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Efficiency and/or equity? Understanding and planning bike-sharing based on spatial fairness

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Abstract

Transport resources are limited, so they have to be spatially distributed according to certain criteria among the population. When economic efficiency is the key to transport design and planning, the spatial distribution of transport supply may be prioritized to those who can afford it. Given the example of bike-sharing systems (BSS) with a user profile and infrastructure oriented to the privileged population, is it fair that this transport service benefits the most privileged if we all pay taxes, and all own the public space.

Therefore, in this study, I developed a decision-making tool to implement or expand BSS considering spatial fairness as input. This tool might contribute to the development of active transport modes and mitigate the negative social, environmental, and economic effects of private motorized transport. The main objective of this research is to develop a method for planning the "first draft" of the location of BSS stations and their service area based on spatial fairness. The planning of BSS would prioritize their supply based on spatial equity (giving priority to those most in need), or spatial efficiency (giving priority to those who contribute most), or a combination of both, as the rule for the spatial distribution of resources.

The core of this research is to first comprehend BSS. Therefore, I looked into the public discussion about their benefits, limitations, and future using a qualitative and quantitative topic clustering of postings on the social network Twitter. The results show that BSSs achieve a high level of acceptance as electrically powered, free-floating systems, and integrated with public transport in terms of infrastructure and price. It was recommended that infrastructure allocation should be based on public participation and people's needs.

Due to the perceived inequity in the design of BSS and their unequal use, I developed and applied a method to explore qualitatively and quantitatively which spatial fairness criterion or criteria are present in the distribution of the BSS supply. I used for the assessment: a) data from previously conducted interviews with people in households without motorized vehicles who felt socially excluded in Strasbourg (France), and b) quantitative methods to spatially compare the access to the BSS supply among "milieus" (categorization of people based on social status and values) in Munich (Germany). The interviewees perceived BSS as not being oriented to the underprivileged population and that the service was not provided in disadvantaged neighborhoods. Finally, the quantitative approach showed that distribution of supply of the Munich scheme was economically efficient, mostly oriented to progressive people, however, not to those with traditional values.

Furthermore, if BSS infrastructure allocation is prioritized for economic efficiency, the spatial factors associated with their utilization may indicate where stations and service area allocation should be prioritized. Therefore, linear and non-linear regressions were performed in six German cities and three international cities to find built-environment variables associated to BSS usage

across geographic boundaries. The city population, distance to the city center, recreational facilities, and transportation-related infrastructure were the most common spatial factor associated with BSS usage.

Finally, I developed a spatial fairness approach to planning BSS, in which fairness is an input for the location of stations and service areas. Thus, the supply of BSS could be prioritized according to the desired justice focus, where there is greater deprivation (spatial equity), greater potential demand (spatial efficiency), or a mix of both. The potential demand was estimated on the basis of structural equation models that include variables of the built and social environment, which were identified in this research. The structure of the interrelationships between spatial factors follows a combination of theoretical models of land use and transport interactions and urban mobility cultures.

In conclusion, planners now have a deeper understanding of BSS, including their public discussion, the spatial factors associated with the usage, a method for assessing how fair systems are, and a decision-making tool for infrastructure allocation considering spatial fairness as an input. This research could improve the socio-economic efficiency of BSS and transparency in the design. Consequently, the approach could achieve a greater acceptance and usage of BSS, and be an alternative for distributing transport benefits to the most needed. Further research could focus on the application and adaptation of the methodologies developed in this research in other BSS around the world, and also in other transport systems.

Zusammenfassung

Die Transportressourcen sind begrenzt, so dass sie nach bestimmten Kriterien verteilt sein müssen. Wenn wirtschaftliche Effizienz der Schlüssel zur Verkehrsgestaltung und -planung ist, könnte bei der räumlichen Verteilung des Verkehrsangebots denjenigen Vorrang eingeräumt werden, die es sich leisten können. Ist es angesichts des Beispiels von Bike-Sharing-Systemen (BSS) mit einem Nutzerprofil und einer Infrastruktur, die sich an der privilegierten Bevölkerung orientiert, gerecht, dass dieses Verkehrsangebot den Privilegiertesten zugutekommt, wenn wir alle Steuern zahlen und der öffentliche Raum uns allen gehört?

Um zur Entwicklung aktiver Verkehrsträger beizutragen und die negativen sozialen, ökologischen und wirtschaftlichen Auswirkungen des motorisierten Individualverkehrs abzuschwächen, habe ich ein Entscheidungsinstrument entwickelt, um BSS so zu implementieren oder zu erweitern, dass ihre Barrieren für Infrastruktur und Gerechtigkeit verringert werden. Das Hauptziel dieser Forschung ist die Entwicklung einer Methode zur Planung des "ersten Entwurfs" der Lage von BSS-Stationen und ihres Versorgungsgebiets auf der Grundlage räumlicher Fairness. Bei der Planung von BSS-Stationen würde deren Versorgung auf der Grundlage der räumlichen Gerechtigkeit (mit Vorrang für die Bedürftigsten) oder der räumlichen Effizienz (mit Vorrang für die Bedürftigsten) oder einer Kombination aus beidem als Regel für die räumliche Verteilung der Ressourcen priorisiert werden.

