1	0.54	0.83	0.92	0.96	0.98	0.98	0.99	0.99	0.99
1.60	0.01	0.1	0.54	0.83	0.93	0.96	0.98	0.99	0.99	0.99	0.99
1.80	0.01	0.1	0.54	0.83	0.93	0.96	0.98	0.99	0.99	0.99	0.99
2.00	0.01	0.1	0.54	0.83	0.93	0.96	0.98	0.99	0.99	0.99	1

(b) Melbourne City

Figure 4.11: Network Bikeability tables. Each cell shows the percentage of OD pairs (over all the possible OD pairs) that offer at least one route with discomfort and circuity both lower or equal to the value reported on the column and row header respectively.

Bikeability tables

In order to have a more systematic approach to interpret how bikeable the network of a city is we build the bikeability table as in Figure 4.11. In each cell we report the percentage of OD pairs (over all ODs in the network) that offer at least one route with discomfort and circuity both lower or equal to the value reported on the column and row header respectively. The bikeability tables (in Figure 4.11), show that the two cities offer a different ratio of routes with zero discomfort value, across all circuity values (first row of the tables). Zero discomfort value (as defined in the "edge weights" section 4.5.2) means that the entire trip is on bike tracks and bike lanes streets (resulting in no increase in perceived travel distance). For example, in Amsterdam 83% of OD pairs are connected with maximum circuity of 2. In Melbourne, instead, only 8% of all the OD pairs are connected with zero discomfort and maximum circuity of 2. By considering the ratio of routes within a circuity of 1.20 we observe that Amsterdam has 13% of ODs with zero discomfort, 21% of ODs with discomfort below or equal to 0.20, and 31% of ODs with discomfort below or equal to 0.40 whereas Melbourne respectively has 1%, 3%, 6% of ODs. The analysis makes clear that a higher percentage of Amsterdam's routes has a low discomfort value, compared to Melbourne's, given the same circuity factor. Meaning that on average Melbourne serves only low comfort seekers whereas Amsterdam serves both low and high comfort seekers, within acceptable detour rates.

4.5.4 Inclusion of travel demand

This section analyses how the bikeability curve changes when travel demand on the network is considered. Namely, how well does the network accommodate observed and potential bicycle demand? Increasing connectedness per se can be a waste of resources if there is no demand between two specific zones.

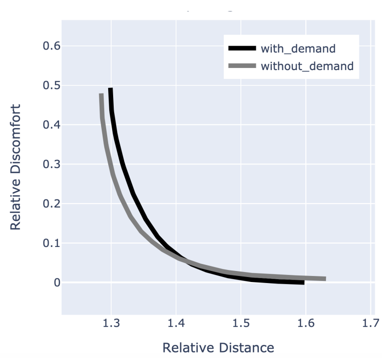


Figure 4.12: Comparison between average bikability curve of Amsterdam, with and without demand.

The demand is used to define probability values to weigh each OD pairs (zones) in the network. Including the demand shows a less bikeable average bikeability curve of the whole city. In Figure 4.12 the curve weighted on travel demand between zones has higher discomfort values for detour until 1.4, meaning that there is more demand between zones of a city that are not as comfortable nor as direct. There is space for improvement on how the network accommodates demand, especially with regards to the users that do not want to detour more than 40%. Instead, the demand-weighted curve performs better for larger detours values. The overall differences between the analysis with and without demand, at city level scale, are minor. A similar analysis was conducted on a smaller portion of the network, to identify differences within the same city.

Neighbourhood level bikeability assessment

In this section we showcase how the methodology can be applied to areas within the same city. This allows to compare areas with the same road standards (e.g. cycling rules and culture). The analysis focuses on north, centre, and south of Amsterdam, as delimited in Figure 4.13(a).

Analysing the zones without demand (dashed line in Figure 4.13(b)). The centre is serving confident and sporty cyclists better, than the vulnerable or commuters that don't accept high discomfort. In order to cycle with low discomfort in the centre, higher levels of circuity are needed, which makes the low discomfort routes in the centre more suitable for recreational cyclists than commuters, according to findings in section 4.2. The north part of the city has more direct routes for lower discomfort levels, thus this part of the city serves another type of user compared to the city centre: those who like separated facilities and low detour. Finally, the southern sub-network performs worse, in terms of bikeability, than the centre and north on average. However, for circuity values greater than 1.40 it offers lower discomfort and lower detour rates compared to the centre.

Once the demand is used to weigh bikeability curves (solid lines in Figure 4.13(b)) the average curve of the north improves, meaning that the travel demand is concentrated between zones that have better (more direct and comfortable) routes. The centre and south, instead, perform worse when the curves are weighted with the demand. This shows that

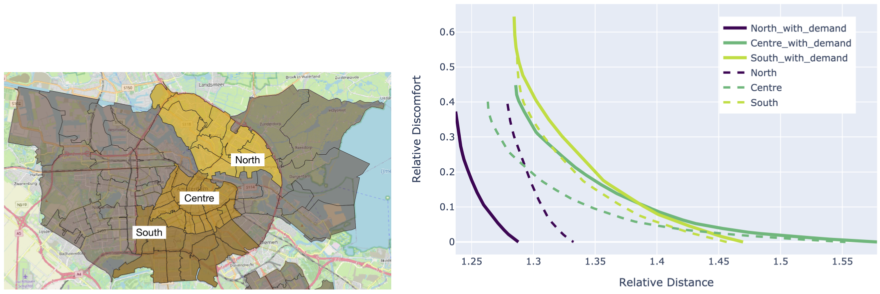


Figure 4.13: Comparison between average bikability curve of north, centre, and south neighbourhood of Amsterdam, with and without demand. (a) Neighbourhoods under analysis. (b) Neighbourhood-wide bikeability curves.

the ODs with high concentration of trips, in the centre and south, are not the most bikeable ones. Speculating on the reasons for the better performance of the north compared to the south, when demand is added, we think it is more the infrastructure type (thus comfort level) rather than the circuity to make the difference. If we observe the infrastructure type of the OD pairs with the highest demand we see that the North has more kilometers of medium discomfort (ℓ_2) infrastructure and less of high discomfort (ℓ_3) infrastructure, compared to the south which has less medium and more high discomfort infrastructure. The inclusion of travel demand in the analysis has shown to have an important effect on the results of the analysis and thus for decision making, since the outcome of the analysis shows substantial differences between the zones.

4.6 Discussion

This section discusses possible applications for practice as well as implications of the proposed methodology for future research. Finally, we acknowledge the limitations related to our methodology.

The presented methodology enables cities to make trade-off analysis for bike network infrastructure. For example, a city may want to improve bikeability among popular origins and destinations. By examining the bikeability curves associated with different OD pairs city planners can pinpoint the locations that need to be better connected for cycling. Then, the improvements can be made by reducing detour on routes with low discomfort or by reducing the discomfort on routes with a low detour. Besides using the proposed methodology to assess the bikeability of existing routes, urban planners can also use it to evaluate and prioritize investments. For example by prioritizing projects that improve the bikiability of the worse performing ODs (according to the OD bikeability curves).

The proposed methodology to assess the bikeability of an OD pair can be employed by bicycle route planner apps. There are two main limitations in this regard: 1) computational time is far from real-time route guidance and 2) the user should know its trade-off profile. The first challenge is being investigated by (Hrncir et al., 2015, 2017). For the second point, since it is not realistic for cyclists to know their willingness to detour and accepted discomfort quantitatively, one option is to include a stated preference survey to users of the app to quantitatively measure their trade-off profile and recommend them specific routes from all those on the Pareto front.

Users might choose non-optimal routes, ones that lie at a band-with from the indifference curve with maximum utility. Studies in the transport field have developed the idea of indifference curves into indifference bands (Vreeswijk et al., 2013). Future research could generalize the bikeability curves to bikeablity bands by investigating to what extent cyclists are aware of routes on the Pareto front.

We identify two limitations, which do not reducing the validity of the methodology but may represent challenges in the implementation phase. First, the availability of data on discomfort and safety on a network level is not easily accessible. In our case study, we made use of OSM facility types as a proxy for discomfort. However, the discomfort and safety of bicycle facilities can be highly context-dependent. For example, these attributes are influenced by the presence of on-street parking, the volume, and the speed of vehicular traffic, as well as local traffic laws. Secondly, the computational burden of working with large-scale detailed networks, is a concern for network-wide implementation. At this point, high-level analysis on coarse-grained networks is more feasible than on fine-grained ones.

4.7 Conclusions

This work introduced a new methodology to assess bikeability of urban networks free from user preference assumptions, so as to provide an exhaustive overview of what routes the network supplies to its users and not the average cyclist. Bikeability is visualised and analysed through the concept of network-wide “bikeability curve" elaborated in this work. The methodology has shown to provide means to study the relationship between directness and comfort of routes over an entire network by modelling the heterogeneity of streets that build up a bicycle network and not making a priori assumptions on users’ preferences between contrasting objectives.

Via a case study, we analysed and compared different bike networks based on large-scale real-world topological data, and showed the validity of the proposed methodology. Amsterdam’s bicycle network showed to supply users with more direct and comfortable routes compared to Melbourne which on average supplied trips with a significantly longer detour for low levels of discomfort. An application to neighbourhoods within Amsterdam showed that different parts of the city accommodate different types of cyclists, the centre is more for recreational and high detour acceptance cyclists, whereas the northern part has more direct routes, preferred by commuter type of cyclists. The inclusion of travel demand in the analysis has shown to have an important effect on the results of the analysis and is crucial for decision-making for network improvements.

The methodology presented in this paper can be of interest to transport planners and policymakers to understand and evaluate urban bicycle networks without making assumptions on user preferences. Planners will gain extensive insight into the bicycle networks by identifying which type of users (high discomfort acceptance or high detour acceptance users) are better accommodated by the network and which origin-destination pairs need to be prioritised for an infrastructural improvement. The generalisability of the methodology allows practitioners to apply it in different scenarios, depending on their data and network evaluation criteria.

Code availability

A working example of the code is available at: https://github.com/giuliaregg/UnderstandingBikability

4.8 Supplementary material

Hereby we report the queries used to extract the bicycle network layers (ℓ_1, ℓ_2, ℓ_3, ℓ_4) in section 4.5, using the python library OSMnx (imported as "ox"). To install and use the OSMnx package we refer to the decriptive paper from the author of the package (Boeing, 2017).

ℓ_1 is defined as:

```
G_1=ox.graph_from_place(place, retain_all=True, custom_filter='["
    highway"~"cycleway|path|living_street"]["bicycle"!~"no"]')
G_2=ox.graph_from_place(place, retain_all=True, custom_filter='["
    cycleway"~"lane"]')
L1=nx.compose(G_1,G_2)
```

ℓ_2 is defined as:

```
G_1=ox.core.graph_from_place(place, network_type='all', simplify=True
    , retain_all=True, infrastructure='way["highway"]', custom_filter=
    '["highway"~"cycleway|path|living_street|residential"]["bicycle
    "!~"no"]')

G_2=ox.graph_from_place(place, retain_all=True, custom_filter='["
    cycleway"~"lane"]')

L2=nx.compose(G_1,G_2)
```

ℓ_3 is defined as:

```
L3=ox.graph_from_place(place, retain_all=True, network_type='bike',
    simplify=True)
```

ℓ_4 is defined as:

```
L4=ox.graph_from_place(place, retain_all=True, network_type='drive',
    simplify=True)
```

Part II

Street scale

Chapter 5

Estimating travel time of cyclists approaching an intersection

"Machine learning is like teenage sex: everyone talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claims they are doing it."

— derived from Dan Ariely's tweet

Where chapters 2 and 3 investigated cities and chapter 4 examined both city and zone levels, chapter 5 takes an even more microcosmic approach: its focus is on the link, which could be a bicycle street or a part of it. The remainder of this thesis concentrates on the link-level assessment of bicycle paths. Since by combining the link-level information one can have a more realistic assessment of the whole bicycle network.

Bike paths are particularly critical at intersections: that is, at points where different modes interact and users need to give or receive right of way. In case of a forced stop due to a red light, a cyclist may experience discomfort because she needs to decelerate and then re-accelerate, using up her personal energy to regain speed. In case of a long queue at a traffic light, a cyclist may need not only to stop but also to wait for the queue to discharge before crossing the intersection. This has a clear impact on the cyclist's travel time. Travel time, then, is the first measure that this thesis aims to estimate on a signalized link.

A tool for estimating the travel time of cyclists approaching a traffic light can monitor the level of service (quality) of a signalised link in bike-crowded cities. This work represents a first exploration in developing such a tool. Artificial neural network models are evaluated on how they perform in estimating the individual travel time of cyclists approaching a signalized intersection in different simulated scenarios.

This chapter is published as a conference proceeding article: G. Reggiani, A. Dabiri, W. Daamen, and S. Hoogendoorn Exploring the Potential of Neural Networks for Bicycle Travel Time Estimation. Traffic and Granular Flow (2019)

5.1 Introduction

While some cities are struggling to increase bicycle usage, others are successful in encouraging adoption of cycling but become victims of their own success. Such 'cycling cities' struggle with high levels of bike flows, long queues at traffic lights and discontent cyclists due to the delay in their travel time. Traffic management solutions can mitigate the situation by reducing delay using adaptive traffic controllers or rerouting users to intersections with short delays. In order to deploy such systems, a tool that estimates cyclists travel times, as proxy for bike level of service at intersections, is crucial.

To develop a tool that serves the needs of a bike travel time monitoring system at intersections the following data requirements are set: 1) enabling to derive travel time 2) collected over an extensive time frame, 3) representative of user population, 4) readily and real-time available and 5) privacy proof. Some studies investigated the potential of GPS to measure delays (see (Strauss & Miranda-Moreno, 2017) and references therein). However, GPS only fits the first of the five data requirements: GPS data are collected either via sport apps which enable collection over extensive time frames, but can only represent the "sport" trips, or it is collected via expensive data collection methods, which can equip a representative sample of the population with GPS trackers, but for a limited amount of time (thus not satisfying condition 2). In addition GPS data is not readily available from municipalities and stores sensitive user information. Therefore, this research will use a data set, potentially available from an intersection equipped with loop sensors, a traffic light and a bike queue measurement system because such simulated data set has the potential of meeting all data requirements. Part of this data is readily available to dutch municipalities, due to the extensive deployment of loop sensors on signalised intersections in the Netherlands. Loops are usually installed as shown in Fig. S1: 2 upstream of the traffic light (for direction measurement) and one downstream at the stop-line.

Within this work we investigate the properties of a Neural Network (NN) model, when estimating individual cyclists' travel times. Previous studies have explored the possibility of extracting travel times with more "easy to interpret" models like regressions but were not successful (Duives et al., 2017). Our work will go one step further by exploring the potential of a more complex models like NNs.

The wide applicability of NN in the transport domain (Teodorovič & Vukadinovič, 1998) and scalability would allow these models to easily scale up to incorporate more variables from the same intersection but also from other intersections in a network-oriented approach. We train and test the model on simulated data because it allows for the evaluation of both the model and its input variables.

Section 5.2 presents the methodology describing the simulation settings, the input features and the model. Section 5.3 contains the performances of NNs, in order to investigate if the deployment of these models in reality is effective. Finally, the conclusions are reported in section 5.4.

5.2 Research Methodology

Our research methodology consists of 3 major steps: 1) Simulation of the arrival-departure process of cyclists at the traffic light, 2) Identification of variables to extract from the sim-

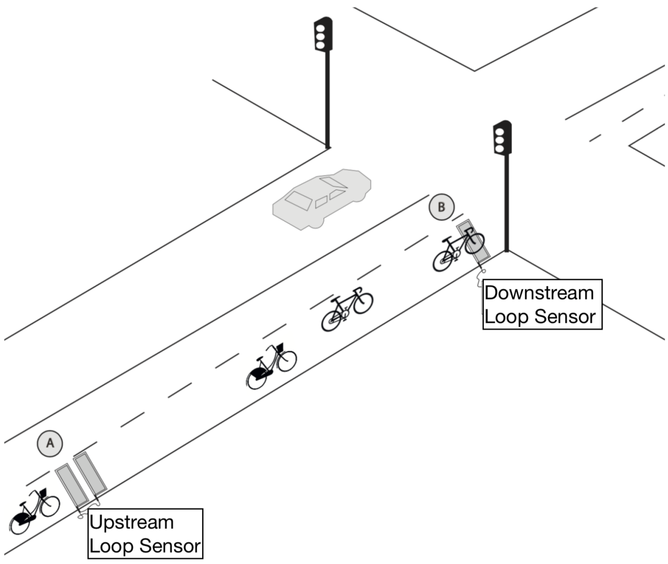


Figure S1: Position of bicycle loop sensors at intersections.

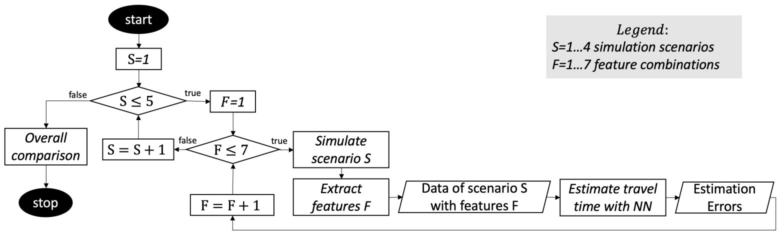


Figure S2: Flow of the research steps.

ulation to use as features for the NN, and 3) Computation of estimation error. Fig. S2 shows how the research steps interrelate. We decide to test different feature combinations on each scenario (see Table S3), in order to investigate which feature variables carry more information depending on the simulated setting.