Der Kern dieser Studie besteht darin, zunächst die BSS zu verstehen. Daher untersuchte ich die öffentliche Debatte über Vorteile, Grenzen und Zukunft der BSS anhand einer qualitativen und quantitativen thematischen Bündelung der Beiträge im sozialen Netzwerk Twitter. Die Ergebnisse zeigen, dass BSS als öffentliche elektrische Systeme mit der Option des Free-Floating mehr akzeptiert sind und in Zukunft akzeptiert werden könnten und dass sie in Bezug auf Infrastruktur und Preis in andere gemeinsame Verkehrsmittel und den öffentlichen Verkehr integriert werden könnten. Es wurde empfohlen, dass die Zuweisung der Infrastruktur auf der Grundlage der Beteiligung der Öffentlichkeit und der Bedürfnisse der Menschen erfolgen sollte (Gleichheit).

Aufgrund der wahrgenommenen Ungerechtigkeit bei der Gestaltung von BSS und ihrer ungleichen Nutzung entwickelte und wandte ich eine Methode an, um quantitativ und qualitativ zu untersuchen, welche Kriterien der Raumgerechtigkeit bei der Verteilung des BSS-Angebots vorhanden sind. Ich verwendete: a) Daten aus zuvor durchgeführten Interviews mit Personen in Haushalten ohne motorisierte Fahrzeuge, die sich in Straßburg (Frankreich) sozial ausgegrenzt fühlten, und b) quantitative Methoden, die in München (Deutschland) den Zugang zur BSS-Versorgung unter "Milieus" (Kategorisierung von Personen auf der Grundlage von sozialem Status und Werten) räumlich verglichen. In den Interviews wurde festgestellt, dass die BSS nicht auf die weniger privilegierte Bevölkerung ausgerichtet sind und dass die Dienstleistung nicht in benachteiligten

Stadtvierteln angeboten wird. Darüber hinaus ist die Verteilung der Dienstleistungen im Münchner System wirtschaftlich effizient und richtet sich vor allem an progressive Menschen, nicht aber an solche mit traditionellen Werten.

Wenn die wirtschaftliche Effizienz bei der Zuweisung der BSS-Infrastruktur berücksichtigt wird, können die mit ihrer Nutzung verbundenen räumlichen Faktoren darüber hinaus eine Vorstellung davon vermitteln, wo bei der Zuweisung der Stationen und des Versorgungsgebietes Prioritäten gesetzt werden sollten. Daher habe ich lineare und nichtlineare Regressionen in sechs Städten in Deutschland und drei in internationalen Städten durchgeführt, um Faktoren der bebauten Umgebung zu identifizieren, die mit der Nutzung der BSS in mehreren Städten verbunden sind. Die am häufigsten mit der Nutzung verbundenen räumlichen Faktoren waren die städtische Bevölkerung, die Entfernung zum Stadtzentrum, Freizeiteinrichtungen und die Verkehrsinfrastruktur.

Schließlich entwickelte ich einen Ansatz für räumliche Fairness bei der Planung von BSS, bei der räumliche Fairness ein Input für die Standortwahl von Stationen und Versorgungsgebieten ist. So kann das BSS-Angebot entsprechend dem gewünschten Gerechtigkeitsansatz priorisiert werden, wenn eine größere Benachteiligung (räumliche Gerechtigkeit), eine größere potenzielle Nachfrage (räumliche Effizienz) oder eine Mischung aus beidem vorliegt. Die potentielle Nachfrage wird auf der Grundlage von Strukturgleichungsmodellen geschätzt, die Variablen des gebauten und sozialen Umfelds einbeziehen, die in den bisherigen Ansätzen dieser Forschung identifiziert wurden. Die Struktur der Wechselbeziehungen zwischen räumlichen Faktoren folgt einer Kombination theoretischer Modelle der Flächennutzungs- und Verkehrsinteraktionen und städtischer Mobilitätskulturen.

Zusammenfassend lässt sich sagen, dass die Planer nun über ein tieferes Verständnis von BSS verfügen, einschließlich ihrer öffentlichen Diskussion, der mit der Nutzung verbundenen räumlichen Faktoren, einer Methode zur Beurteilung der Fairness von Systemen und eines Entscheidungsinstruments für die Infrastrukturzuweisung unter Berücksichtigung der räumlichen Fairness als Input. Diese Forschung könnte die sozioökonomische Effizienz von BSS und die Transparenz des Entwurfs verbessern. Folglich könnte der Ansatz zu einer größeren Akzeptanz und Nutzung von BSS führen und eine Alternative für die Verteilung der Verkehrsvorteile an die Bedürftigsten darstellen. Weitere Forschungsarbeiten könnten sich auf die Anwendung und Anpassung der in dieser Forschung entwickelten Methoden in anderen BSS auf der ganzen Welt und auch in anderen gemeinsam genutzten Verkehrsträgern oder öffentlichen Verkehrssystemen konzentrieren.

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Dedication

I dedicate my project to my wife, parents, siblings, grandparents, and the rest of my family. I dedicate my work to that young man who had to drop out his studies and to that old woman who could not go to the hospital because they did not have enough money to take the bus, to the woman who has six children, an alcoholic husband and has to walk six kilometers through the mountains to perhaps be able to access public transportation, to that girl who was harassed on the subway, to my friend who was shot because they wanted to steal his bike, to my friend who did not use a bicycle again because she was run over by a bus, to my colleague who was hit by a car coming back from school, to the forest that is destroyed to give access to oil and mining companies, and to future generations that because of our comforts will not have our privileges.

Preface

***"If I chose to be an eagle it was for love of the worm"* – Facundo Cabral**

I am a privileged person. Life allowed me to be born and grow up in a family with economic privileges that made it easy for me to enter college and achieve a high level of education. In addition to these privileges, I am a heterosexual man with Western physical characteristics in the context of Latin America. For these reasons, I have not felt injustice or discrimination, however, I have seen them throughout my life. Injustice invoked in me a feeling of sadness, frustration, and at the same time guilt for only seeing it and not doing anything against it. I feel like an eagle because I can have the opportunity to participate in decisions making and be heard because of my social advantages. This study, though, is my new beginning.

I focused my undergraduate studies in civil engineering on designing roads to defend rights and mitigate impacts when roads affect society and nature. Then, my interests changed after working on the assessment of the first mobility station in Munich (Germany) (Miramontes, 2018) and seeing the benefits of shared mobility. I thought that Latin America should give priority to new forms of mobility, before focusing only on road infrastructure.

During the assessment of the mobility station, I noticed that car-sharing rentals were increasing near the tram stops. I formulated my first hypothesis: car-sharing rentals could be associated with spatial factors (Schmöller et al., 2015). The analysis of spatial factors and their association with car-sharing rentals could help to efficiently implement stations or establish their service area. With this hypothesis and the literature review, I applied for a Ph.D. with the topic 'Influential factors on the demand for shared mobility' in the multidisciplinary doctoral research group mobil.LAB.

When I started with the in-depth literary review, I realized that car-sharing has a nice last name: "sharing", but in the end they are cars. They may have their benefits, but do we really need them? I think what we need is to move actively in a fun and safe way and have livable cities without pollution or machines occupying our public space.

Furthermore, during this literature review process, I would like to share a personal experience that influenced the focus of my study when my father-in-law came to visit Munich. While walking through the city center, my father-in-law saw some bikes with the same design in the middle of the sidewalk. Oddly enough, he asked why those bikes are there. I answered that the bikes belong to a bike-sharing system, and they can be rented. I offered to use one of them to continue the city tour. This system of renting bikes in the public space gave him the opportunity to use a bike after thirty years. His happy face while using a bike after so long was part of my motivation to focus on the development of public bike-sharing systems.

“Sometimes I think that if I had studied geotechnics it would have been easier. Soil is simpler to understand than people."

Now, if you allow me, I want to tell you about the mobil.LAB, my research group. The mobil.LAB is a group of friends, all a little crazy, with different backgrounds from political science to engineering. We focus on understanding and contributing to the development of more sustainable mobility. Working in an interdisciplinary group opened my perspective to include people in my study of mobility research (Villeneuve et al., 2020). Without people, there is no mobility, and without infrastructure people cannot move. We need to understand people to understand their needs and behavior, and we need to build models to generalize behavior in order to plan mobility.

Imagine that you have to build an ant farm. For it, you have to observe the behavior of an anthill to build an efficient farm. For example, you have to explore how much distance the ants travel, when and for which purpose they leave the anthill, what products they bring, how they behave among themselves, etc. Then, based on this historical data, you analyze the most favorable and efficient conditions for an ant farm to last over time. When providing them similar favorable conditions to the observed, it is expected that in the farm the ants behave similarly as in the anthill.

The disadvantage of my approach was to pretend to study people like ants. Unlike ants, we have communication, beliefs, political, social, and cultural components that allow us to behave differently among us. The rich, the poor, the men, the women, the traditional, the liberal, the tall, the short; each one behaves differently and responds to a different mobility culture. Mobility culture is the essence that explains why, when, how, and where people move. Therefore, to learn and replicate a mobility system like bike-sharing in other areas with a similar culture, I should study and understand mobility cultures.

Therefore, I combined traditional transport models with the concepts of mobility cultures by including social factors such as values and lifestyles in the planning of BSS. In addition, if I wanted to implement bike-sharing systems in other regions, I had to study what factors are associated with the use of public bicycles without depending on geographical boundaries. So I did an analysis in several cities across continents to get the common factors associated with the usage of bike-sharing.

I don’t study ants, so I talked to people from my social environment. By talking to people, I could validate and falsify what I was reading in literature. Thus, people have been the real experts. But I didn’t want to know the opinion of just a few friends. I wanted to know the opinion of many people. This reflection led me to collect posts and study the public debate concerning bike-sharing on social media.

“What is fair to me may not be fair to others."

A topic of debate in social media that caught my attention was that bike-sharing is commonly used by the most privileged people and their service area is oriented to where these people live. In addition, people perceived that bike-sharing benefitted the most privileged people. From this analysis, I asked myself: if my research focuses on learning from historical behavior and if the bike-sharing system is unfair; am I therefore developing unfair systems?

Consequently, I considered assessing how fair a bike-sharing system is. Which social groups have access to them and which groups are favored by their service and which are not? In addition, people have the right to know who is favored and not in access to systems that use our public resources and public space. I never imagined that I would read and understand the theories of "justice". It was difficult, I wasn't used to so many theories. So, I summarized them in a flow chart, like the engineer that I am. Thanks to the influence of the interdisciplinary research group, I assessed how fair a system is in a qualitative and quantitative way. The qualitative analysis helped me understand what people think and feel, and the quantitative analysis helped me to generalize it. The two methods complemented each other.