5.2.1 Simulation for Data Generation

We use simulation and not real data from a signalised intersection with sensors because of 4 main reasons. 1) Simulation allows a controlled environment to measure the performances of NNs as complexity is added. 2) We can simulate data not yet available (like queue of cyclists) and assess if collecting such data is valuable for a NN. 3) It allows us to train the model on correct ground truth data that loop sensors alone are not able to deliver, due to occlusion error (see (Proulx R et al., 2016) for the definition) in the downstream loop. 4) Based on the NN performance on simulated data, it will be clear if to pursue testings on real data.

Data is simulated based on four scenarios which vary depending on the cycling time, queuing model of cyclists, and high demand of cyclists. Hereafter the four scenarios simulating arrival-departure process of cyclists are described (from simple to more complex):

- Deterministic scenario: cycling time is the same for all individuals and cyclists depart from the stop line as soon as the traffic light turns green.
- Discharge Rate scenario: similar to the deterministic scenario with the added complexity that cyclists do not depart from the downstream sensor all at the same time but with a discharge rate.
- Stand over queues scenario: road capacity constraints are considered and arrival rate is modelled to simulate high cyclists demand, so more cyclists are in the queue than can be discharged in one cycle. Cyclists may stay in the queue for more than one red light cycle.
- Stochastic scenario: based on a random arrival-departure process, cycling time between 2 loops is not fixed but modelled according to a normal distribution .

5.2.2 Selection of Feature Variables

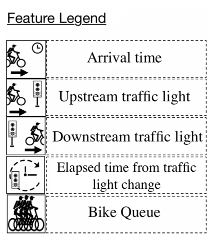
Hereafter, a set of five features has been defined based on the data potentially available, the moment a cyclist approaches the upstream senors of bicycle intersections, in the Netherlands.

- Arrival time: this variable contains date-time information of the moment a cyclist reaches the upstream loop sensor.
- Upstream traffic light: carries a 0-1 information to represent green (0) and red light (1) state when the cyclist reaches the upstream sensor.
- Downstream traffic light: carries a 0-1 information to represent green (0) and red (1) light state when the cyclist reaches the upstream sensor (this data might not be available in real settings, but is used as a check).
- Elapsed time from traffic light change: defines, at the arrival time of the cyclist, the seconds passed since the last change in state of the traffic controller.
- Bike queue: defines the number of cyclists waiting for a green light.

Seven combinations of these five features define the data-sets used for the different experimental scenarios (see Figure S3).

5.2.3 The Model

NN models have shown to be extremely versatile and perform well even without a priori assumption on the variable distribution. Their generalization properties make NNs suitable for our purpose. Like all data driven models that learn by minimising the predicted error, NNs need labels (i.e. travel time) of past observations in order to learn how to estimate future ones. Once the NN is trained on past travel time observations (in this case simulated), it will be able to estimate travel time of never seen before observations.



Scenario / Feature combinations	Deterministic	Discharge Rate	Stand Over Queue	Stochastic
1)	0.15	5.64	396.34	19.19
2)	0.00	6.10	300.91	1.58
3)	0.16	5.08	306.26	19.34
4)	0.13	5.00	391.82	18.66
5)	0.14	6.70	315.25	19.18
6)		1.13	2.23	
7)		1.28	2.08	

Figure S3: Mean square error for bicycle travel time estimation: Estimation performance (on test data) of the NN on the 4 scenarios, tested on different feature combinations. Feature combinations with queue information are not considered in the Deterministic and Stochastic case, since these scenarios are simulated without cyclists' discharge rate.

5.3 Numerical Results

In this section we report results form the numerical experimentations. For reproducibility, we first describe the structure and parameters of the NN used, as resulting form the numerical experiments. Follows, a description of the NN performance, based on mean square errors in the different scenarios tested on the various feature variable combinations.

5.3.1 Neural Network Structure

Throughout the numerical experiments, a shallow Feed-forward Neural Network, with 6 neurons, emerged as the architecture with the smallest validation error. The NN was implemented in MATLAB software. A structured investigation indicated that the network architecture is adequate, because increasing the number of layers or neurons per layer on average did not improve test performances. Where performances were measured through the mean square error (MSE) as performance function.

5.3.2 Model Performance

Via simulation, a data set of 7200 instances is generated, 70% of which is used for training, 15% for validation and 15% for testing the NN model. Estimation performance of the NN on the different scenarios is reported in Fig. S3.

The Deterministic process is the one the NN can estimate better, as expected, since the process is simple. This is deduced by the very small test error, of tenth of a second, on all the scenarios, compared to the other three processes. The data in the feature combination 2 will not be available in real cases; we use it as a check case to see how well the model can predict if we provide it with signal of the traffic light at the time the cyclist would arrive at the downstream (in real life the time the cyclist arrives downstream is not known). The second lowest error in the deterministic scenario is with features: arrival time and elapsed time from traffic light change. This means that, the model estimates better when knowing how many seconds have passed since the change in traffic light state, because it is a FIFO based scenario.

If the process incorporates a queue discharge rate of cyclists, as in the Discharge Rate and Stand Over Queue scenario, feature combinations with bike queue have the smallest estimation error. Having the queue as feature reduces the estimation mean square error up to 2 orders of magnitude. The main reason is that the queue feature incorporates the dynamic information of the arrival-departure process at signalised intersections (i.e. a cyclist has to wait for the queue ahead to discharge, before it can depart again). The Stand Over Queue scenario, incorporated high peak of cyclists arriving at the intersection and Fig. S4 shows how accurately the model can estimate travel times in high peak (longer waiting time) when queue information is provided and how it would perform without it. Without queue information the NN can not reproduce the longer travel times that occur when cyclists need to stand in the queue for more than one traffic light cycle. Among the feature combinations that have queue information including the elapsed time form traffic light change improves estimation error in the Stand Over Queue but not in the Discharge rate process. The reason being that in the former process a cyclist is always discharged within the first traffic light cycle, thus elapsed time does not provide as useful information as when the cyclist stays more than one cycle.

Overall, in the Stochastic process, the reached performances are not sufficiently accurate. As information used in the second data-set is not available, on average the error reached by the NN is of 19 seconds. This indicated that, as the process is more complex, the information considered is not enough for the NN to reproduce the underlying process that generated the data.

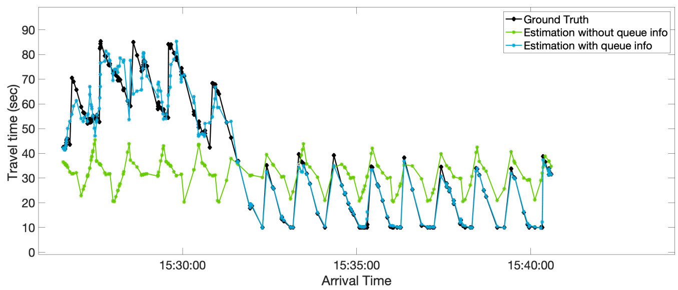


Figure S4: Visualization of model performance in the Stand Over Queue scenario, considering feature combination 3 (without queue info) and 7 (with queue info).

5.4 Conclusions

This work provides a structured investigation, based on a simulation methodology, on how Neural Networks perform for individual travel time estimation. This is the first study on bicycle travel time estimation at intersections, in order to develop real-time bike level of service measures. The investigation of effectiveness of Neural Networks made clear the potentials and limitations of these models. In cities with low bicycle levels (deterministic scenario), NNs are good travel time estimators since with all data sets the reached error is of tenth of a second. Whereas, in places with high bike volumes (where cyclists depart with a discharge rate), only data sets with information on queued cyclists lead to acceptable error of 1 to 2 seconds. The main limitation of using NN models to estimate individual bicycle travel time is the availability and richness of the data.

The results enable us to quantify the estimation error in the four scenarios with the different input data. As a consequence, this quantitatively encourages us in future research to develop queue estimation algorithms (of cyclists) that can improve overall travel time estimation. Moreover, future steps should look into the opportunity to cover more complex processes, and more intersections with this methodology.

Chapter 6

Estimating bicycle accumulation levels on a signalised link

“Ogni realtà è un inganno."
Tr. All reality is a deception.

— Luigi Pirandello, Uno, Nessuno, Centomila.

Chapter 5 quantitatively showed that gathering information about cyclist queues at intersections is critically important when seeking to improve travel time estimation. Moreover, the bicycle queue can measure the quality of a bicycle network link, which is a piece of crucial information for the adoption of intelligent transport systems, which help to better manage cyclists in cities. Consequently, chapter 6 aims to estimate queue levels of cyclists at signalized intersections based on loop sensor data, which is widely available in the Netherlands.

In this chapter, an unsupervised machine learning methodology is deployed to estimate accumulation levels based on data retrieved from a bicycle street in Utrecht, the Netherlands. The use of a clustering-based approach combined with conceptual insight into the bicycle accumulation process makes the applied methodology less dependent on sensor errors. This clustering-based methodology clearly identifies levels of cyclists accumulated in front of a traffic light.

This chapter is published as a conference proceeding: G. Reggiani, A. Dabiri, W. Daamen, and S. Hoogendoorn Clustering-based methodology for estimating bicycle accumulation levels on signalized links: a case study from the Netherlands. IEEE Intelligent Transportation Systems Conference (ITSC 2019), 1788-1793.

6.1 Introduction

There is an evident increase of bicycles trips in cities (ITF, 2013). This leads, among other things, to long waiting times at traffic lights and unsafe situations such that municipalities, in some countries like the Netherlands, are struggling to manage bicycle traffic. Intelligent Transportation Systems (ITS) can mitigate the situation, as already proven effective in vehicular transport management, by e.g. 1) reducing delay using adaptive traffic signal controllers (Le et al., 2015), or 2) reducing discomfort by providing real time traffic information (de Moraes Ramos et al., 2012), valuable for user's route choice. In order to deploy such ITS, real-time and accurate information about bicycle accumulation on urban cycle paths is crucial.

The fundamental difference between car and bike queues, depends on the unstructured and non lane based behaviour of cyclists. Consequently, fixed location sensors incorporate counting errors which have an effect on flow data of bicycles, leading to growing cumulative errors while estimating accumulation. In vehicle queue estimation studies, the cumulative error problem is a well-known research topic investigated by Amini et al. (2016) and van Erp et al. (2017), to name but a few. To the best of the authors' knowledge, the cumulative error problem has not been addressed yet in the bicycle domain.

We propose a clustering-based methodology for bicycle accumulation estimation, applicable to various kinds of unlabeled and error prone data. Although, to the best of the authors' knowledge clustering has never been applied to bike accumulation problem, for an overview of its applications in transport domain see Weijermars (2007); Ali Silgu & Berk Çelikoğlu (2014). The use of a clustering-based method combined with a conceptual insight into the bicycle accumulation process and various data sources make the applied methodology less dependent on sensor errors. The methodology is tested on field data retrieved from inductive loop sensors and represents the first step in setting up a methodology for bike accumulation estimates.

Supervised machine learning techniques require a large amount of labels (i.e. ground truth), not always available, to train the models. Instead, the low data requirements of unsupervised machine learning techniques make this methodology attractive and easy to implement for practitioners. The achieved bicycle accumulation levels can be used as real time traffic level indicators of edges of a cycle network or as input for data driven control measures.

This article is organized as follows. Section 6.2 presents the methodology (i.e. the general research approach). Whereas, section 6.3 illustrates, through a case study, the methods used within the methodology and evaluates the proposed clustering-based estimation approach, by comparing it with other estimation techniques. Finally the conclusions are reported in section 6.4.

6.2 Research methodology

Fig.S1 shows, on the left side, the general unsupervised approach for researchers that aim to estimate bicycle accumulation on a signalized link. It consists of seven steps, each is explained in the following subsections. The grey diagram, on the right in Fig.S1, illustrates the steps performed in the case study of section 6.3. Practitioners addressing scenarios similar to the one of the case study (i.e. same data availability and setting) can estimate bicycle accumulation by applying steps 4, 5 and 6 of the methodology.

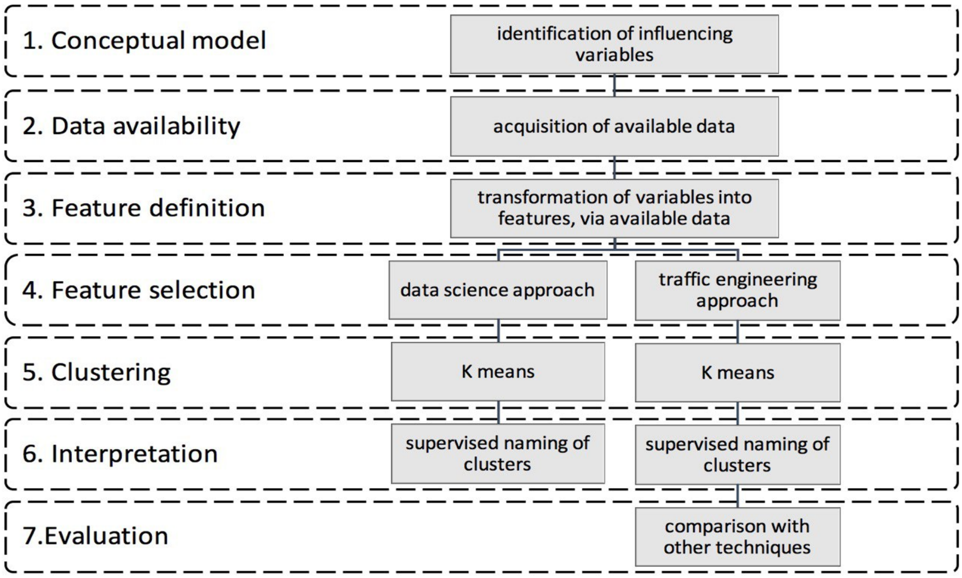


Figure S1: Steps of the research methodology.

6.2.1 Conceptual model

The conceptual model, as shown in Fig. S2, highlights the influencing factors for bicycle accumulation and their mutual relationships. This conceptual model is used to 1) understand which are the influential factors that can be included as features in the learning process 2) avoid using available data without motivated correlation to bicycle accumulation 3) improve the estimation model by identifying which additional variables to measure in future studies. Only dominant relationships are included in the figure.

The conceptual model shows, above all, that:

- macroscopic variables have a direct effect on bicycle accumulation, while individual and external variables have an indirect effect, since they influence some macroscopic variables that in turn determine bicycle accumulation.

- local density, depending on its location (either the cyclist's position or the sensor location), can influence the outflow, individual velocity and queue discharge rate. If local density can be used to approximate average density (i.e. number of accumulated cyclists) then it can also be seen as a direct influencer of bicycle accumulation.

- inflow and outflow have a direct influence on bicycle accumulation. Theoretically, inflow and outflow could fully determine the accumulation through the bicycle conservation law.

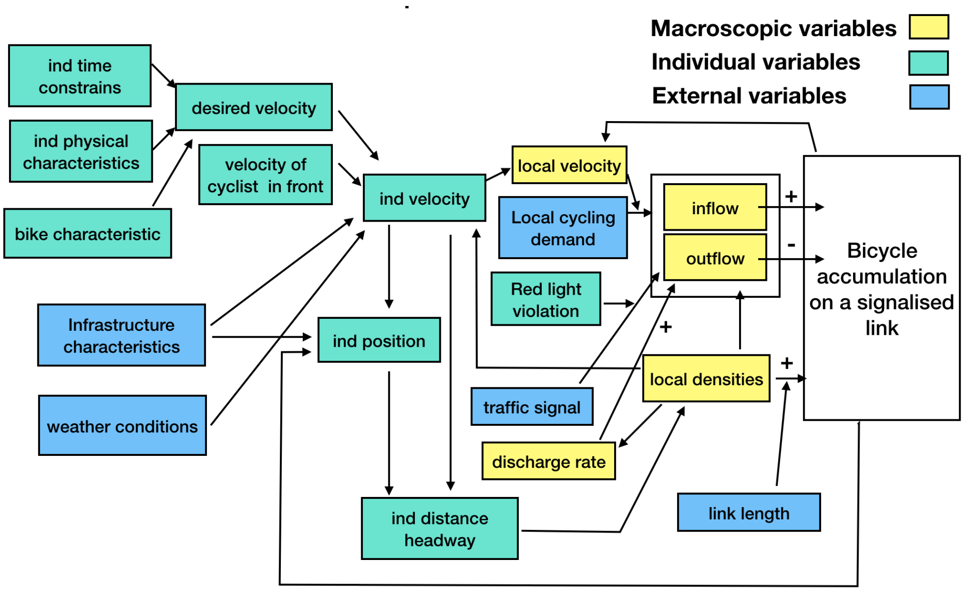


Figure S2: Conceptual model for bicycle accumulation.

6.2.2 Data Availability

This step seeks for data sources that can measure influential variables of the conceptual model. Data availability in general depends on the type of sensors road authorities have deployed. We provide an insight into specific data availability based on inductive loop sensors, which are used the case study of section 6.3.

Theoretically, inductive road sensors provide bike counts, occupancy of the sensor over time, and speeds (from two loops close to each other). Having bicycle counts upstream and downstream (i.e. inflow and outflow) we can define bicycle accumulation, through the bicycle conservation law. However, as shown in section 6.3.6, using this conservation law based on bicycle loop sensor signals leads to a cumulative error due to inaccuracies in the downstream loop counts[1]. As a result, we need additional information either continuously or at specific moments to correct for the accumulated error. Thanks to the conceptual model, it is possible to see what other variables to extract from loop sensors to compensate flow errors while estimating bicycle accumulation on a link.

6.2.3 Feature Definition

In this step, the output from the previous two steps are combined in order to translate the variables of the conceptual model into features, defined for each observation period δt. An observation period is represented by a vector made of features, that represent the numerical value of one or more independent variables during the observation period. The bicycle accu-

[1] Whilst cyclists predominantly pass over the upstream sensor one at a time, they tend to cycle over the stop-line sensor (when the traffic light turns green) very close to each other, with a slight sidewise shift.

mulation, to be estimated, is the number of bikes, on the link, at the end of each observation period.