However, I could not conclude my study with just an assessment of how fair a system is and what factors are associated with its use. I also wanted to apply what I had learned in the planning and designing of them. I wanted to open a door for transport planners to design efficient systems that are also available to the less privileged. I concluded this study with a heuristic method based on spatial data and spatial fairness. This method was developed and inspired by historical data, talking to people, social media, interviews, and also, concepts including statistics, machine learning, text analysis, social justice, transportation and land-use interactions, and mobility cultures. This approach provides planners and decision-makers with a method to choose the degree of spatial justice with which they want a transportation system to be implemented, to make it transparent to the public, and to give them the option of balancing economic efficiency with equity.

When I started my doctoral studies, I was told that my study would not change the world, and naturally, that is true. But with my study, I hope to open a door for people who make policy and design mobility systems to consider the social factor, to the people who need them most, and those who are excluded from society. Bike-sharing was an application of how we can plan transportation systems by talking to and understanding people and their culture, and what factors can make a system more efficient and equitable at the same time.

I hope that my study and motivation will serve as inspiration for future projects where the neediest people are involved. I invite my Latin American colleagues who have the privilege of doing research to focus on our region. My only non-conformity of the study is that my project was based on industrially and economically developed regions but not on Latin America where more of these projects are need.

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Chapter 1

Introduction

1.1 Background

Although CO_2 emissions have decreased 21% from 1990 to 2017, CO_2 emissions in Europe from road transport have not been reduced (Kinigadner et al., 2020; Commission et al., 2019). Private motorized transportation is responsible for about 14.5% of CO_2 emissions in Europe (Commission et al., 2019). Additionally, to direct impacts such as noise and emissions, the increase in private motorized transport has indirectly contributed to climate change, habitat loss, depletion of non-renewable resources, and water and soil pollution (Rodrigue et al., 2016; Litman and Burwell, 2006).

In addition to environmental issues, private motorized transport has shown potential negative impacts on the economy and society, such as increasing inequalities, acting as barriers to community interactions and cities livability, increasing fatal accidents, wasting time and money due to traffic congestion, increasing cardiovascular illnesses, consuming space, among others (Litman and Burwell, 2006; Rodrigue et al., 2016; Larsen et al., 2006). Moreover, traffic congestion in Europe costs about 1% of the gross domestic product (EC, 2016). In many cities around the world, roads and parking lots occupy between 30% and 60% of the total built-up area (Roca-Riu et al., 2020).

Despite efforts by researchers and transportation experts to improve road safety, road traffic crashes are a major social problem worldwide, with more than 1.35 million deaths per year (WHO, 2018). More than half of those killed in road crashes are pedestrians, bicyclists, or users of two-wheeled motor vehicles (WHO, 2018). Between 2010 and 2018, collisions with motor vehicles were responsible for 99% of pedestrian fatalities and 83% of cyclist fatalities in Europe (Adminaité-Fodor and Jost, 2020).

To mitigate the negative impacts of private motorized transport, planners face the challenge of developing and promoting more environmentally friendly, and space-efficient modes of transport (Banister, 2008; Shaheen et al., 2012; Koning et al., 2020; Litman and Burwell, 2006). Therefore, new forms of mobility have emerged that promote and facilitate active mobility, such as Bike-Sharing Systems (BSS). BSS provide short-term rentals of bicycles that are made available in the public space (Büttner and Petersen, 2011). They have emerged in major cities around the world, with significant growth from a few systems in the 2000s to about two thousand systems worldwide in 2020 (Shaheen et al., 2020; Meddin and DeMaio, 2020).

BSS can potentially improve access to cycling and its benefits as an active and convenient transport mode, enhance last-mile connections to transit, increase transport resilience, help build support for future cycling initiatives, and change attitudes towards cyclists (Cohen and Shaheen, 2018; Shaheen et al., 2014; Teixeira and Lopes, 2020; Manca et al., 2019; de Chardon, 2019; Bauman et al., 2017). BSS may also contribute towards reducing CO2 emissions in a city, depending on the balancing system of bicycles and their ability to replace trips that would otherwise be made by private motorized vehicles (Ricci, 2015).

These potential benefits and continued growth leads to the further implementation or expansion of BSS in additional regions.

1.2 Motivation

For implementing or expanding BSS, expected ridership has been generally the basis for station allocation, service area boundaries, and bikes balance (Shaheen and Cohen, 2019). “Most bike share schemes were never designed with equity or social justice in mind . . . [but] designed around environmental and economic goals intended to stimulate urban renewal" (de Chardon, 2019; Hoffmann, 2016, p.410). Planning for monetary efficiency can lead to a concentration of transport opportunities on the already privileged populations. It can also lead to the exclusion of people with limited economic resources, technological affinity, and living in areas where the systems would not be profitable being (e.g. low dense populated or remote areas) (Lucas, 2019).

Particularly in the global North, this planning approach has contributed to BSS' unequal use and location of infrastructure. The common users' profile in the Global North tends to be male, young, Caucasian with high income and education, and already engaged with cycling (Table 1.1). In addition, the distribution of stations and service areas are mostly focused on central and densely populated regions (Fishman et al., 2015; Duran-Rodas et al., 2019b; Chen et al., 2019) with a predominance of young Caucasians, and highly educated residents (Chen et al., 2019; Ursaki and Aultman-Hall, 2015; Mooney et al., 2019). Consequently, deprived and low-income areas have reported less access to BSS infrastructure (Ursaki and Aultman-Hall, 2015; Mooney et al., 2019; Ogilvie and Goodman, 2012; Smith et al., 2015) (Table 1.2). For example, in London in particular, "women and those living in deprived areas are less likely to register to use the scheme" (Ogilvie and Goodman, 2012).