6.2.4 Feature selection

Feature selection is needed in order to remove irrelevant or redundant variables. Practical experience with machine learning shows that reducing features can improve learning performance by increasing learning accuracy, lowering computational cost, and improving interpretability (Alelyani et al., 2013). The improved performance of clustering with less variables is also confirmed in our case study (see Table S2).

Features can be selected by means of a pure data science approach or by means of traffic engineering domain knowledge. The former approach looks at correlation between features and between features and a sample of ground truth accumulation, whereas the latter selects features that are more meaningful from a theoretical point of view, based on the conceptual model.

6.2.5 Clustering

This is the core step of the methodology that learns latent patterns within the data without being trained on the corresponding ground truth (i.e. labels). Unsupervised approaches, such as clustering, are preferred to supervised due to the fact that labels are not easily determined for bicycle accumulation level. If the results are to be sufficiently reliable for training purposes, such information needs to be manually extracted from video footage, through a very time- consuming process. By making use of a clustering technique, less ground truth data needs to be extracted because labels are not needed for the training but are only used for the interpretation, as well as the evaluation, of the results.

6.2.6 Interpretation

To interpret the latent clusters found in the previous step, a limited amount of ground truth is used. The interpretation step is used to 1) understand if the groups found by the clustering algorithm have a physical meaning from bicycle accumulation point of view and 2) give names to the classes, according to the accumulation level they represent.

6.2.7 Evaluation

For the evaluation of the methodology, other estimation techniques should be used to assess how the clustering methodology estimates compared to other methods. In this paper, the comparison is made with methods based on conservation of bicycle law and a corrected version of it.

6.3 Case Study

In this section, we use real data to show how unsupervised machine learning can be applied for estimating bicycle accumulation. The structure of this section follows the same steps of the methodology (section 6.2), starting from data availability. The aim of the case study is twofold: 1) test if a clustering methodology achieves accurate estimations of bicycle accumulation and 2) determine if incorporating transport domain knowledge in the feature selection process improves the estimations.

6.3.1 Data availability

The most common sensor technology on cycle paths in the Netherlands is inductive loop sensors, usually in a configuration as shown in Fig. S3. Two sensors are installed, one 20 meters at the upstream of the traffic light and one downstream, at the stop-line. Currently this technology is simply used to request a green light if at least one bike is on the link, but it does not count the amount of bicycles.

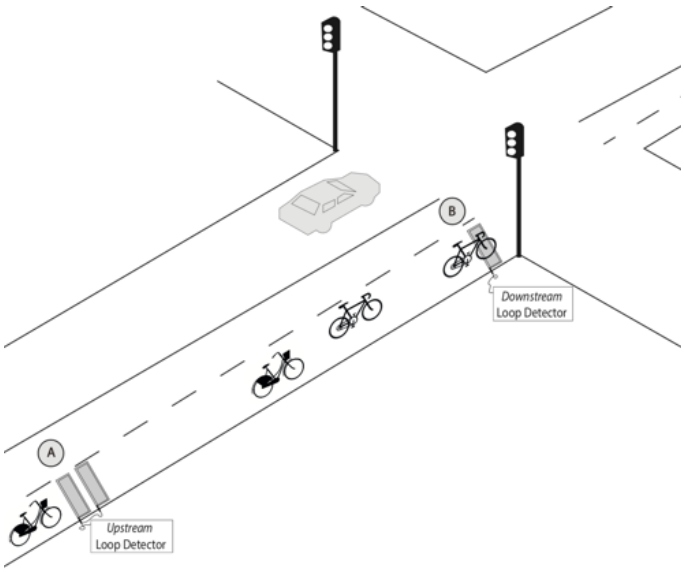


Figure S3: Loop sensors configuration on cycle paths.

The location used as a case study is a signalized intersection, located in the city of Utrecht, the Netherlands, which has very busy morning peak hours. The upstream loop sensor reported over one thousand bikes per hour, during the morning peak. The data from loop sensors were collected over 5 working days, from Monday to Friday, for 4 morning hours, from 6.30 a.m. to 10.30 a.m., and 4 afternoon hours, from 2.30 p.m. to 6.30 p.m.. Overall, 38 hours of loop sensor data (i.e. on-off continuous signal) and its corresponding traffic light signal and camera footage of a 4-hour sample, were made available from the municipality of Utrecht.

6.3.2 Feature Definition

Based on the data availability of inductive loop sensors and the insight on the first order influencial variables (from the conceptual model), features that carry information on inflow, outflow, local density, traffic signal and speed have been defined. In order to deploy the estimations in real-time applications, we chose δt to be 30 seconds. In total 14 features are defined for each observation period. Table S1 lists all the defined features and their corresponding variable of the conceptual model.

Table S1: List of defined features and corresponding variables.

N.	Defined Feature	Conceptual model variable
1	Occupancy Up	local density
2	Occupancy Down	local density
3	Bike Passes Up	inflow
4	Bike Passes Down	outflow
5	Red Occupancy Down	traffic signal & local density
6	Green Occupancy Down	traffic signal & local density
7	Switch	traffic signal
8	Transit	traffic signal
9	Occupancy Up - Green Occupancy Down	traffic signal & local densities
10	Bike Passes Up - Bike passes Down	inflow & outflow
11	Occupancy Up / Occupancy Down	local densities
12	Sum of Speeds	local speed
13	Sum of Occupancies	approx. avg density
14	Occupancy Up - Occupancy Down	local densities

Hereafter, we explain how the fatures in Table S1 were obtained:

- **Occupancy** is the percentage of time, within one observation period, that the loop sensor is occupied by a bike passing or standing on top of it.
- **Bike passes** measures the number of times the sensor signal has changed within one observation. This is a lower bound estimation of the number of bikes that have passed (i.e. bicycle flow).
- **Red or Green Occupancy** represents occupancy information when the traffic light is either red or green. These features are defined only for the downstream loop because cyclists stop on top of it when the traffic light is red. This results in a high occupancy level downstream, during a red light, that does not reflect a high bicycle density, whereas high occupancy level during the green signal most probably reflects high bicycle density.
- **Switch** and **Transit** features carry information on the traffic light signal. Switch is a percentage that gives information on when, during an observation period, the traffic light last switched from green to red or vice versa. Transit is a binary feature indicating the traffic light state, at the end of each observation period.
- **Speed** feature is a representative approximation of velocities at the sensor location. Speed can be derived from the ratio between flow and density (Athol, 1965). We approximate flow with bike passes and density with occupancy.

To visualize the relation of each defined feature with the true accumulation of bikes on a signalized link we report scatter plots with 120 observation periods from one morning hour, for which the ground truth has been manually extracted. Above each scatter plot we report the correlation coefficient between the two variables.

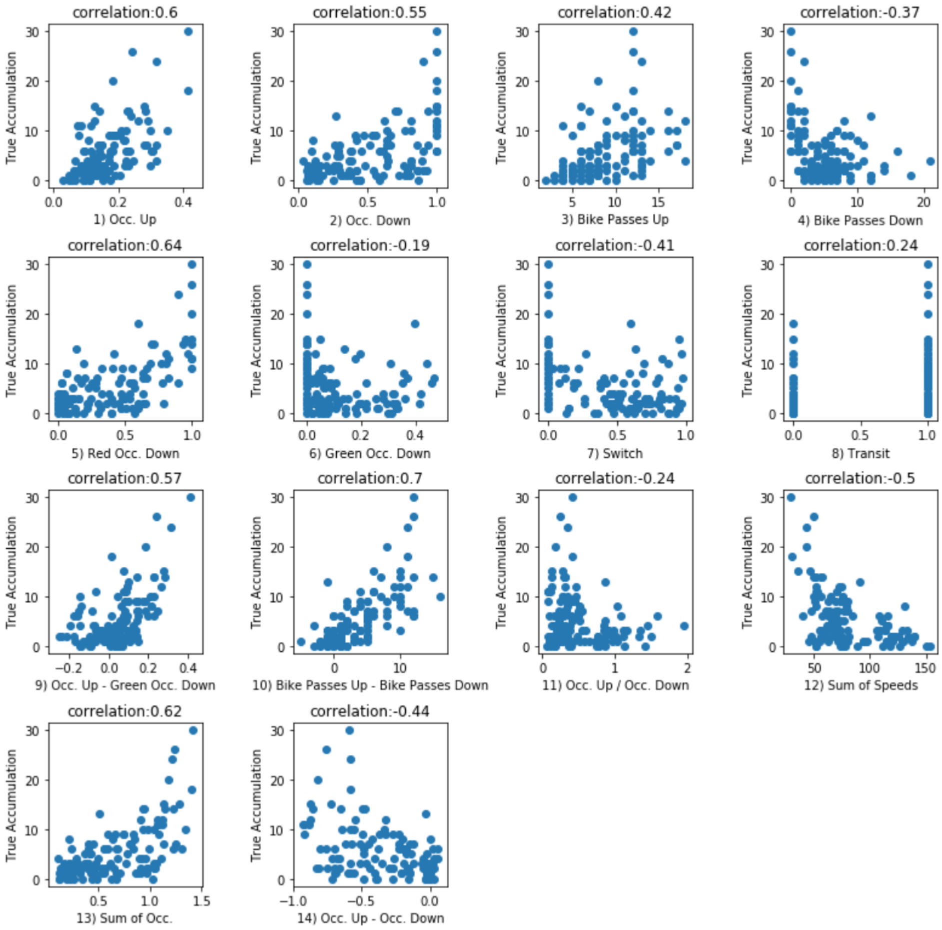


Figure S4: Relation between features and bicycle accumulation.

As expected, Bike passes Up (approximation of inflow) has positive correlation to bike accumulation and Bike passes Down (approximation of outflow) a negative one. Upstream and downstream occupancy and downstream occupancy during red light have a positive correlation, since occupancy is an approximation of local densities. Moreover, features 9 and 10, which respectively represent the difference between upstream and downstream densities and the difference between the inflow and outflow have a strong positive correlation to the bicycle accumulation. This correlation overview will serve as a starting point for feature selection.

6.3.3 Feature Selection

From our observations, applying a clustering algorithm directly over all the 14 features does not lead to satisfying results, and the algorithm is not able to cluster together points with similar accumulation. A selection is needed to improve the unsupervised estimation. We propose and implement two different feature selection approaches: 1) a pure data science approach and 2) a domain knowledge approach. The aim is to understand if data driven techniques select the same features as would traffic engineers and if their selections perform differently.

Following a data science approach, we have defined some thresholds, based on observed correlations to bicycle accumulation and among features. This approach first selects the features with a high correlation to the dependent variable, by means of a threshold $T_1 \in \{0.3, 0.4, 0.5, 0.6\}$. Then it drops out all the redundant features by excluding the ones that have a high correlation, with other selected independent variables, by means of a second threshold $T2 \in \{0.5, 0.7, 0.9\}$. Combinations of selected features are ranked based on the average silhouette value S (Rousseeuw, 1987). Top ranking combinations are reported in Table S2. The silhouette value is calculated as:

$$S = \sum_{i=1}^{m} s(i) \tag{6.1}$$

$$s(i) = \frac{b(i) - a(i)}{\max[a(i), b(i)]} \tag{6.2}$$

Where:

- $a(i)$ is the average distance between point i and all points within its same cluster
- $b(i)$ is the smallest average distance of point i to all points in any other cluster
- m is the number of all points in all clusters

The silhouette coefficient gives an indication of how similar a point (i.e. an observation period) is to points within its own cluster and how different it is compared to points in other clusters. Hence, this coefficient gives a quality score on how well each observation period has been clustered, given the selected features. The silhouette value is also used to find the best number of clusters, given the selected features.

Alternatively, from a domain knowledge perspective, we look at the conceptual model (Fig. S2). The model shows that inflow and outflow have a direct influence on bike accumulation, for this reason the difference in upstream and downstream bicycle counts (feature 10) is selected. As seen in Fig. S2, local densities can influence several variables including bicycle accumulation. As a feature to represent densities, feature number 9 is selected because it incorporates the information of both up and downstream densities and also part of the traffic signal downstream. In particular, feature 9 defines the difference between the occupancy upstream and occupancy downstream during a green traffic light. Including more correlated features did not improve clustering performances, thus, from now on, when referring to the features selected through a knowledge-base approach we refer to features 9 and 10.

Table S2: Feature combinations selected based on pure data science approach (only combinations with S ≥ 0.4 are reported).

Feature selections	silhouette value	number of clusters	Occupancy Up	Occupancy Down	Bike Passes Up	Bike Passes Down	Red Occupancy Down	Green Occupancy Down	Switch	Transit	Occupancy Up - Green Occupancy Down	Bike Passes Up – Bike passes Down	Occupancy Up / Down	Sum of Speeds	Sum of Occupancies	Occupancy Up - Down
	0.44	5							✓		✓					✓
	0.60	3									✓				✓	
	0.45	2	✓								✓	✓		✓	✓	
	0.72	2													✓	
	0.60	2										✓			✓	
	0.40	2	✓	✓					✓		✓					
	0.40	2	✓	✓	✓				✓		✓	✓		✓		
	0.52	3	✓	✓							✓					
	0.45	2	✓	✓							✓	✓		✓		
	0.77	2					✓									
	0.63	2					✓					✓				

6.3.4 Clustering

As unsupervised methodology, we apply k-means clustering. This is the starting point for exploring unsupervised machine learning in many domains due to its simplicity and low computation time (Hastie et al., 2009). K-means algorithm finds a predetermined number of clusters in a dataset. Data are grouped into clusters by minimising the distance between each point and the mean (i.e. centroid) of the assigned cluster. Many distance functions can be used; however, it is common practice for the k-means to use the euclidean distance between points and the centroid. The number of clusters is decided based on the highest silhouette value for a given feature data set. The data science approach, tests 2,3,4,5 number of clusters and selects the one that returned the highest silhouette value.

6.3.5 Interpretation

We interpret the unsupervised learning methodology by using ground truth of 120 observation periods of one morning hour. This sample of ground truth is an unbiased representative of our dataset, because it includes a wide range of accumulation values (0 to 30 accumulated cyclists) and not only low accumulation values, as it is the case for other hours within a day.

The interpretation step uses box plots showing bicycle accumulation values, of a sub sample of the dataset, contained in each identified cluster. Fig. S5 reports box plots for the best feature combination (i.e. highest *S*) of the data-approach and knowledge-approach. The best feature combination based on the data-approach results to be one feature: Red occupancy Down. Clustering performed on this feature vectors results in two classes which have different mean values, but overlap with respect to the amount of cyclists, as shown in Fig. 6.5(a). Whereas, the knowledge-based approach clusters observations into 4 classes (which we name *very low*, *low*, *medium* and *high* accumulation) with lower overlap in values (Fig. 6.5(b)).

In general, four classes are more valuable than two, from a traffic engineering perspective. The knowledge-based feature selection clearly distinguishes the high and medium bicycle accumulation class, from other classes (i.e. there is low overlap between accumulation in the high and medium classes). The low and very-low accumulation class represent similar true accumulation levels. However, from a traffic engineering perspective it is more crucial to have an accurate estimation of the high and the medium accumulation class, compared to the low and very low accumulation. As a fact, it is the high accumulation levels that require real time ITS solutions. Comparing the figures, it can be inferred that the better feature combination is the one selected with a knowledge-base approach.The data driven feature selection does not perform as well as the domain knowledge selection. The reason behind such discrepancy requires further investigation but one reasoning may be that the data driven approach selects features that separate points in space better than the features selected with domain knowledge. However those points are separated into clusters which do not relate to bike accumulation but some other, less interpretable, traffic variable. In the following, we proceed by comparing the clustering results from the knowledge-based approach with other accumulation estimation methods.

6.3.6 Evaluation

This section shows how estimation based on the proposed clustering methodology performs compared to the two following approaches:

- Estimation without correction, which is based on the conservation of bicycle law:

  $Acc(i) = Acc(i-1) + Inflow(i) - Outflow(i)$

  where i is the i-th 30-sec period and $Acc(i)$ is the accumulation of bikes at the end of the i-th period.

- Benchmark estimation, which is based on the assumption that all the accumulated cyclists discharge within the first green light phase they encounter

  $Acc(i) = Inflow(i) - Outflow(i)$

This last assumption is based on empirical observations indicating that all accumulated cyclists discharge within the next green light. This means that if we compute estimations every traffic light cycle (start of the green phase), then the accumulation can be calculated as inflow minus outflow. It seems reasonable to extend this assumption to estimate accumulation over fixed time intervals of 30 seconds.

To evaluate the methodology, clustering estimations are represented by the mean accumulation value of the cluster they are part of. Comparison of the methods in Fig. S6 indicates that unsupervised learning methodology has two advantages: it avoids the cumulative error problem and it reduces the means square estimation error compared to the benchmarking method. From Fig. S6 it is evident that estimation based on conservation of bicycle law, leads to a huge cumulative error due to the inaccuracies in the downstream loop counts. Fig. S6 clearly illustrates how closely the estimates from the other two methods, benchmark estimation and clustering-based, follow the ground truth. If we compare

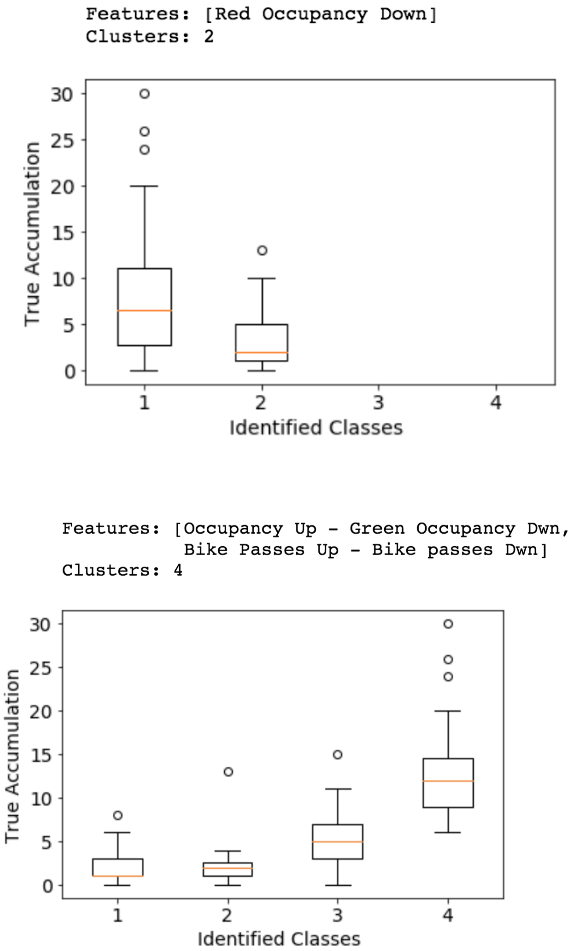


Figure S5: Interpretation of the 2 feature selection approaches. Top subfigure shows the data-based feature selection, bottom subfigure reports the knowledge-based feature selection.

these two methodologies based on the mean square error (MSE), the clustering methodology overall performs better, by having MSE=13.75 compared to MSE=17.64 resulted from the benchmark estimation approach.