Using BSS as an example, which has a user profile and infrastructure tailored to the privileged; is it fair that the infrastructure should benefit the most privileged if we all pay taxes and the public space belongs to all of us? Distribution of resources is judged as fair if it adheres to certain criteria that individuals believe is fair (Leventhal, 1980). The most common criteria for determining whether a spatial allocation of resources is fair are: a) spatial equity (prioritizing resources to the neediest population), b) spatial equality (equal distribution of resources, no prioritization), c) spatial efficiency (prioritization of resources according to people's ability to contribute or access resources) (Leventhal, 1980; Talen, 1998; Duran-Rodas et al., 2020a).

If spatial efficiency is considered, systems may be more profitable, but disadvantaged areas may be excluded. In contrast, when spatial equity is considered, resource allocation in disadvantaged areas would be prioritized. Spatial equity has a broader justice focus that can lead to a

Table 1.1: Socioeconomic characteristics associated to BSS users

Characteristic	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
	References										
Male	✓	✓			✓	✓	✓	✓	✓	✓	✓
Young	✓	✓	✓	✓	✓		✓	✓	✓		
High income	✓	✓	✓	✓	✓	✓	✓			✓	
High educated	✓	✓	✓	✓							
Caucasian		✓	✓	✓		✓					✓
Already engaged with cycling	✓				✓						

I=Shaheen et al. (2012), II=McNeil et al. (2017), III=Fishman (2016), IV=Howland, V=Winters et al. (2019), VI=Buck (2013), VII=Murphy and Usher (2011), VIII=Vogel et al. (2014), IX=Wang et al. (2018), X=Goodman and Cheshire (2014), IX=Steinbach et al. (2011)

Table 1.2: Socio-spatial inequalities of BSS

	Type of areas	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
		References										
Areas with low BSS access	Low income	✓	✓		✓	✓	✓	✓	✓		✓	
	Households without cars							✓				
Areas with high BSS access	Higher educated				✓				✓			
	Central & denser populated			✓						✓		
	Caucasian people				✓			✓		✓	✓	✓
	Native language speakers							✓				
	Younger people				✓					✓		
	Higher access to opportunities								✓			

I=Ogilvie and Goodman (2012) II=Goodman and Cheshire (2014) III=Fishman et al. (2015) IV=Ursaki and Aultman-Hall (2015) V=Hosford and Winters (2018) VI=Smith et al. (2015) VII=Barajas and Drive (2018) VIII=(Mooney et al., 2019) IX=Chen et al. (2019) X=Smith et al. (2015) XI=Couch and Smalley (2019) reduction in social disparities and social exclusion (Fainstein, 2009), resulting in less social conflict and more social peace (Tomlinson, 2016). Even lower-income neighborhoods with BSS supply have shown low usage (Caspi and Noland, 2019), a high level of justice perceived by the population can reduce resistance towards implementation, increase project consent, or generate greater political acceptance (Ariely and Uslaner, 2017; Wüstenhagen et al., 2007). However, there is a possibility that systems may become less profitable.

1.3 Research Objectives

The implementation and expansion of BSS are increasing. In addition, BSS planning with a focus on spatial efficiency or spatial equity has strengths and limitations. Therefore, the main contribution of this study is to develop a method to 1) create scenarios for allocating BSS stations and service area boundaries, and 2) base planning on a user-preferred fairness criterion: spatial efficiency, spatial equity, or a balance of them. Therefore, the main objective of this study is to:

Develop a heuristic-based method for planning the allocation of BSS stations and their service area based on spatial equity, spatial efficiency, or a balance of both.

In order to achieve the main goal, the specific objectives of this study are:

1. To understand bike-sharing systems based on:
   (a) Patterns and topics of the public discussion regarding BSS on an international level based on interviews, and qualitative and quantitative analysis of social media.
   (b) Spatial factors from the built and social environment associated with BSS usage.
2. To build a conceptual framework regarding spatial fairness that synthesizes the concepts of justice, social and spatial fairness, and distributive rules.
3. To develop methods to:
   (a) Assess whether the distribution of BSS supply follows the criteria of spatial equity, spatial efficiency, or a mixture of these.
   (b) Build scenarios for allocating stations and limiting service areas of bike-share systems based on spatial efficiency, spatial equity, or a balance of both.

To achieve the research objectives, a combination of qualitative (e.g. qualitative data analysis) and quantitative (e.g. descriptive statistics, regressions, structural equation models) methods was applied. Moreover, concepts of urban mobility cultures and traditional transport planning were combined with the theory of transport justice.

The core of this study is to first understand BSS. BSS were explored based on three approaches. First, the public discussion on the advantages, shortcomings, and future of BSS was investigated to explore what people like and dislike about them. This knowledge can help determine what to do and what not to do in the design and planning of social security systems for economic efficiency and social benefits. Second, existing BSS were assessed based on the followed spatial fairness criterion. Third, spatial associations were identified from the built environment and the social environment with BSS ridership to plan BSS in an economically efficient manner. Finally, I developed a spatial fairness approach to planning BSS, in which fairness is an input for the location of stations and service areas. Thus, the supply of BSS could be prioritized according to the desired justice focus, where there is greater deprivation (spatial equity), greater potential demand (spatial efficiency), or a mix of both.

1.4 Thesis Structure

This thesis follows a paper-based approach consisting of three parts (see Figure 1.1) with a total of nine chapters as follows:

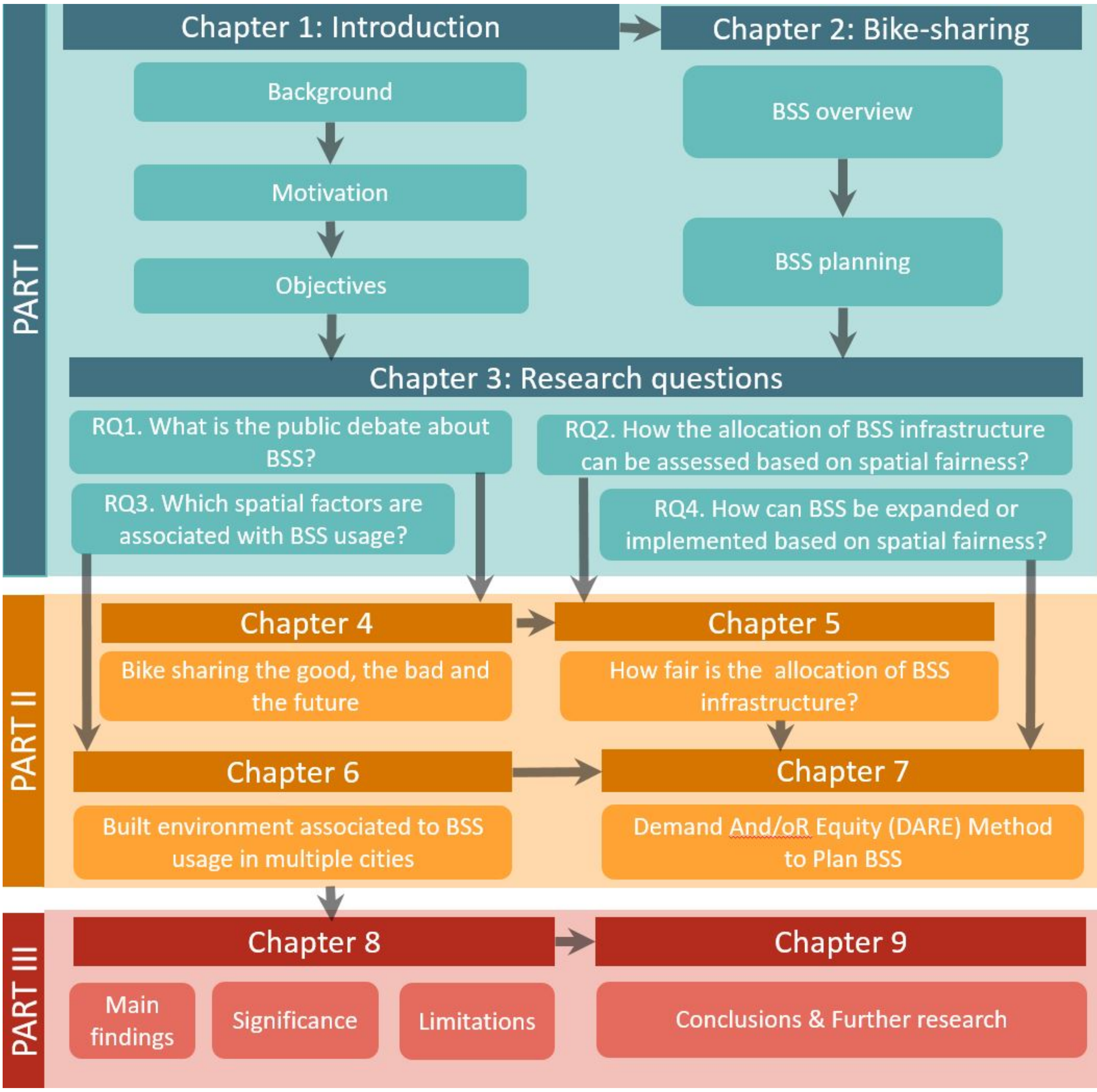

Figure 1.1: Thesis structure

PART I: Introduction The first part is the introduction. It includes the background, motivation, and research objectives. Chapter 2 summarizes a literature review regarding BSS and their common planning process. Chapter 3 describes the research questions, their significance, and the proposed methodology.

Chapter 2: Bike-sharing: overview and planning In this chapter, benefits, drawbacks, and the traditional planning process for BSS are summarized. Previous research on the spatial factors associated with the usage and methods for allocating stations are reviewed.

Chapter 3: Research questions The third chapter explains the four main research questions, how they are connected to each other, their significance and proposed methodology.

PART II: Scientific papers The second part of this book includes four chapters: two exploratory (Chapter 4 & Chapter 6) and two methodological (Chapter 5 & Chapter 7) studies that contribute to the achievement of the research objectives. These chapters are scientific papers peer-reviewed in scientific journals. Chapter 4 explores the public discussion in the social media Twitter about the benefits, drawbacks, and future of BSS. In Chapter 5, a methodology was developed to assess how spatially fair are BSS planned and which population groups benefit from them. To understand where BSS can be more profitable, Chapter 6 examines the built environment factors associated with BSS usage in multiple cities. The last three Chapters merge in Chapter 7, in which a method was developed to allocate BSS stations and the service area according to spatial efficiency, equity, or a balance of both.