6.4 Conclusions

This work proposes a methodology to estimate the bicycle accumulation levels on a signalized link by using an unsupervised learning technique. The estimation of accumulation levels based on this unsupervised learning method does not require large amounts of ground truth to train the model. Field testing of the methodology on real data indicates an accu-

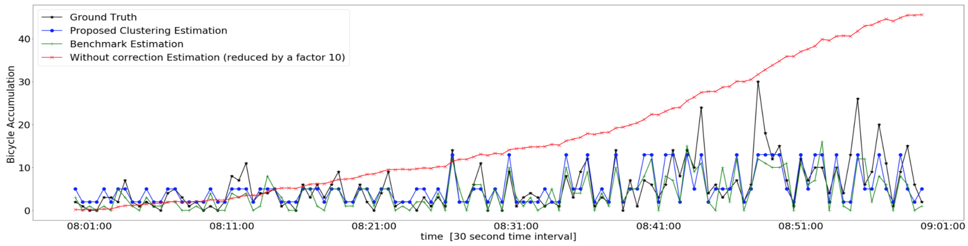


Figure S6: Evaluation of clustering-based estimation: comparison of 3 accumulation estimation methods.

rate estimation performance with low data requirements, which make it an easily applicable estimation method.

Results from the interpretation step show that incorporating traffic domain knowledge is important to select features for clustering. Instead, applying a pure data driven feature selection, based on correlation values and silhouette coefficient did not show valuable clustering of the data.

Thanks to loop sensor data, which is largely available in urban cycle paths of the Netherlands, a clustering technique can identify the levels of bicycle accumulation. Such information can be used as real time traffic information over an urban network or transmitted to traffic responsive signal controlers, in order to optimally determine green and red light phase of the signal. Clustering can only estimate levels of accumulation and not the exact amount of accumulated bikes. However this characteristic makes the method suitable to be used in many data driven control measures that, for computation reasons, do not require exact but average accumulation levels (El-tantawy, 2012).

Future works should assess how the difference between car and bike data, might affect performance of the method if applied to car queue estimation. Moreover the number of clusters and their interpretation highly depends on the amount and quality of the ground truth data. To overcome this limitation, it is recomended to apply and evaluate the methodology to more than one intersection, with different traffic pattern. Finaly, it is of interest to consider different unsupervised techniques, such as the fuzzy clustering to overcome some of the limitations of the k-means method. So far, our focus is on using largely available data (such as inductive loop sensors) without the need of deploying new or more sophisticated bicycle sensor on the roads. However, the proposed unsupervised approach can be applied in different settings and with various data sources.

Chapter 7

Relation between subjective and objective factors of Bicycle Level of Service

"While physics and mathematics may tell us how universe began, they are not much use in predicting human behaviour because there are far too many equations to solve."

— Stephen Hawkings

In chapters 5 and 6 we have investigated data-driven methods to measure objective factors that influence the quality (bicycle level of service) of a link. Chapter 5 looked at methods to estimate travel times and chapter 6 looked at queues on a link. The current chapter aims to add the subjective factor to the link assessment, broadening the scope of bikeability to include perceptions (which play a role according to the conceptual model in Figure 1.1).

This chapter studies the statistical relation between the objective traffic variables and cyclists' perceptions. We set out to measure subjective variables, like perceived bicycle level of service (BLoS) and perceived busyness, statistically correlated them to objective flows and densities of cyclists. This preliminary study was conducted during the coronavirus outbreak, which altered the conditions for the empirical data collection and limited the generalisability of the findings. Despite these unexpected conditions, the result of this analysis can be used as initial findings and motivates future research to develop BLoS measures based on perceptions and their relation to bicycle traffic conditions.

7.1 Introduction

The bicycle level of service (BLoS) of a street is determined by the physical environment as well as the perceptions of its users (Kellstedt et al., 2021). Several measures have been developed to measure objective and subjective components of BLoS of road segments (Landis et al., 1997; Harkey et al., 1998; Mekuria et al., 2012). However, these studies focus on infrastructure characteristics and how cyclists perceive them; only a few consider the presence of cyclists as a factor influencing BLoS.

The amount of cyclists on the road is a growing concern in bicycle-friendly cities, and it is likely to become a problem for cycling comfort, in the near future, to the many cities that are now starting to promote bicycle use. There are places where the presence of other cyclists is one of the most common stressors among cyclists (Gadsby et al., 2021) and congestion of bicycles was found to influence cyclists' perception (Wahlgren et al., 2010). This motivates us to unravel the statistical relations between perceived BLoS and the objective amount of cyclists on the cycle path.

To estimate the number of cyclists on the cycle path we can use the well-known traffic variables of flow and density. To date, only a limited amount of BLoS studies have researched upon flows and their effects on perceptions (Kazemzadeh et al., 2020). While bicycle traffic volumes were found to affect cycling experience (Bai et al., 2017; Wahlgren et al., 2010) none of the existing works has made clear the type of statistical relation that exists between quantitative measures of bicycle traffic (e.g. flow and density) and perceived BLoS. Neither have previous studies pointed out the conceptual difference between perceived BLoS and the perceived busyness and how the latter can help understand the perception of BLoS. These relations have not been largely investigated by previous works (as reported in the literature review in section 7.2) mainly because the amount of cyclists on a cycle path is a stress factor that is currently affecting only a few bike-oriented cities. However, as cycling is promoted as a transport mode, more cities will likely experience bicycle congestion. Findings from this analysis, and its future developments, will help urban planners design bicycle lanes with higher perceived BLoS.

This study aims to investigate the link between objective (quantifiable) bicycle traffic variables and subjective perceptions. Motivated by the research gaps found in the literature review (section 7.2), this work explores the relationship between perceived 1) BLoS and flow and density, 2) perceived busyness and flow and density, and 3) perceived busyness and perceived BLoS. We structure our analysis by defining three research questions (RQ):

1. Which relation exists between the objective measures, density and flow, and the perceived BLoS?

2. Which relation exists between the objective measures, density and flow, and the perceived busyness?

3. How strong is the correlation between perceived BLoS and perceived busyness?

In Figure S1 we report the main factors that influence BLoS perception in a conceptual model and the relations investigated through our *research questions* (RQ). To answer these questions information on 1) the objective conditions of the bicycle path and 2) the subjective perception of cyclists on BLoS and the busyness of a cycle path is needed. The objective data is collected with smart sensors whereas the subjective data is collected via interview questions (IQ) as explained later in section 7.3.4. The external conditions of this study were

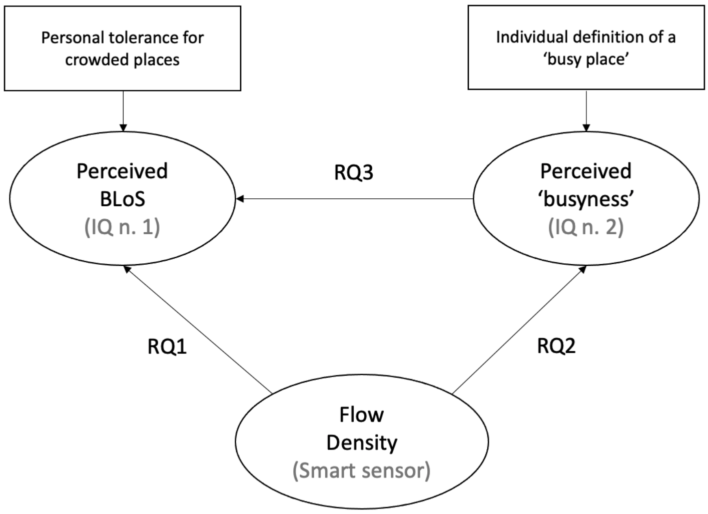


Figure S1: Relation between perceived BLoS and objective traffic flow conditions, only the main influencing factors in analysis in this study are reported. In brackets, we refer to how the data was collected, either smart sensors or interview questions (IQ). Rectangles indicate external factors that are beyond the scope of this work.

modified by the coronavirus pandemic outbreak, which inevitably represents a limitation to our findings. Despite this limitation, the broader implications of this and future studies relate to bikeability evaluations of places, urban plans, and traffic management solutions that can adapt to consider the density and flows of bicycle users as a stress factor.

The chapter is structured as follows. First, previous literature is reviewed in section 7.2. Then, section 7.3 describes the research method used to collect and analyse the data. Section 7.4 explains the main results obtained from the study and discusses implications. Conclusions on our initial findings are reported in section 7.5. Finally, in section 7.6 and 7.7 limitations and recommendations for future research are presented.

7.2 Background literature

While research on bicycle flows and bicycle dynamics has grown (Kazemzadeh et al., 2020; Wierbos, 2021; Jiang et al., 2017) there are only a few studies relating bicycle traffic flow variables to cyclists' perception of BLoS. Since the concept of BLoS is referred to in literature with a variety of terms (e.g. bikeability, and comfort) we first report background information on the concept of BLoS, then we review studies that have attempted to model BLoS and finally we present the few studies that indicate that BLoS is also influenced by the presence of other cyclists.

More than one study has pointed out that there is no consistent terminology in the BLoS domain. Different terms have been used to refer to the BLoS such as comfort, level of stress, bikeability, suitability, and bicycle friendliness(Kazemzadeh et al., 2020; Gadsby et al., 2021). Similarly, there are multiple methods to assess objective and subjective aspects of BLoS like the Bicycle Level of Service (BLOS) (Landis et al., 1997), Bicycle Compatibility Index (BCI) (Harkey et al., 1998), and Level of Traffic Stress (LTS) (Mekuria et al., 2012). The variety of terminology hinders accessibility of the literature and may undermine comparison between methods and slow the learning from previous findings. For an overview on terms and methods we refer the reader to (Gadsby et al., 2021). In the remainder of this chapter, we refer to BLoS which defines levels of service as the quantitative stratification which describes from travellers' perspective how well transportation facilities or services operate (HCM, 2010). BLoS is also the most common terminology on a link-level scale.

Many factors influencing BLoS have been evaluated in previous studies such as the type of bicycle infrastructure, the width of the bicycle lane, separation from motor vehicles, motorized traffic volumes and speeds, pavement conditions, parked cars (Landis et al., 1997; Foster et al., 2015; Caviedes & Figliozzi, 2018; Zhu & Zhu, 2019; Liu et al., 2020). However, most of the previously mentioned works on BLoS have focused on infrastructure characteristics and how cyclists perceive it. Only a limited number of works incorporate the number of other cyclists as an influencing factor for cyclists. Botma (1995) was among the first to use the number of passings and meetings of bicyclists on a path to evaluate BLoS, the study was further developed by HCM (2000). The main limitation of these studies is that the amount of other cyclists is incorporated as average hourly flow, which might not be what an individual cyclist is experiencing. Furthermore, such works provide guidelines on how to evaluate bicycle infrastructure based on cycling volumes but don't relate the BLoS to cyclists' actual perceptions. For this reason, in our study, we consider per minute dynamic traffic conditions and relate them to the cyclists' perceptions.

A few recent studies provide initial evidence of the importance of other cyclists on the cycle path as an influencing factor of BLoS. A semi-naturalistic survey compared BLoS influencing factors between cyclists in Atlanta and Delft. Results showed that the presence of other cyclists was the third most common stressor among cyclists in Delft, whereas it was never mentioned as a stressor by cyclists in Atlanta (Gadsby et al., 2021). A study in China, considering over 30 different locations, made clear that there was a statistical negative relation between the volume of cycle path users (in a 5-minute interval) and users' comfort perception (Bai et al., 2017).

Still, we argue that more insight is needed to better understand the statistical relation of bicycle traffic on perceived BLoS. Further investigations can disentangle the influence of perceived busyness on BLoS perceptions. Perceived busyness has been neglected by previous works but we hypothesise that it is a crucial explanatory factor for perceived BLoS. With the ambition to define BLoS and perceived busyness as a function of flow and density, we set out to study this relation at one bicycle path, in the proximity of an intersection.

7.3 Method

In this section, we illustrate the method used in this study by identifying the information and data requirements, which lead to the choice of the data collection methods, the selection of location, time and duration of the study, and the analysis to perform.

7.3.1 Information and data requirements

To gather information on the objective conditions of the bicycle path we use the macroscopic traffic flow variables of flow and density. *Flow (cyclists/min)* reports the amount of cyclists per time interval passing a certain cross-section and *density (cyclists/m*^{2}*)* measures the the number of cyclists in an area (or in this case a road stretch). Flow, by definition, is collected over a time interval, whereas density is measured at one point in time. To collect information on flow and density, based on the needs of this project, the data requirements are high measurement frequency - meaning that the time interval is such that it is at least smaller than the period reflecting the experience of the interviewee - and variation in the flow and density levels. These data requirements are the basis for measuring flow and densities, quantifying perceptions and identifying the relation between traffic variables and cyclists' perceptions.

To have objective measurements on flow and densities an automated data collection system based on smart cameras was selected. To collect information on the subjective perception of cyclists we need to have data from the cyclists perspective. These data are not easy to collect using a sensor[1], thus, the main data collection options are surveys or structured interviews. We opted for the latter to have quicker response times and also to avoid miss-interpretations as much as possible. The following sections provide greater detail about the methods used to collect and analyse the data in the study.

7.3.2 Location choice and timing

The location was selected among the cycle paths of the university campus which had smart sensors for bicycle detection. Based on the information needs we looked for the intersection with the highest flows and selected the Mekelweg-Jaffalaan intersection (52°00'11.6"N 4°22'16.4"E), in Delft, the Netherlands, as the study location. This location was is usually a very busy intersection along the main cycle path connecting the city centre and the train station to the university campus of Delft. The intersection used to be so busy, that human, and later automated, traffic controllers were introduced to prevent accidents involving cars and cyclists. The traffic controller helps the formation of queues and thus it increases the chance to observe higher densities. An overview of the intersection is provided in Figure S2. The bicycle jam densities before the Covid-19 pandemic ranged between 0.2 and 0.6 bic/m^2 with a mean of 0.4 bic/m^2 and standard deviation of 0.086 bic/m^2 according to observations carried out in October 2014 (Wierbos, 2021). These traffic values motivated the choice of the location— at least in normal conditions— to observe the relation between bicycle traffic conditions and perception of BLoS.

A smart 3D camera was installed at the Mekelweg-Jaffalaan intersection (together with other bicycle and pedestrian sensors throughout the university terrain) as part of the 'Outdoor Mobility Digital twin' project (in 2020) to monitor crowds and mobility patterns during and after the pandemic period. The smart camera in this study measures flows (in both directions) and densities of cyclists upstream of the traffic light, in the direction 'from campus'(zone 'A' in Figure S2). Whereas for safety and practical reasons (of not interrupting

[1]Smart cameras with emotion recognition software have been developed but the deployment is not easy due to privacy concerns.

the flow of bicycles crossing the intersection) we stopped cyclists for the interviews downstream of the intersection (zone B in Figure S2).

Figure S2: Configuration of the location in analysis.

The study was carried out on May $7th$, 2021, a fine-weather weekday. The interviews were carried out between 14.30-18.00. The selected time period allowed to capture first a low peak period, where not many cyclists cycled on the cycle path, and then a high peak, where cyclists were travelling back home from campus. The study was carried out during the coronavirus pandemic outbreak when social distancing restrictions (e.g. maintaining a minimum of 1.5 metres from other people and work/study from home) were in place in the Netherlands. Consequently, we observed that the cycling activity at the intersection was significantly lower than before the coronavirus outbreak. This means that the range of densities and flows become smaller with, in particular, fewer observations of high flows and densities. Although the number of cyclists was overall visibly lower than before the coronavirus outbreak, the flow measurements fall in the same range observed by Bai et al. (2017); Bai et al. (2017) observed between 15 to 122 cyclists per 5-minute interval and we observed 1 to 20 cyclists per 1-minute interval. So, despite the exceptional circumstances of the coronavirus pandemic which lowered the cycling activity in proximity of the university campus, our data is validated based on the previous study of Bai et al. (2017). To take into consideration how the pandemic may have altered perceptions (due to social distancing measures), we included some questions on the perception during the pandemic period (these will be presented together with the limitations of the study in section 7.6).

Due to the proximity to the university, the sample resulted in a rather homogeneous population. The observed cyclists consisted predominantly of students, and to a lesser extent of university staff, who cycle regularly and are familiar with the location. This is to keep in mind when trying to generalise results because students could have a different tolerance towards crowds compared to adult (or elderly) cyclists.