Chapter 4: Bike-sharing: the good, the bad, and the future Due to the dilemma of bike-sharing in terms of its benefits and drawbacks, and its unclear future, this chapter focuses on a mixed-methods approach to analyze this public discussion in the social media channel Twitter. For about six months, about 12,000 tweets in English were collected, including bike-sharing-related terms. Topic clustering and sentiment analysis were conducted in a) bike-sharing-related terms, and b) "future" and bike-sharing-related terms.

This chapter has been published in Duran-Rodas, D., Villeneuve D., & Wulfhorst, G. Bike-sharing: The good, the bad, and the future. Twitter's mixed-methods approach for public discussion. European Journal of Transport and Infrastructure Research. doi.org/10.18757/ejtir.2020.20.4.5307 (Duran-Rodas et al., 2020b).

Chapter 5: How fair is the allocation of bike-sharing infrastructure? Based on the concept of spatial fairness and its subjectivity, this chapter includes a framework to help decision-makers and the public to evaluate how spatially fair the allocation of BSS infrastructure is.

An own definition and a qualitative and quantitative assessment of spatial fairness was developed based on who is privileged in the spatial distribution of resources. The qualitative assessment aims at understanding how underprivileged people perceived the spatial fairness of BSS using as a case study non-motorized households that felt socially excluded in Strasbourg (France). The quantitative assessment helps to numerically determine which distribution rule (equity, equality, efficiency, or mix of them) the infrastructure of a bike-sharing scheme follows. This assessment was applied to residential blocks within the service area of the hybrid BSS in Munich (Germany). The concept of availability was defined as an accessibility indicator. As social indicators, social milieus, access to other opportunities (e.g. health, education) were quantified to develop a deprivation index that is a combination of these two.

This chapter was published in Duran-Rodas, D., Villeneuve, D., Pereira, F. C., & Wulfhorst, G. (2020). How fair is the allocation of bike-sharing infrastructure? Framework for a qualitative and quantitative spatial fairness assessment. Transportation Research Part A: Policy and Practice, 140, 299-319. doi.org/10.1016/j.tra.2020.08.007 (Duran-Rodas et al., 2020a).

Chapter 6: Built environment factors associated with bike-sharing ridership In this chapter, a data-driven method is formulated to correlate the arrivals and departures of station-based bike-sharing systems with built environment factors in multiple cities. Ridership data from stations of multiple cities are pooled in one data-set, regardless of their geographic boundaries. The method bundles the collection, analysis, and processing of data, as well as, the models' estimation using statistical and machine learning techniques. The method was applied on a national level in six cities in Germany, and also, on an international level, in three cities in Europe and North America.

This chapter was published in Duran-Rodas, D., Chaniotakis, E., & Antoniou, C. (2019). Built environment factors affecting bike sharing ridership: a data-driven approach for multiple cities. Transportation research record, 2673(12), 55-68. doi.org/10.1177/0361198119849908 (Duran-Rodas et al., 2019b)

Chapter 7: Demand And/oR Equity (DARE) Method for planning BSS A data mining and heuristic-based method was developed to weight efficiency and equity in the planning process of BSS. The primary inputs are the predicted potential demand (efficiency) and a spatial deprivation index (equity). Potential demand is predicted using structural equation models (SEM) to understand the relationship between predictors and to test and validate the theoretical links. The theoretical links were taken from the models of urban mobility culture (Deffner et al., 2006) and interactions of land-use and transport (Wegener and Fürst, 1999). DARE was applied to a hybrid bike-sharing system in Munich (Germany) to evaluate the distribution of stations according to criteria of spatial efficiency and/or equity.

This chapter was published in Duran-Rodas, D., Wright, B., Pereira, F. C., & Wulfhorst, G. (2021). Demand And/oR Equity (DARE) method for planning bike-sharing. Transportation Research Part D: Transport and Environment, 97, 102914. https://doi.org/10.1016/j.trd.2021.102914 (Duran-Rodas et al., 2021)

PART III Finally, the third part includes two chapters summarizing the main findings, the significance and limitations of the research (Chapter 8), and the conclusions and further research (Chapter 9).

Chapter 8: Key findings and discussion across the papers Chapter 8 discussed the results of the study across the papers. Moreover, it included the discussion of each research question including the key finding, strengths, and also limitations.

Chapter 9: Conclusions Chapter 9 summarizes the recommendations for the implementation or expansion of BSS that bring together the findings of the study. Finally, an outlook on possible future research is given concerning each research question.

Chapter 2

Bike-sharing: Overview and Planning

This chapter includes an overview of BSS and the state-of-the-art of their traditional planning process. Additionally, previous approaches for finding the potential location of stations and estimating potential demand were described.

2.1 Bike-sharing overview

Shared economy is a socio-economic phenomenon that prioritizes use over ownership. People can share their underutilized belongings, and products can become cheaper than buying or renting from traditional suppliers. It has become a practical business model in recent years, as well as raising environmental awareness (Cheng, 2016; Böckmann, 2013). Shared mobility is a component of the shared economy, and it is defined as the "shared use of a vehicle". It provides users with short-term access to a mode of transportation on an "as-needed basis" (Shaheen et al., 2015, pg. 4). Bike-sharing is the shared mobility component when the shared vehicle is a bicycle. It allows users to rent or borrow bicycles without owning them. When bike-sharing is not a peer-to-peer service, it is a self-service short-term rental of a bicycle offered in the public space within a coverage (business, catchment, or service) area (Büttner and Petersen, 2011).