7.3.3 Flow and density data collection

Flow is measured as the total number of cyclists detected by the smart camera over a fixed time interval. Density in this study is computed as the average density of cyclists upstream of the traffic light within a time interval. The single observations of density are measured as the number of cyclists over the area of the cycle path in the view of the smart camera. The density is measured every 5 seconds by default of the sensor. After the preliminary round, it was clear that the interview did not take more than 1 minute and that flows of cyclists were changing very rapidly. Thus having an aggregation of 2 or more minutes would average very different situations. For this reason, the data measurement frequency (i.e. aggregation) was fixed to 1 minute to have the average density and flow rate of every one-minute interval. Responses of the cyclists were then matched with the closest 1-minute data measurement.

7.3.4 Perceived BLoS and busyness data collection

The BLoS perception related to comfort was measured using a five-level scale. Each level was associated with an emoji face and number (for an idea on the emoji used see the abscissa in figure S7). Level 1 represented the least comfortable and level 5 the most comfortable (this was made clear to the respondents in the interview rounds). The purpose of classifying the comfort perception of cyclists into five scales was to identify and generate well-defined and distinguishable categories for the riders of two-wheeled vehicles to rate their comfort perception. Previous studies have used three, five, or six levels of BLoS (HCM, 2000; Bai et al., 2017; Kang & Lee, 2012). In this study, the five-level scale was selected because a three-level scale is too limited to describe the comfort perception of the cyclists and that a six-level scale does not have the neutral option.

Preparatory interviews

The collection of perception data was carried out in two steps. First, a preparatory round was executed on May $6th$ to 1) test the interview questions and identify and re-phrase difficult wording or misunderstanding of questions, 2) identify factors influencing the cycling experience at the selected intersection via open questions and 3) investigate the difference of perceptions before and after the outbreak of the coronavirus pandemic.

The trial interviews were longer than the final ones, as cyclists were asked open questions to understand the factors influencing their cycling experience. This confirmed that the presence of other cyclists on the cycle path was an influencing factor at the selected intersection. The answers from the interviewees are classified in Table S1. Among the main influencing factors, both before and after Covid-19, is the presence of users on the cycle paths. An equally mentioned factor, in the current situation, is the possibility of maintaining one's desired speed. The latter also relates to the presence of other cyclists since in most cases the presence of other cyclists determines if one can maintain its desired speed or not. Another influencing factor, before as well as after the Covid-19 outbreak, turned out to be the queue of cyclists.

Although longer and more unstructured, the trial interviews were important to identify the change in cycling perception between the present situation and cycling on campus before Covid-19.

The preparatory interviews were an indication that higher flows and densities (as was before Covid-19 on campus) lead to a lower perceived bicycle level of service. However, we should take these results with care because when answering about the past we don't know to which memory or situation the respondent refers to. Moreover, questions about past situations led to misunderstandings. For this reason, we decided to re-structure the

Table S1: Factors influencing the cycling experience at the JaffalaanMekelweg intersection, before and after the coronavirus outbreak.

Current

too many cyclists	4
I kept my desired speed	4
almost absent queue	2
low waiting time	1
surprises from other cyclists	1
1.5 compliance	1

Before Covid-19

too many cyclists on the path	5
too long queue	3
low waiting time	1
mopeds	1

interview questions for the final round and leave out the ones asking about perceptions of past situations. In general, ‘BLoS’ is a non-intuitive term for the average respondent as well as ‘cycling experience’, whereas comfort is a term that users can relate to and know how to grade. This leads to the formulation of the interview questions in the final interviews (see section 7.3.4).

Nine cyclists were interviewed during the preparatory interview round. The small sample size was sufficient to test the interview protocol and refine the questions. The preparatory round made clear the difficulty of stopping cyclists along their work-home trip. Therefore, chocolates were used as an incentive to stop cyclists at the interview location (zone B in Figure S2). Moreover, signs before and at the traffic light were set up to indicate that there was an *interview + free snack* location a few meters ahead.

Final interviews

The final interviews were conducted with three closed questions. The answers were reported on a digital system that tracked the time the interview ended. This enables to match the objective data collected by the sensor to the interview responses. Hereafter we report the interview questions (IQ) asked in the interviews.

1. How comfortable did you feel at the traffic light with the number of cyclists around you?
   - very uncomfortable =1, 2, 3, 4, 5=very comfortable
2. How busy did you perceive the road and intersection before stopping?
   - empty=1, 2, 3, 4, 5=very busy
3. Are you more uncomfortable in busy areas since Covid-19 times?
   (a) yes, I am more uncomfortable
   (b) no, I am the same

The close option answers for the first question were associated with an emoji face, as shown in figure S3, to ease interpretation of the answer to the respondents. *Questions 1 and*

Figure S3: Close option answers for interview question n. 1.

2 pertain to the subjective perception of level of service and busyness of the place at the time of the interview. The results will be matched to the objective data measured by bicycle sensors. *Question 3* is asked to explore how perceptions changed due to the coronavirus pandemic. Results from this last question will be used to understand the alteration of perceptions due to the pandemic and will be presented in the limitations (section 7.6) of this work.

7.3.5 Data analysis method

This section explains how we analyse the collected empirical data to answer the three research questions (RQ). RQ1 and RQ2 are analysed similarly, building an ordered logit model. Whereas RQ3 is investigated via a statistical Spearman correlation.

Perceived BLoS and busyness in relation to flow and density [RQ1, RQ2]

RQ1 and RQ2 are investigated with a similar method since in both cases we aim to build a statistical model to relate ordinal data (BLoS or busyness) to ratio data (density and flow). Thus, to avoid repetitions we will describe the process for RQ1 and the research approach for RQ2 can be derived by substituting perceived busyness to perceived BLoS. The remainder of this chapter refers to perception data as either one, perceived BLoS or perceived busyness.

First, we combine objective data with perception data. Then we plot the data to visualise whether any visible relation between perceptions and flow or density exists. Finally, to model the relation between the perceptions (of BLoS or busyness) of cyclists and the objective measurements of density and flow, the ordered logistic regression was chosen as a statistical tool. The ordered logit model (also ordered logistic regression or proportional odds model) is a regression model to predict a variable that is discrete and ordered (McCullagh, 1980). This is, as in our case when the dependent variable can be thought of as categories of contiguous intervals. The ordered logit model will enable to identify if there are significant statistical relations and if, and to what extent, the perceptions of cyclists can be estimated based on the easier to measure objective variables.

The ordered logit model is described by this probability function

$$logit[P(Y \leq j)] = \alpha_j - \sum \beta_i x_i, \tag{7.1}$$

$$j = 1, \ldots, J-1 \qquad i = 1, 2.$$

On the right side of the equal sign there is linear model with slope, β_i, that changes depending on the independent variable i and an intercept, α_j, that changes depending on the level j of an ordered category with J levels. In our case there are 5 ordered categories of BLoS, $j = 1$ would be “very uncomfortable” and $j = 4$ would be "comfortable". So we see we have a different intercept depending on the level of comfort. In this model, we are modelling the probability of being in one category (or lower) versus being in higher-order categories. Thus, we’re using the levels as boundaries. In this case, for example, $P(Y \leq 2)$ means the probability of being “very uncomfortable or “uncomfortable” versus being “neutral” or above. In this model the highest level (i.e. the probability of being in the highest level or any of the ones below) returns a probability of 1 (i.e., $P(Y \leq J) = 1$), thus it isn’t modeled in 7.1.

Perceived BLoS in relation to perceived busyness [RQ3]

The relation between perceived BLoS and perceived busyness is investigated with a Spearman rank-order correlation. The Spearman rank-order correlation is used to measure the strength and direction of the relation between two variables measured on an ordinal scale.

The investigation of RQ3 is not affected by matching issues of the data as could be the case in RQ1 or RQ2. This is because both data are collected by the same data collection system: structured interviews. Whereas for the previous questions the investigations proceed by matching data collected by interviews and smart cameras. So this reveals how the perception of BLoS relates to the subjective perception of busyness, of the cycle path, at the same moment in time.

7.4 Results and discussion

The final interview round succeeded in interviewing 56 cyclists. A description of the subjective and objective data is reported in Table S2. We report the results and discuss them in three subsections themed around perceived comfort, perceived crowdedness, and perceptions in a pandemic era.

Table S2: Statistical description of the collected data in the final interview round.

	perceived comfort	**perceived crowdedness**	**age**	**flow**	**density**
mean	4.28	2.08	28.38	10.82	0.04
std	0.92	0.9	10.95	3.83	0.03
min	1	1	19	3	0
max	5	4	65	21	0.15

Perceived comfort (*RQ 1*).

The majority of the respondents reported perceived comfort levels of 4 or 5 out of 5. Indicating that the current flow and density levels were not strongly negatively affecting their comfort perception. Figure 7.4(a) shows that there is a relationship between perceived comfort and average density. As the average per minute density becomes larger than $0.05 bic/m^2$ the majority of respondents reported a comfort level of 4 instead of 5.

Figure 7.4(b) shows no clear trend between the total flow of cyclists in the one minute before the end of the interview and the perceived comfort of the respondent. This can be explained by the fact that flow measures the number of cyclists in a time interval but not how these cyclists were grouped. Flow is also more closely related to the moment the traffic light is green. Thus, flow is not sufficiently representative of the distribution in space of the cyclists.

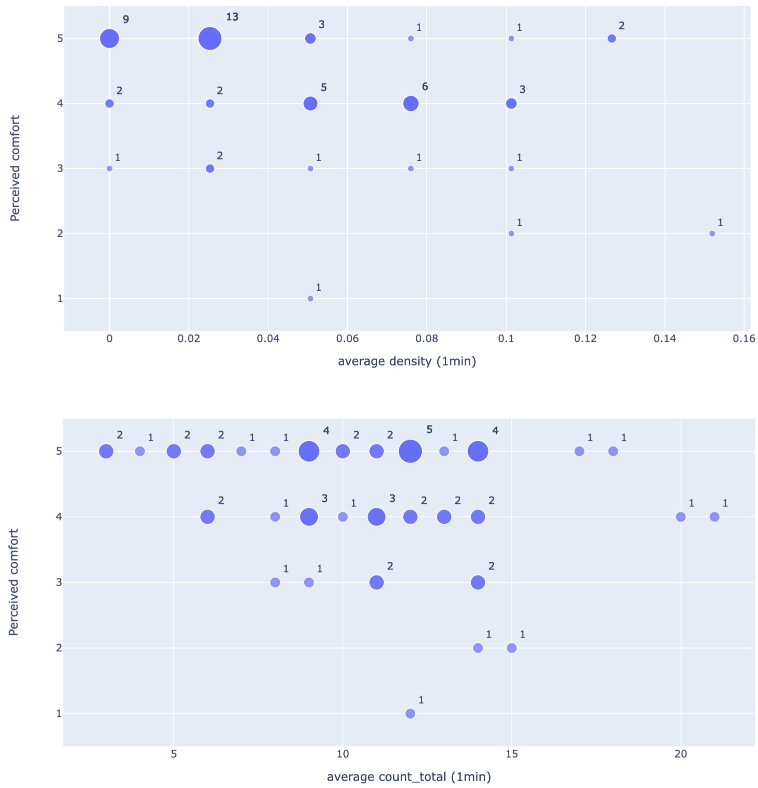


Figure S4: Response data pertaining to the question:"How comfortable did you feel at the traffic light with the number of cyclists around you?".

Based on the perceived comfort level of the cyclists and the objective density and flow measured from the smart cameras, we build an ordered logit model. The summary output of our model is reported in Table S3. The model has two slope coefficients since we include two independent variables (flow and density) and, given the 5 levels of dependent variables, there are $5-1=4$ intercepts. As we see from Table S3 the density is statistically significant at 5% level (p-value of 0.011) whereas the flow variable is not. Thus, the model shows a significant negative relation between the measured density and the perceived BLoS.

Table S3: Ordered logit model, dependent variable = perceived comfort on the cycle path.

	coef	**std err**	**z**	$P > \|z\|$	**[0.025**	**0.975]**
density	-10.8862	4.302	-2.531	0.011	-19.317	-2.455
flow	-0.0413	0.045	-0.915	0.36	-0.13	0.047
α_1	-3.3106	0.687	-4.817	0	-4.658	-1.964
α_2	-0.5938	0.663	-0.895	0.371	-1.893	0.706
α_3	-0.336	0.384	-0.874	0.382	-1.089	0.417
α_4	0.0447	0.205	0.218	0.827	-0.357	0.446

Although we interviewed cyclists both during off-peak and on-peak periods the density levels were moderate because of the recommendation to work/study from home due to Covid-19. Results show that if the average density per minute is below 0.15 cyclists per square meter, we do not observe a wide variability of perceived comfort of cyclists. The majority of the respondents felt positively comfortable with the current amount of cyclists on the cycle path. Therefore, we should take care in drawing conclusions based on the behaviour of the ordinal logistic model for unobserved values of density and flow.

Perceived busyness (*RQ 2*)

Figure 7.5(a) and 7.5(b) show the perceived busyness of the intersection in relation to flow and density. A weak positive trend can be seen in both figures. As the objective variable (density or flow) grows also the subjective perception of busyness increases. Also in this case density seems to correlate more to the subjective variable compared to flow.

We built an ordered logit model based on the perceived business level and the objective density and flow measured from the smart cameras. From the model fit none of the objective variables, of flow and density, were statistically significant to estimate perceived busyness. We don't report the model fit parameters for a matter of clarity of the paper. With regards to the collected data, we don't see a statistically significant relation between the perceived level of busyness at the intersection and the measured bicycle flow and density.

We attempt to explain why the perceived busyness does not correlate to objective variables whereas the perceived BLoS does. The word 'busy' refers to very high crowds or congestion. During the Covid-19 outbreak, busy bicycle paths were not a common situation, and especially if people remember the intersection before the pandemic they would not consider it busy. When asking how comfortable they are with the number of people around them, this probably evokes more a feeling of safety and ease of travel, which is not only affected by busyness but also by a smaller number of cyclists on the path.

Perceived BLoS and perceived busyness (*RQ 3*)

Figure S6 illustrates the relation between the perception of comfort and the perception of busyness. A Spearman's rank-order correlation was run to determine the relationship between the 56 respondents' perceived BLoS and the busyness of the bicycle path. There is a negative monotonic correlation, with medium intensity, between the perceptions of BLoS and busyness, which is statistically significant (S= -0.45, p = 0.0004). The negative monotonic correlation confirms the relation hypothesised in the conceptual model (Figure S1).

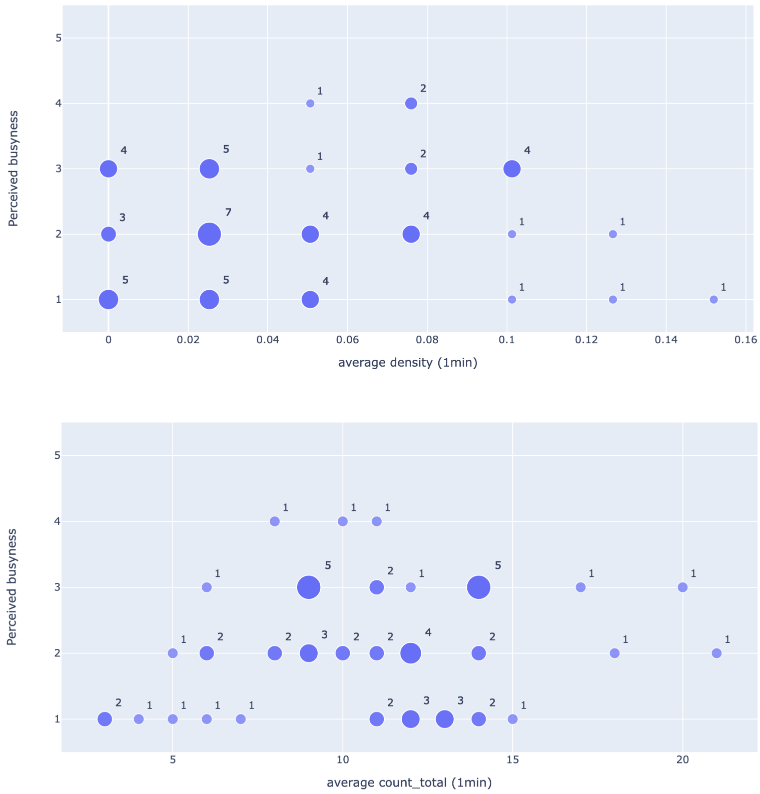


Figure S5: Response data pertaining to the question:"How busy did you perceive the road and the intersection before stopping?".

We expect to identify a stronger relation when larger variations in actual flows and densities are observed.

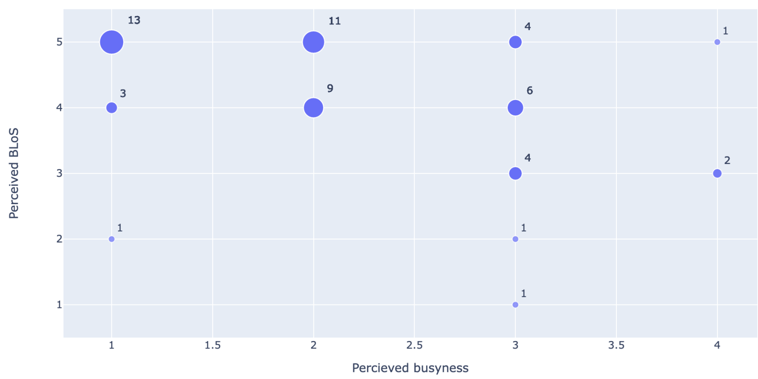


Figure S6: Response data pertaining to interview questions 1 and 2.

7.5 Conclusions

Motivated by growing bicycle congestion and stress provoked by other cyclists on cycle paths we set out to build a model to estimate perceived bicycle level of service as a function of objective and easily measurable variables such as flow or density. The coronavirus outbreak, which was initially thought of as a major disruption in this study, altered but did not cancel the effects of density and flow on the perception of bicycle level of service. The results of this work are the first step towards building a model to estimate the perceived comfort of the cyclists as a function of the objective density and flow of bicycles on the cycle path.

The Covid-19 pandemic changed the conditions of this part of the PhD project, undermining the generalisability of the findings. As a result of the 'working/studying from home recommendations' our observations did not incorporate very high crowdedness levels, nor very low bicycle level of service perceptions. However, despite the data limitations, our empirical results suggest that the assumption of lower perceived comfort with increasing densities on the cycle path holds. Respondents reported a more enjoyable cycling experience after Covid-19 than before due to the lower bicycle volumes on the measurement site. Moreover, in the circumstances of our study, perceived comfort-related better to densities (and perceived busyness) than to flows. This result should be taken with care and further investigated before generalizing it.

These initial findings motivate more research on estimating the subjective level of service by means of objective traffic flow measures. Future developments of this research bear promise to assist urban planners and transport engineers in evaluating the bikeability of a cycle path and making improvements to the bicycle street design. Route choice modellers often attribute to each route a (dis-)utility value which is often modelled as the sum of the costs or qualities of the route segments. Cyclists are assumed to be rational users, thus to be utility maximisers (or disutility minimisers) when selecting their route. In this perspective, BLoS can be used as a value to input to the utility function to compute the overall route utility. Relating traffic variables to perceived BLoS can improve the evaluation of link-level quality. In the following section, we describe the limitations of the current study and propose recommendations for future work.

7.6 Limitations

The main limitations of this study arose because of the Covid-19 pandemic outbreak. As a fact, due to the recommendations to work (and study) from home, the densities and flows at intersections were well below average. The preparatory interview round suggested that the lower volumes resulted in very few respondents with a comfort level below 3 (on a scale from 1 to 5). In the preparatory interview rounds, all respondents reported positive levels of cycling experience at the moment of the survey. When asked how they remembered the cycling experience before Covid-19 on campus their perception is less positive. Figure S7 shows the difference in cycling experience before and after the coronavirus outbreak. As a consequence, our sample observations of perceived BLoS are not uniformly distributed in the five-level scale of BLoS (or busyness). This limits the generalization of our findings to higher levels of flows and densities.

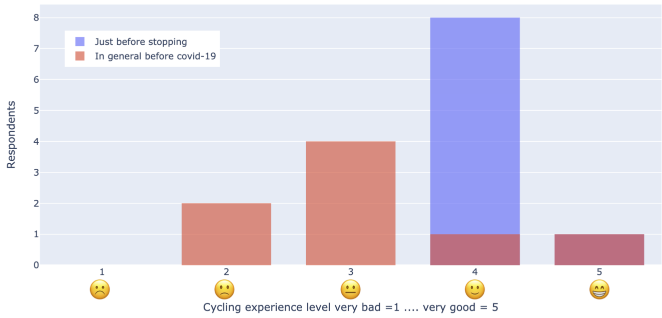


Figure S7: ***Cycling experience perceptions before and after the coronavirus outbreak.*** *Answers to the question: 'How was the cycling experience at this intersection just before stopping?' and 'Before Covid-19, how do you remember the cycling experience on campus in general?'.*

Moreover, the Covid-19 outbreak may have altered the comfort perception of cyclists relative to the number of cyclists present on the cycle path. Based on the third question of the final interview we were able to verify if this was the case to some extent. 50% of respondents reported feeling more uncomfortable in a busy area than before Covid-19, 46% reported feeling the same and just 4% reported feeling more comfortable. To understand if the age group of the respondent played a role in the perception of busy places we carried out a t-student test. The results of the t-test did not report a statistically significant difference in the means of the two independent groups. Thus we can't conclude that age is significantly different between those who feel less comfortable and those who feel comfortable as before the coronavirus pandemic. Although age does not explain the alteration of comfort perception, half of the respondents confirmed they have lower comfort levels than compared to Covid-19 in busy places. This means that we may be observing lover levels of comfort also at relatively lower densities and flows just due to the pandemic circumstances.

7.7 Directions for future research

Based on our findings and the related discussion presented in the sections 7.4 several directions for further research arise. First, the weak relations identified between objective and subjective despite the low bicycle activity, due to the coronavirus pandemic encourage to pursue this research field further. Higher cycling activity (in normal circumstances) could disentangle the question 'what is the relation between objective and subjective variables when there are high levels of density and flows?'. Next, different data collection methods to measure the perceived comfort and BLoS of cyclists could further unravel the relation between objective traffic flow variables and cyclists perceived level of service. Possible options in this direction could be on-bike-installed buttons as well as on-bike sensors to measure objective bicycle flow variables. This would allow recording perceptions without interfering with the cyclist's ride. So the subjective and objective data would have simultaneously been recorded (no matching issues). While exploring different data collection systems, future researchers should also consider the relation of subjective BLoS with other objective variables like variation in speed, but also individual characteristics like the position of the cyclists in the queue, and destination activity. Future research may also use objective data collection methods that distinguish between dam densities and moving densities. As a fact jam density results in the complete stop of the cyclists and thus may show a more negative perception of users.

Finally, the end goal of future studies should be to extend the existing bicycle level of service (BLoS) evaluation methods of a street segment to incorporate the stress factor provoked by other cyclists. By doing so the method would bring together the perception and actual quality of the built environment as well as the change in the level of service due to the presence of other cyclists on the cycle path.

Chapter 8

Conclusions, implications and recommendations

“If you get tired, learn to rest not to quit."

— Bansky

This final chapter presents the main findings and overall conclusions of this dissertation, as well as the implications for practice and recommendations for future research.

8.1 Main findings

The main objective of this dissertation is to gain empirical knowledge on bicycle infrastructure networks and develop methodological tools to assess infrastructure-related bikeability, at different scales. To achieve this goal six research questions (RQ) were investigated in this thesis. In the following, the main findings are presented by answering the research questions formulated in section 1.2.

As different definitions of bicycle networks exist, how does the bicycle network scale for different definitions of the bicycle network as the population grows and what are the structural characteristics worldwide for these different definitions? (RQ1)

Cities are efficient systems since bigger cities have relatively less transport infrastructure. The multi-city analysis on scaling relations between infrastructure and population, in chapter 2, showed that the relation is different between different modes of transport in general, and specifically for active mode and non-active modes. In particular, we found that the bicycle dedicated infrastructure grows the least among all types of transport infrastructure. On average, a city with twice the population has 80% more car streets but only 26% more bicycle roads. Not only do larger cities build less bicycle-dedicated infrastructure they also allocate smaller shares of street space to cycleways compared to any other infrastructure type.

To study the structural characteristics of the networks, we identify four types of bicycle networks, defined by including different infrastructure types. We observe that according to the definition used, networks grow at diverse rates with population size. Our results show that the scaling relation between kilometres of bicycle network and population is faster if the bike network includes multi-modal streets. This implies that the fastest way for a city to increase kilometres of bike network per person is to improve safety and comfort of multi-modal streets (for instance by reducing speed limits) rather than building new separated bike paths. Multi-modal streets are vehicular roads where cycling is allowed, however, they are not always perceived by cyclists as safe nor as comfortable as the separated bike tracks. Moreover, results show that worldwide structural characteristics of networks significantly change between the different bicycle network definitions. The physically separated bike network is significantly less extended, dense and connected and more coarse-grained and circuitous than other bicycle networks. This suggests that in most cities, the physically-separated network is not sufficient for people to reach their daily activity destinations by bicycle. Whereas, our results show that the combination of separated cycle tracks, residential streets, and multi-modal streets improves the network structure resulting in higher connectivity, directness, and lower fragmentation. This implies that the choice of the bicycle network definition, in a research study or urban planning project, is a fundamental one and has consequences on accessibility, equity, and safety evaluations of a city.

What type of bicycle network needs do cities have and which network development solution, in combination with data collection systems, can satisfy the different needs? (RQ2)

Bicycle network needs (BNNs) are defined in this thesis as the set of requirements that a street network should meet to improve its bicycle operating functions given its level of bicycle culture (LoBC). Going from lowest to highest, we identify the following level of BNN: 1) basic and direct paths, 2) safety and accessibility, 3) connectivity, 4) comfort, 5) mitigate congestion. As a city grows in level of needs (going from level 1 to level 5), the type of network development solutions to improve the bicycle network performance shift from a predominance of hardware solutions (e.g. construction of new bike paths, bike parking, intersection redesign) towards software types of solutions (e.g. demand-responsive traffic controllers, route planner apps, dynamic route recommendations). Once the solution is identified we determine the necessary input information, data requirements and data collection techniques to implement the solution. Chapter 4 links all the aforementioned steps by proposing a framework to establish what type of data cities should collect, conditional to their level of bicycle culture and network needs.

Empirical evidence from the Netherlands and from Australia reflects and showcases the logic of the framework. Bicycle ‘ignorant’ and ‘emerging’ cities focus on origin-destination and trip data to develop a strategic starting point for their cycling network development. Our survey also shows that bicycle ‘friendly’ and ‘dominant’ cities focus on comfort and congestion needs and collect different types of data, related to the real-time use of the network and its intersections. The proposed framework (on network needs, solutions, information, data requirements, sensors and data collection systems) provides a guideline for data collection plans for cities by improving the synergy between needs and data collection systems.

How should a bicycle network be assessed in order to take into consideration multiple infrastructure characteristics and the diversity of user preferences? (RQ3)

The complexity of assessing bikeability of a network or set of origin-destination (O-D) pairs relates to the fact that bikeability is the result of multiple, sometimes conflicting, objectives (e.g. distance, comfort, travel time, aesthetics of the route). To address such complexity chapter 4 introduced a multi-objective methodology to assess bikeability. The result of a multi-optimization process is a set of Pareto optimal solutions. Selecting the best alternative among the Pareto optima, in this case, is a matter of user preferences. Since a bikeability measure should consider the different users of the system, the methodology we develop — denominated 'the bikeability curve'— incorporates the entire set of optimal routes for all user types, and does not reduce the evaluation to a value that represents bikeability for the 'average user'.

The bikeability curve allows visualising factors influencing bikeability and assessing the quality of bicycle infrastructure in a city network with respect to the heterogeneity of user preferences. The number of points on the curve represents how many optimal route alternatives there are to go from origin to destination, and the slope of the curve indicates the trade-off between factors. The case study reported in chapter 4 has tested the methodology to provide means to evaluate concurrent factors for bikeability by studying the relationship between directness and comfort of routes over an entire network.

To what extent can Artificial Neural Networks (ANNs) exploit loop sensor data to estimate bike travel times in proximity to signalised intersections? (RQ4)

We investigate to what extent loop sensor data can be used as input for an Artificial Neural Network (ANN) model, to estimate individual travel times of cyclists approaching a signalised intersection. Data retrieved from loop sensors, which are used in the Netherlands for observing bicycle flows for instance at controlled intersections, suffer from counting errors when there are high volumes of cyclists. To assess the performance of an ANN in estimating the individual travel times in an ideal scenario without counting errors, and to work in a controlled environment where the actual travel time of each agent is known, the loop sensor signals were simulated.

The simulation study in chapter 5, showed that in cities with low bicycle levels (deterministic scenario), loop sensor data can be used to estimate the travel time of individual cyclists approaching a signalised intersection. Whereas in places with high bike volumes (where cyclists depart with a discharge rate) raw loop sensor data (time signals) are not sufficient, information on queued cyclists is crucial for travel time information. Based on the ANN's performance on the simulated loop sensor data, it is clear that additional data is required to have accurate estimations of individual travel times (i.e. data fusion with data derived from other data collection systems). These preliminary findings show the difficulties of only using loop sensor signals for training ANNs and encourage research on queue estimation algorithms (of cyclists) that can improve overall travel time estimation.

To what extent can loop sensors be used to estimate queue accumulation in front of traffic lights, which ultimately measures bicycle level of service? (RQ5)

Given the difficulty in retrieving ground truth queue information from loop sensor signals, an unsupervised machine learning methodology was used in chapter 5.1 to estimate accumulation levels based on data retrieved from loops sensors on bicycle streets of the Netherlands. Loop sensor data, combined with a clustering-based approach and conceptual insight into the bicycle accumulation process and various data sources, make the applied methodology less dependent on sensor errors (occlusion is the main error with loop sensors counting bike passes). Field testing of the methodology on real data indicated an accurate estimation performance with low data requirements, in a setting where the number of queued cyclists varied between 0 and 30 when defining 4 main clusters of queue level (from very low to high). Selecting the data features resulted to be a crucial step, as with most of the data-driven algorithms. The study revealed that traffic flow domain knowledge is important to select features for clustering. Instead, applying a pure data-driven feature selection did not show valuable clustering of the data.

What type of relation exists between perceived bicycle level of service and presence of other users on the cycle path? (RQ6)

The exploration of this question was carried out during the coronavirus (Covid-19) pandemic. This inevitably affected the findings and conclusions we can draw on this research question. Despite the data limitations because of low bicycle flows (due to the work-from-home advice of the government), the empirical results suggest that the assumption of lower perceived comfort as densities on the cycle path increase holds. A weaker relation was observed between perceived comfort and bicycle flows. These initial findings are very encouraging and motivate more research on estimating the subjective level of service by means of objective traffic flow measures.

The weak relations identified between objective and subjective variables encourage to pursue of this research field further. Higher cycling activity (in normal circumstances) could disentangle the question ‘what is the relation between objective and subjective variables when there are high levels of density and flows?’.

8.2 Overall conclusions

Based on the findings of the individual chapters, this section draws overarching conclusions to the main research objective. The section provides conclusions on the knowledge developed on bicycle networks as well as the methodologies to evaluate the quality of the infrastructure.

From the knowledge perspective, the conclusions relate to novel insight that future studies can depart from for new investigations. This work suggests that the bicycle network system is not only difficult to evaluate but also difficult to define. As different definitions can be used, these may have large implications on the results of the bikeability analysis. The comparison of cities worldwide showed that larger cities systematically have less bicycle-dedicated infrastructure. This should be kept in mind, together with multi-modal trips, when developing theories and plans on how the sustainable city of the future should look like. Finally, research on bikeability made clear that it is a complex concept that is difficult to reduce to one numerical value. Although we do not exclude this can be done, we advise assessing bikeability in relation to the different user groups and their perceptions.

From the perspective of developing bikeability assessment models, conclusions pertain to the data availability and methodological considerations. Our case study on data collection methods in the Netherlands revealed that more data is becoming available as cities have a more bicycle mature culture. This will enable more quality assessment models to be developed that measure local usage and performance of bicycle facilities. Local-level data and assessments methods are necessary to evaluate bikeability at a city level. The data-driven models in the link scale part of the thesis showed the potential as well as the limitations of bicycle loop sensor data. More accurate data systems like smart cameras can be used to enrich bicycle level of service assessment with density and flow measurements, which our initial findings seem to relate to the comfort perception of users.

8.3 Societal relevance

This thesis has been elaborated with the goal of contributing to science, policy-making and ultimately to society. With this objective in mind, conversations with Dutch and Italian policy-makers were initiated to understand their (respectively different) point of view and make this work relevant to the present and future needs of decision-makers. After having illustrated the scientific contributions (in the previous section) here we discuss how these findings can be used in practice by policy-makers and urban planners.

Identification of bicycle network definitions for hierarchical planning of networks

The last decade has seen a rise in bicycle research. Yet, a clear and concise overview of what can be defined as a bicycle network does not exist. Consequently, studies on space allocation, accessibility, safety and network developments are fundamentally different and incomparable due to the tailored bike networks they analyse in their studies. Thus, there is a need to reach an agreed definition of what type of bicycle networks exist in cities and how this affects network evaluations and the functioning of a city. So that policymakers and planners can refer to the same definitions to evaluate their networks and design improvements.

Chapter 2 provides four bicycle network definitions and quantitatively describes the structural network characteristics of each of them. The lower densities and kilometre extension of the physically-separated-from-traffic bicycle network confirms that in most city contexts, the bicycle-dedicated network is not sufficient for people to reach their daily activity destinations by bicycle. However, our results show that the hierarchical combination of separated cycle tracks and residential streets (used by multiple modes) improves the network structure allowing cyclists to reach more destinations within their neighbourhood.

This means that a policymaker aiming to improve structural characteristics of the bicycle street network can focus its efforts on making the infrastructure of the multi-modal bike network truly bikeable, instead of expanding the size of the physically separated network. We show that one type of bike street is not sufficient and does not lead to good structural characteristics of the network. Urban planners can compensate for the difference in bicycle infrastructure per capita by making multi-modal use of the streets safe for both modes, and across user groups.

Data collection systems to improve urban bicycle plans

Based on the framework developed in chapter 3, we see that cities have different needs in terms of bicycle data collection according to the level of bicycle culture they have. Urban planners can use the proposed framework to understand which type of bicycle data should be collected in order to transform policy objectives into urban plans. For example, a city with an emerging bicycle culture (i.e. that has just started to build some bicycle lanes) will have a hard time dealing with drivers discontent on reallocating space from cars to bikes. Although expensive, it is critical for them to collect data before and after the infrastructure change in order to measure the effects of their design. By doing so the policy-maker closes the Plan-Do-Check-Act (PDCA) cycle and can illustrate the benefits of their policy to bicycle sceptics who argue against reallocation of space. More mature bicycle cities have inherently different needs compared to bicycle emerging cities. However, a bicycle emerging city could, over time, evolve into a mature bicycle city and require a whole new set of data collection systems. While this thesis does not explore how quickly this change occurs over time, we do advise urban planners to investigate the time required for such a change to occur. This new piece of information will prevent installing expensive data collection systems that may quickly become obsolete in a bicycle mature context.

Planning for bikeable routes for all types of users

The methodology to assess the bikeability of a street network (presented in chapter 4) can be of interest to transport planners and policymakers to evaluate urban bicycle networks without making a priori assumptions on user preferences. By examining the bikeability curves associated with different OD pairs city planners can pinpoint the locations that need to be better connected for cycling. Incorporating demand in the methodology is fundamental to identify where network improvements are most required. However, the use of a demand matrix imposes a normative judgment on how network improvements should be identified. In particular, depending on the OD matrix used (e.g. standard O-D matrix or equity-weighted O-D matrix) different routes will be prioritised, this has a practical implication on how costs and benefits are distributed among city locations (Yap et al., 2021).

Evaluating the quality of a (bike) network is the first step to identify and prioritize infrastructure investments. Ultimately this will have implications on the accessibility, safety and liveability of cities. Having a better bicycle network means being able to reach more activity locations by bike and with less discomfort and risk of accidents. This will lower the resistance of bicycles as a mode of transport, in general leading to higher bicycle trip shares. There are many positive outcomes to more trips in the city being done by bike such as lower air pollution and car congestion, healthier lifestyle of residents, more fair and accessible transport options, lower noise pollution, happier residents and a greater feeling of freedom and independence of youths. The reader should note that, as more trips are made by bike the number of absolute bicycle accidents can increase because the exposition to risk increases. However, research shows that the net positive effects of cycling are much higher than the risks involved, also at higher levels of trip share (de Hartog et al., 2010).

Bicycle level of service (BLoS) evaluations based on presence of other cyclists

Increasing the comfort (and safety) of the cycling experience is on the agenda of many bicycle mature cities. This thesis has initial findings on how the presence of other cyclists (in terms of flow and densities) affects perceived comfort. And provides insight into how to estimate the level of queued cyclists in front of a traffic light. Measuring and ultimately incorporating these variables in the BLoS indexes has several practical implications. It first leads to less resistance and thus more attractive bicycle streets. Implications on BLoS based on the presence of other cyclists are of particular interest to traffic engineers and urban planners in bicycle mature contexts like the Netherlands, Copenhagen region and other cities which were so successful in attracting cyclists that now have to deal with bicycle congestion problems.

8.4 Directions for future research

This thesis has made a step forward in understanding and evaluating the bikeability of urban bicycle networks. However, the understanding is far from complete and several opportunities remain to unravel factors influencing bikeability in urban areas.

- **Large cities and active mode challenges.** Sustainable and active mode challenges in urban mobility seem to lie in the large cities. In this thesis, we identified that larger cities systematically invest less in cycling dedicated infrastructure, which may lead to a less positive attitude towards the bike. Further investigations on understanding the network scaling relations would explain why such differences exist between modes of transport. In practical terms, active modes in large cities could be researched by analysing the trip chain complexity and the use of one or multiple modes per trip. Higher multi-modal trips or more complex trip chains, in large cities, could partially explain the lower investments in active mode infrastructure. Moreover, not all cities are alike, so investigating the land use system differences (e.g. activity locations) would also help in the understanding of active mode potential demand and supply of infrastructure.

- **Develop solutions for bicycle dominant types of cities.** Bicycle mature cities were so successful in attracting cyclists that now have to deal with bicycle congestion problems. The increasing availability of bicycle data in these types of cities, pointed out by the study in chapter 4, is often not employed to its full extent. Thus, a future research direction should focus on novel data-driven traffic management solutions that can make use of the large amount of bicycle data coming from inductive loop sensors, Bluetooth and WiFi sensors and smart cameras. The traffic management solutions could be of two types: operational and strategic. The former requires real-time estimations of traffic flow to make real-time decisions (e.g. route advice or traffic controller) the former relates more to network planning and management and requires off-line information to identify criticalities in the network.

- **Relation between chosen routes and bikeability curves.** In chapter 4 we design a multi-objective methodology to evaluate the bikeability of an origin-destination. Future research on bikeability evaluation tools could link the evaluation method to the actual choices of users. By doing so we would enter the domain of route choice modelling, where factors and weights that influence one's route selection are studied. It is plausible that such a study would reveal that users choose non-optimal routes because of not full knowledge of the network or due to indifference to small changes. This would mean that the chosen routes of cyclists don't lie on the bikeability curve but a bikeability band. Studies in the transport field have developed the idea of indifference curves into indifference bands (Vreeswijk et al., 2013). Future research could investigate to what extent cyclists are aware of routes on the Pareto front and estimate the width of such bikeability bands.

- **Role of artificial intelligence and data fusion information quality improvement.** Data in the bicycle domain tend to be error-prone. Differently from the cars' environment, where agents are constrained to move within the long lanes, in the bicycles environment agents have a much higher degree of freedom. Consequently, fixed location sensors tend to incorporate counting errors which affect flow data of bicycles and can lead to growing cumulative errors while estimating queues of cyclists in front of a traffic light. Our work explored initial steps in using machine learning techniques to improve the quality of the estimated traffic states, however the main limitation appeared to be in the lack of accurate ground truth data. While we think machine learning models and data fusion deserve future attention in the bicycle traffic state estimation, we recommend researchers plan a phase of ground truth data collection, by manual or automated means, to enable data-driven methods to accurately estimate traffic states.

- **Further insights into subjective and objective relation of BLoS.** The preliminary findings on the relation between subjective comfort perception and the presence of other cyclists on the cycle path confirm the hypothesis that higher densities may lead to lower bicycle level of service (BLoS). Further investigations on the BLoS should focus on a larger sample size and different data collection approaches. In order to capture the effects of high bicycle volumes and densities on BLoS data collection should be carried out in busy places and the subjective data should aim to reach a wide diversity of user groups. As observed in our interview-based study, the main limitation of such type of study relates to the subjective data collection process. Interviews impose an inevitable bias towards users that are not in a hurry and have time to stop. Other data collections should be tested, such as on-bicycle reporting systems (e.g. GPS + push buttons to measure subjective comfort). While these on-bike systems would not impose an activity-based bias they may filter out non-tech-savvy people. To reduce the sample bias, we recommend combining different data collection techniques. By doing so, future research can unravel the link between the presence of other cyclists and perceived comfort, and contribute to making the bicycle an even more attractive mode of transport.

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Summary

Although many agree that the use of bicycles improves mobility and quality of life in a city, much less clear is how to assess the progress being made in this direction and how to plan bikeable cities. The bikeability of a city depends on many diverse and interrelated factors such as the land use and transport system, culture and social norms, as well as individuals' perceptions. Among the many factors influencing bikeability the infrastructure network, made of streets and intersections, is a fundamental component to allow safe and convenient cycling in a city. For this reason, this thesis focuses on infrastructure-related bikeability aspects and how to assess them. Planning for bicycle infrastructure has been piece-wise and location-specific resulting in every city developing its own best practices without contributing to a more general theoretical guidance on how to assess and develop attractive and convenient bicycle networks. Since a systematic approach to bicycle infrastructure evaluation and planning is lacking we formulate the following research goal:

To gain empirical knowledge on bicycle infrastructure networks and develop methodological tools to assess infrastructure-related bikeability.

To achieve the goal, first, we set out to define characteristics, needs and assessment methods of the city-wide networks. Second, given that a network is the combination of its components (streets and intersections) we narrow the focus to street-level (i.e. link) to gain information on the cycling quality on parts of a network. At the network level, we define and analyse the structural characteristics of 47 urban bicycle networks (chapter 2). In doing so we investigate how bicycle dedicated infrastructure scales with population and compare it to infrastructure dedicated to other modes such as cars, pedestrians and metro. We continue the network-level exploration by identifying the bicycle network needs of a city and relating them to solutions and data collection systems to improve bicycle network performance (chapter 3). After having identified different types of bicycle network infrastructure, we propose a methodology to assess a network based on multiple objectives and consider the diverse preferences of users (chapter 4).

At the link level, this thesis focuses on aspects of bicycle level of service (BLoS) of part of a bicycle street. BLoS depends on infrastructure characteristics of the bicycle path (paving conditions, width, separation from vehicular traffic) as well as the presence of users on the cycle path (queues, congestion etc.). This thesis looks at the latter, which are characteristics that are more relevant for bicycle mature places with high bicycle flows. To have a dynamic picture of the BLoS, we explore data-driven methods for travel time estimation (chapter 5) and queue estimation (chapter 6). Finally, we investigate the relation between objective traffic flow variables (flow and density) and perceived BLoS (chapter 7).

The following sections summarise for each of the analyses the data and methods used and discuss the main findings. Finally, we present overall conclusions and highlight the most important implications for future research and practice of our findings.

Scaling relations and structural characteristics of urban bicycle networks

Since many definitions of bicycle networks exist (made of different infrastructure types) it is crucial to bring them together and understand their structural differences. We investigated what infrastructure types are part of a bicycle network and proposed four bicycle network definitions to facilitate analysis and comparison of bicycle network characteristics. We retrieved street networks from open street map (OSM), a crowd-sourced and open source project. Networks of 47 cities were analysed to observe how the bicycle network kilometres scale with population growth and if there are significantly different structures worldwide.

Results show that all types of infrastructure scale sublinearly and that active mode infrastructure, bicycle dedicated infrastructure, in particular, scales slower than non-active mode infrastructure. We observed that cities that have double the population appear to have 80% more car road infrastructure but only 26% more kilometres of bicycle dedicated infrastructure. These results confirmed that cities are efficient systems where there are economies of scale but pointed out at the less liveable and sustainable side of large cities. Larger cities seem to systematically invest less in bicycle dedicated infrastructure.

In addition, this empirical multi-city analysis showed the importance of residential streets which, by creating within-neighbourhood connections, increase the network density, directness, connectivity, and significantly extend its size. This implies that city authorities could focus more on improving the bikeability of residential streets that already exist rather than predominantly focusing on developing new separated or semi-separated bicycle streets.

Data collection systems for bikeable urban areas

Given a bicycle network and the bicycle culture of the city, there are specific sets of potential improvements (bicycle network needs) suitable for the context. We defined a framework to relate the needs, and bicycle maturity of a city, to the data collection systems. To do so we identified network solutions to improve bicycle network performance. Then we combined the network solutions to the bicycle maturity of a city, to understand at what maturity stage a city should make use of these solutions. Finally, the network solutions were combined with the data collection technique required to implement the solution. We showcased the need-driven framework through a case study of Melbourne, Australia (a bicycle ignorant city) and surveying 15 municipalities of the Netherlands (bicycle-friendly cities).

The empirical evidence from the case studies showcased the framework, albeit further research is needed to explore hostile and ignorant cities. Previous works have reported that bicycle ignorant and emerging cities focus on origin-destination and trip data in order to develop a strategic starting point for their cycling network and this was confirmed when reviewing literature from Melbourne. Whereas our survey showed that bicycle-friendly and dominant cities focus on comfort and congestion needs and collect different types of data, related to the real-time use of the network and its intersections. The proposed need-driven framework serves as a guide for planners and policy-makers to understand how to fully exploit bicycle data collection systems and make a systematic and long term plan for the bicycle infrastructure network.

Multi-objective bicycle network assessment

We proposed a multi-objective methodology to evaluate the quality of the bicycle network. The methodology contributed to the literature on bicycle network evaluation techniques by quantitatively comparing the quality of bicycle connections for the different user groups. We developed 'the bikeability curve', a visual instrument, to analyse the trade-offs that users need to make between different characteristics of a bicycle route. This methodology aimed to assess the bikeability of urban networks free from user preference assumptions; meaning that the method evaluates the network based on all the user types and not based on the average user.

The methodology was tested on two cities with very different bike cultures—Amsterdam and Melbourne. The two objectives on which we evaluated the networks of the two cities were detour and discomfort. The results showed that Amsterdam's bicycle network supplies users with more direct and comfortable routes compared to Melbourne which on average supplied trips with a significantly longer detour for similar levels of discomfort.

By examining the bikeability curves associated with different OD pairs city planners can pinpoint the locations that need to be better connected for cycling. Then, the improvements can be made by reducing detours on routes with low discomfort or by reducing the discomfort on routes with a low detour. Besides using the proposed methodology to assess the bikeability of existing routes, urban planners can also use it to evaluate and prioritize investments.

Data-driven method for estimation cyclists' travel time

When assessing the whole bicycle network having accurate local information on the quality of its links (components) is required. Besides fixed infrastructure data also information on the use (level of service) of a link is important. For example, at a traffic light a cyclist may need not only to stop but also to wait for the queue to discharge before crossing the intersection. This has a clear impact on the cyclist's travel time. Travel time was the first link-level measure that this thesis aimed to estimate on a signalized link.

A tool for estimating the travel time of cyclists approaching a traffic light was developed to monitor the level of service (quality) of a signalised link in bike-crowded cities. We investigated the performance of artificial neural network models in predicting individual travel times at an intersection based on inductive loop sensor data. The investigation was carried out in a series of simulated scenarios to keep under control the sensor's detection errors. The analysis made clear that the main limitation of these models lies in the availability and richness of the data.

Data-driven method for estimation queued cyclists

In order to estimate the number of queued cyclists at a signalised intersection, we investigated a data-driven method based on inductive loop sensor data. To this end, we used an unsupervised learning method so as to not require large amounts of ground truth to train the model.

Results from the interpretation step showed that incorporating traffic domain knowledge is important to select features for clustering. Instead, applying a pure data-driven feature selection did not show an interpretable clustering of the data. A case study at a signalised intersection in Utrecht, the Netherlands, showed that loop sensor data combined with a clustering technique can identify the levels of bicycle accumulation. This information can be used as real-time traffic information over an urban network or transmitted to traffic responsive signal controllers, to optimally determine the green and red light phase of the signal.

Objective and subjective bicycle level of service

This analysis studied the statistical relation between the objective traffic variables and cyclists' perceptions. We measured subjective variables, like perceived bicycle level of service (BLoS) and perceived busyness, statistically correlated them to objective flows and densities of cyclists. This preliminary study was conducted during the coronavirus outbreak, which altered the conditions of the empirical data collection and limited the generalisability of the findings.

Despite these unexpected conditions, the result of this analysis can be used as initial findings and motivates future research to develop BLoS measures based on perceptions and their relation to bicycle traffic conditions. Our empirical results suggested that the assumption of lower perceived comfort with increasing densities on the cycle path holds. Whereas a weaker relation was found between perceived comfort and flows. These results should be taken with care and further investigated under different circumstances before generalizing them.

Relating traffic variables to perceived BLoS can improve the evaluation of link-level quality. Future developments of this research bear promise to assist urban planners and transport engineers in evaluating the bikeability of a cycle path and making improvements to the bicycle street design.

Conclusions and implications

Conclusions can be drawn with regards to the knowledge developed on bicycle networks and on the methodologies proposed to evaluate the quality of the infrastructure. The knowledge developed on bicycle networks suggests that the bicycle network system is not only difficult to evaluate but also difficult to define. As different definitions can be used, these have large implications on the results of the bikeability analysis. If we consider only the bicycle dedicated streets, larger cities systematically have less bicycle infrastructure. Things change significantly if we also consider multimodal streets where cars and bikes use the same space. This finding has practical implications for urban planners that should consider a hierarchy of different bicycle infrastructures. Moreover, research on bikeability made clear that it is a concept that is difficult to reduce to one numerical value. Although we do not exclude this can be done, we advise assessing bikeability in relation to the different user groups and their perceptions.

The methodologies proposed to evaluate part or whole networks lead to considerations on user needs and data availability. We propose a methodology to assess a bicycle network taking into consideration the different user needs. This offers a practical contribution to urban planners that can evaluate the quality of a network connection independently from assumptions on the user preferences. In addition, more data on bicycle users and networks are becoming available as cities have a more bicycle mature culture. This will enable novel quality assessment methodologies to be developed that measure local usage and performance of bicycle facilities. The data-driven models in the link scale part of the thesis showed the potential as well as the limitations of bicycle loop sensor data. More accurate data systems like smart cameras can be used to enrich bicycle level of service assessment with density and flow measurements, which our initial findings seem to relate to the comfort perception of users.

Samenvatting

Hoewel veel mensen het erover eens zijn dat fietsgebruik de mobiliteit en de kwaliteit van leven in een stad verbetert, is het minder duidelijk hoe de vooruitgang in deze richting kan worden gemeten en hoe fietsvriendelijke steden ontworpen zouden moeten worden. The "fietsbaarheid" van een stad is afhankelijk van veel verschillende, maar vaak gerelateerde, factoren, zoals landgebruik, het transportsysteem, culturele en sociale normen, maar ook de individuele perceptie. Het infrastructuurnetwerk van een stad, bestaande uit straten en kruispunten, is hierin een fundamentele factor die bepaalt of men zich veilig en comfortabel kan verplaatsen met de fiets, en daarmee de fietsbaarheid van een stad sterk beïnvloedt. Dit proefschrift richt zich dan ook in het bijzonder op infrastructuur-gerelateerde fietsbaarheid-aspecten en op de vraag hoe ze gemeten kunnen worden. Het ontwerp van fietsinfrastructuur heeft zich altijd gericht op zaaksgewijze en plaatsgebonden scenario's, wat erin heeft geresulteerd dat iedere stad zijn eigen 'best practices' heeft ontwikkeld, zonder direct te hebben bijgedragen aan een algemeen theoretisch kader voor het evalueren en ontwerpen van aantrekkelijke en comfortabele fietsinfrastructuur. Vanwege het ontbreken van een systematische aanpak voor het evalueren en ontwerpen van fietsinfrastructuur, formuleren we het volgende onderzoeksdoel:

Het opdoen van empirische kennis van fietsinfrastructuur-netwerken en het ontwikkelen van methodologische hulpmiddelen voor het beoordelen van infrastructuur-gerelateerde fietsbaarheid.

Om dit doel te bereiken definiëren we allereerst de karakteristieken, behoeftes en evaluatiemethodieken van netwerken op stadsniveau. Aangezien een netwerk bestaat uit op zichzelf staande componenten (straten en kruispunten), zoomen we vervolgens in tot op straatniveau (linkniveau), om informatie te verkrijgen over de fietskwaliteit van specifieke gedeeltes van een netwerk. Op netwerkniveau definiëren en analyseren we de structurele karakteristieken van 47 stedelijke fietsnetwerken (hoofdstuk 2). Hiermee onderzoeken we hoe de infrastructuur die gewijd is aan de fietser schaalt met de populatie en hoe dit zich verhoudt tot infrastructuur die gewijd is aan andere tramsportmodi, zoals de auto, de wandelaar en de metro. We vervolgen het onderzoek op netwerkniveau door de behoeftes met betrekking tot het fietsnetwerk in kaart te brengen en ze te relateren aan de oplossingen en dataverzamelsystemen voor het verbeteren van de performance van het fietsnetwerk (hoofdstuk 3). Na verschillende types fietsnetwerk-infrastructuur te hebben geïdentificeerd presenteren we een methodologie om een netwerk te beoordelen op basis van meerdere doelstellingen, daarbij de diversiteit van de voorkeuren van de gebruikers inachtnemend (hoofdstuk 4).

Op linkniveau focust dit proefschrift zich op aspecten van de 'bicycle level of service' (BLoS) van een gedeelte van een fietspad. De BLoS hangt af van zowel de karakteristieken van het fietspad (condities van bestrating, breedte, afscheiding van gemotoriseerd verkeer) als van de aanwezigheid van gebruikers (rijvorming, files, etc.). In dit proefschrift wordt ingegaan op het laatste, waarbij het gaat om de karakteristieken die met name relevant zijn voor hoogontwikkelde fietsinfrastructuur met grote fietsersstromen. Om een dynamisch beeld te vormen van de BLoS, gebruiken we datagedreven methodes voor reistijdschatting (hoofdstuk 5) en schatting van gevormde rijen (hoofdstuk 6). Ten slotte onderzoeken we de relatie tussen objectieve verkeersstroomvariabelen (stroom en dichtheid) en de ervaren BLoS (hoofdstuk 7).

De volgende secties geven een samenvatting van de verschillende analyses door de gebruikte data en methodes en de belangrijkste bevindingen te bespreken. Aan het eind presenteren we algemene conclusies en staan we stil bij de implicaties van deze bevindingen voor toekomstig onderzoek en de praktijk.

Het schalen van relaties en structurele karakteristieken van stedelijke fietsnetwerken

Aangezien er vele definities bestaan van fietsnetwerken (opgebouwd uit verschillende types infrastructuur) is het van groot belang om deze samen te brengen en hun structurele verschillen te begrijpen. We hebben onderzocht welke types infrastructuur onderdeel zijn van een fietsnetwerk en hebben op basis daarvan vier definities van een fietsnetwerk voorgesteld, wat het mogelijk maakt om fietsnetwerken te kunnen analyseren en te vergelijken. We hebben straatnetwerken gebruikt van het platform open street map (OSM), een crowd-sourced en open-source project. Van 47 steden hebben we de netwerken geanalyseerd en hebben we gekeken hoe het aantal kilometers van het fietsnetwerk schaalt met het aantal inwoners en of er wereldwijd significante verschillen zijn.

De resultaten laten zien dat alle types infrastructuur sublineair schalen met het inwonersaantal en dat infrastructuur voor de actieve modaliteiten, fietsinfrastructuur in het bijzonder, langzamer groeit dan infrastructuur voor de niet-actieve modaliteiten. We hebben geobserveerd dat steden met een twee keer zo grote populatie 80% meer autowegen hebben, maar slechts 26% meer infrastructuur die geheel bestemd is voor de fietser. Deze resultaten bevestigen dat steden economisch efficiëntere systemen worden naarmate het aantal inwoners stijgt, maar ze tonen ook de verminderde leefbaarheid en duurzaamheid van een grote stad. Grotere steden lijken systematisch minder te investeren in infrastructuur die is gewijd aan de fietser.

Daarnaast toont deze empirische stedenanalyse het belang van woonstraten, die de dichtheid, directheid, connectiviteit en in sterke mate de grootte van het netwerk doen toenemen, door het leggen van verbindingen binnen een woonwijk. Hieruit volgt dat stadsbestuurders meer focus zouden kunnen leggen op het verbeteren van de fietsbaarheid van bestaande woonstraten, in plaats van zich hoofdzakelijk te richten op het ontwikkelen van nieuwe (semi-)afgezonderde fietsstraten.

Dataverzamelsystemen voor fietsbare stedelijke gebieden

Voor een gegeven fietsnetwerk en fietscultuur van een stad is slechts een specifieke set verbeteringen (behoeftes met betrekking tot het fietsnetwerk) geschikt binnen de geldende context. Daarom hebben we een framework gedefinieerd dat de behoeftes en de 'fietsvolwassenheid' van een stad relateert aan dataverzamelsystemen. Daarvoor hebben we allereerst netwerkoplossingen geïdentificeerd die de performance van het fietsnetwerk verhogen. Daarna hebben we deze netwerkoplossingen gecombineerd met de fietsvolwassenheid van de betreffende stad, waarmee we inzichtelijk hebben gemaakt bij welke mate van fietsvolwassenheid welke oplossing zouden moeten worden overwogen. Als laatste hebben we deze oplossingen gecombineerd met de dataverzamelsystemen die nodig zijn om deze oplossing te realiseren. Dit behoefte-gedreven framework hebben we gedemonstreerd door middel van een case-study in Melbourne (Australië), een fietsonvriendelijke stad, en door het interviewen van 15 fietsvriendelijke gemeentes in Nederland.

Het empirisch bewijs van de case-studies heeft het potentieel van het framework getoond. Desondanks is verder onderzoek nodig naar fietsonvriendelijke steden. Vorig onderzoek heeft uitgewezen dat fietsonvriendelijke en opkomende steden zich richten op herkomst-bestemming en trip data voor het bepalen van een strategisch startpunt voor het ontwikkelen van hun fietsnetwerk. De literatuurreview over Melbourne bevestigt dit beeld. Aan de andere kant heeft onze enquête getoond dat fietsvriendelijke en -dominante steden zich richten op comfort en congestiebehoeftes en verschillende types data verzamelen, gerelateerd aan real-time gebruik van het netwerk en zijn kruispunten. Het geïntroduceerde behoefte-gedreven framework dient als een hulpmiddel voor planners en beleidsmakers om fietsdataverzamelsystemen ten volste te kunnen benutten en voor het opstellen van een systematisch langetermijnplan voor hun fietsinfrastructuur.

Multi-objective fietsnetwork evaluatie

We hebben een multi-objective methodologie geïntroduceerd die de kwaliteit van het fietsnetwerk evalueert. The methodologie levert een bijdrage aan de bestaande literatuur over fietsnetwerk-evaluatietechnieken doordat deze kwantitatief de kwaliteit van fietsverbinding vergelijkt voor verschillende gebruikersgroepen. We hebben hiervoor de 'fietsbaarheidscurve' ontwikkeld, een visueel instrument dat de afweging toont die gebruikers maken tussen verschillende aspecten van een fietsroute. Deze methodologie heeft als uitgangspunt deze zich niet berust op aannames over gebruikersvoorkeuren; de methode evalueert het netwerk door zich te baseren op alle mogelijke gebruikerstypes en niet slechts op de gemiddelde gebruiker.

De methodologie is getest op twee steden met verschillende fietsculturen – Amsterdam en Melbourne. The twee punten waarop we de netwerken evalueerden waren 'de hoeveelheid omrijden' en discomfort. Resultaten laten zien dat het fietsnetwerk van Amsterdam zijn gebruikers meer directe en comfortabelere routes biedt, waar het fietsnetwerk van Melbourne routes met significant grotere omleidingen biedt bij gelijke discomfort levels.

Door de fietsbaarheidscurves van verschillende herkomst-bestemmingsparen te evalueren kunnen stadsplanners de locaties bepalen die een betere fietsverbinding behoeven. De verbetering die wordt doorgevoerd kan zich vervolgens richten op het verminderen van het 'omrijden' op routes met een laag discomfort, of andersom, op het verminderen van het discomfort op de directere routes. Naast het evalueren van de fietsbaarheid van bestaande routes kunnen stadsplanners de methodologie ook gebruiken om investeringen te beoordelen en te prioriteren.

Datagedreven methode voor het schatten van reistijden van fietsers

Wanneer men een compleet fietsnetwerk wil beoordelen dan is accurate lokale informatie over de kwaliteit van de afzonderlijke straatsegmenten (links) essentieel. Naast vaste infrastructuurdata is informatie over het gebruik (level of service) van een link belangrijk. Een voorbeeld hiervan is een fietser die voor een verkeerslicht niet alleen moet stoppen, maar ook moet wachten totdat de wachtrij die voor hem is ontstaan is opgelost, voordat hij het kruispunt kan oversteken. Dit fenomeen heeft grote invloed op de fietser zijn of haar reistijd. Op linkniveau richt dit proefschrift zich dan ook allereerst op het schatten van de reistijd van een fietser op een kruispunt met verkeerslichten. Hiervoor hebben we een tool ontwikkeld die de reistijd schat van fietsers die een verkeerslicht naderen en daarmee de level of service monitort van een link met een verkeerslicht op een locatie met veel fietsers. We hebben geanalyseerd in hoeverre kunstmatige neurale netwerkmodellen in staat zijn om individuele reistijden te schatten op een kruispunt, gebaseerd op lusdetectorgegevens. Deze analyse is uitgevoerd op basis van een aantal gesimuleerde scenario's, zodat sensorfouten onder controle worden gehouden. De analyse heeft aangetoond dat de belangrijkste beperking voor deze modellen ligt in de beschikbaarheid en kwaliteit van de data.

Datagedreven methode voor het schatten van fietsrijen

Voor het schatten van het aantal wachtende fietsers voor een verkeerslicht, hebben we een datagedreven methode op basis van inductieve lusdetectorgegevens onderzocht. Hiervoor hebben we een 'unsupervised learning' clustermethode gebruikt zodat we niet hoefden te beschikken over een grote hoeveelheid ware toestandsgegevens (ground truth).

Interpretatie van de resultaten heeft laten zien dat het voor het selecteren van clusterkenmerken belangrijk is om kennis van het verkeersdomein toe te voegen aan het model. Gebruikt men daarentegen een puur datagedreven methode voor het selecteren van clusterkenmerken, dan zijn de gevormde clusters niet als zodoende interpreteerbaar. Een case-study van een kruispunt met verkeerslichten in Utrecht (Nederland), heeft aangetoond dat lusdetectorgegevens in combinatie met een clusteringtechniek in staat zijn om verschillende levels van accumulatie van fietsers te schatten. Deze informatie kan gebruikt worden als real-time verkeersinformatie binnen een stedelijk netwerk of als input dienen voor responsieve verkeerslichtregelaars, om de groen- en roodfases van het verkeerslicht optimaal af te stemmen op de drukte.

Objectieve en subjectieve bicycle level of service

Deze analyse bestudeert de statistische relatie tussen objectieve verkeersvariabelen en de perceptie van fietsers. We hebben subjectieve variabelen gemeten, zoals de ervaren 'bicycle level of service' (BLoS) en de ervaren drukte, en deze statistisch gecorreleerd met de objectieve fietsersstromen en -dichtheden. Dit verkennende onderzoek is uitgevoerd tijdens de uitbraak van het coronavirus, waardoor de omstandigheden tijdens de empirische dataverzameling afwijkend waren en waardoor de generaliseerbaarheid van de bevindingen gelimiteerd zijn.

Ondanks deze onverwachte omstandigheden kunnen de resultaten van dit onderzoek gebruikt worden als eerste bevindingen en motiveren ze tot verder onderzoek naar het formuleren van BLoS-maten, gebaseerd op percepties en hun relatie tot fietsverkeercondities. Onze empirische resultaten ondersteunen de aanname dat het ervaren comfort vermindert met een toenemende dichtheid van fietsers op een fietspad. Een minder sterke relatie werd gevonden tussen het ervaren comfort en de fietsersstroom op een fietspad. Deze resultaten dienen zorgvuldig te worden gebruikt en verder worden geanalyseerd, onder andere omstandigheden, voordat ze kunnen worden gegeneraliseerd.

Het relateren van verkeersvariabelen aan de ervaren BLoS, kan de beoordeling van straatsegmentkwaliteit verbeteren. Toekomstig onderzoek zou stadsplanners en transport engineers hulpmiddelen kunnen bieden bij het bepalen van de fietsbaarheid van fietspaden en het verbeteren van fietspadontwerpen.

Conclusies en implicaties

De conclusies van dit proefschrift hebben betrekking op zowel de verbeterde kennis over fietsnetwerken als op nieuwe methodes om de kwaliteit van infrastructuur te beoordelen. De opgedane kennis over fietsnetwerken leert ons dat het systeem van een fietsnetwerk niet alleen lastig is te beoordelen is maar ook lastig om te definiëren. Het gebruik van verschillende definities kan grote invloed hebben op het resultaat van een fietsbaarheidsanalyse. Als we alleen maar kijken naar echte fietspaden, dan hebben grotere steden systematisch relatief minder fietsinfrastructuur. Dit beeld verandert significant als we ook multimodale straten, waar auto's en fietsers de ruimte delen, in beschouwing nemen. Deze bevinding heeft praktische gevolgen voor stadsplanners die een hiërarchie van verschillende types fietsinfrastructuur ter beschikking hebben. Verder heeft onderzoek naar fietsbaarheid duidelijk gemaakt dat het lastig is om dit concept te definiëren met een enkele numerieke waarde. We raden dit niet expliciet af, maar wij adviseren om de beoordeling van fietsbaarheid te relateren aan de verschillende gebruikersgroepen en hun percepties. De geïntroduceerde methodes om netwerken gedeeltelijk of in zijn totaliteit te evalueren leiden tot overwegingen rond gebruikersbehoeften en beschikbaarheid van data. We introduceren een methode om een fietsnetwerk te beoordelen op basis van verschillende gebruikersbehoeften. Dit is een praktische bijdrage voor stadsplanners om de kwaliteit te meten van de verbinding binnen een netwerk onafhankelijk van aannames over de voorkeuren van haar gebruikers. Daarnaast komt er steeds meer data over fietsers en infrastructuur beschikbaar wanneer steden zich ontwikkelen op fietsgebied. Dit biedt mogelijkheden voor nieuw te ontwikkelen methodes voor het meten van lokaal gebruik en performance van fietsfaciliteiten. De datagedreven modellen in het gedeelte van het proefschrift dat zich richt op het linkniveau hebben zowel het potentieel als de tekortkomingen van lusdetectorgegevens van fietspaden laten zien. Datasystemen met een hogere accuraatheid, zoals slimme camera's, kunnen gebruikt worden om de 'bicycle level of service' beoordeling te verrijken met dichtheid- en stroommetingen, die volgens onze initiële bevindingen gerelateerd lijken aan het ervaren comfort van de fietser.

About the author

Giulia Reggiani was born in Rome, Italy on June 27th, 1993. After finishing her high school in classical studies in 2012 she pursued an engineering degree at Sapienza University of Rome. In 2015, she completed her Bachelor in Management engineering with distinction.

She conducted her Master's study in the same department, with a focus on optimization methods and simulation studies of real problems. She was selected for the Excellence Program and the Erasmus project which allowed her to spend half a year at Delft University of Technology at the technology, policy and management faculty. During that period she worked as tutor for international students coming to Rome to facilitate the integration of foreign students in the Roman context. In 2017, she obtained her masters degree, with distinction, with a thesis on Optimization Methods for Cruise Itinerary Planning and Design.

Having lived most of her life in a chaotic city like Rome, she discovered that she has a large interest towards sustainable urban transport and smart mobility and decided to come to the Netherlands to research on active modes (cyclists and pedestrians). In November 2017 she was back in Delft, ready to join the department of Transport and Planning to conduct a Ph.D. that is part of a larger European research project called ALLEGRO. Within her PhD project, she was awarded with the Strategic Alliance Student Exchange Program grant from the Department of Civil Engineering, Monash University and had the opportunity to conduct a two month-long research visit at in Melbourne, Australia.

Giulia is fascinated by a wide range of topics going from sustainability to education, as well as urban mobility and network science. In the future, she will steer her career towards sustainability and domains with high societal relevance.

Publications

Journal papers

- **Reggiani, G.**, van Oijen, T., Hamedmoghadam, H., Daamen, W., Vu, H. L., and Hoogendoorn, S. (2021). Understanding bikeability: a methodology to assess urban networks.Transportation, 1-29.

- **Reggiani, G.**, Salomons, A. M., Sterk, M., Yuan, Y., O'Hern, S., Daamen, W., and Hoogendoorn, S. (2022). Bicycle Network Needs, Solutions, and Data collection systems: a theoretical framework and case studies. Case Studies on Transport Policy.

The following articles are currently under review:

- **Reggiani, G.**, Verma, T., Daamen, W., and Hoogendoorn, S. (under review). A multi-city study on structural characteristics of bicycle networks. Environment and Planning B: Urban Analytics and City Science.

Conference contributions

- **Reggiani, G.**, Dabiri, A., Daamen, W., and Hoogendoorn, S. (2019). Clustering-based methodology for estimating bicycle accumulation levels on signalized links: a case study from the Netherlands. IEEE Intelligent Transportation Systems Conference(ITSC), 1788-1793.

- **Reggiani, G.**, Dabiri, A., Daamen, W., and Hoogendoorn, S. (2019). Exploring the Potential of Neural Networks for Bicycle Travel Time Estimation. Traffic and Granular Flow, 487-493.

- Zomer, L.B., Vial, A., **Reggiani, G.**, Ton, D., Wierbos, M.J., Gong, V., Schneider, F., Feng, Y., Sparnaaij, M., Gavriilidou, A., van Oijen, T., Duives, D.C., Yuan, Y., Cats, O., Knoop, V.L., Daamen, W. and Hoogendoorn, S.P. (2019). The Impact of Cycling Research: Connecting Science and Practice. Presented at Cycling Research Board, October 2019, Delft, The Netherlands.

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