The concept of bike-sharing originated with the first bicycles. It started when an individual or a group of people bought a bicycle and shared it with another person such as family members, neighbors, or friends. With the Witte Fietsenplan (the "white bicycle plan"), introduced by Luud Schimmelpennink in Amsterdam in 1965, this concept expanded beyond the personal network to a neighborhood level (Zee, 2016). The Witte Fietsenplan consisted of painting an old bicycle white and leaving it on the street for someone else to use for free. The color white was selected to reflect cleanliness and simplicity. This strategy was part of the Provo group of anarchists, who were against the city's increasing number of cars and wanted to provoke a social reform. According to the literature, the system collapsed after a few days because the bicycles were stolen and thrown into the canals (DeMaio, 2009). However, Schimmelpennink stated in an interview that the bikes were removed by the police, who were against the anarchist movement (Zee, 2016).

In the mid-1990s, Schimmelpennink was invited to set up Bycykle, Copenhaguen's first large-scale system free of charge, and thus the second generation of BSS. Unlike the previous generation, it included a coin deposit to ensure the return of bicycles in racks. These racks were located mainly in the city center, in commercial areas, and near transit stations (DeMaio, 2009).

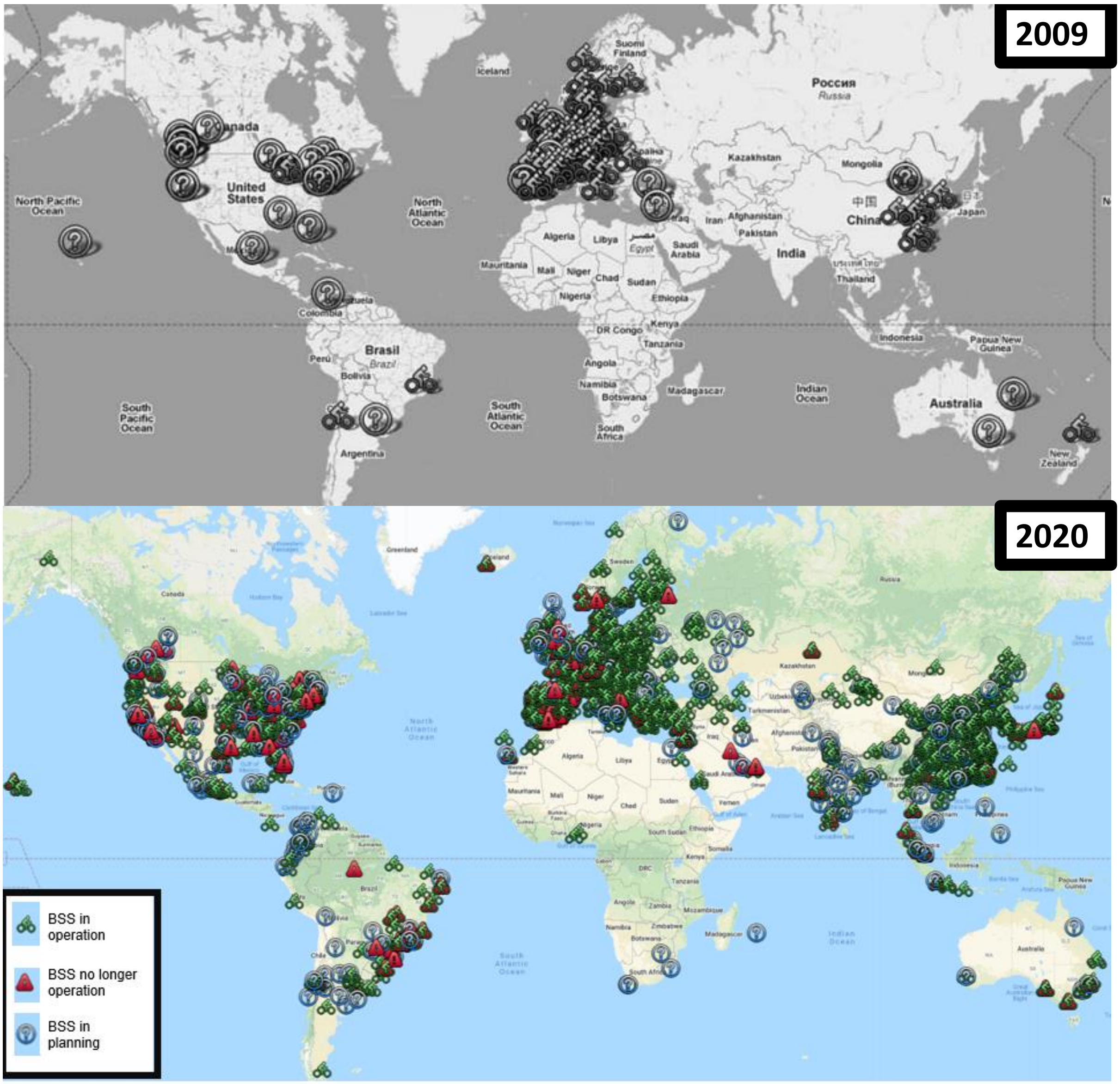

Figure 2.1: Bike-sharing systems worldwide. Source: Meddin and DeMaio (2020); DeMaio (2009)

Bicycle theft was a challenge for the second generation due to users' anonymity. As a result of technological advances, the third generation of bike-sharing was born, and bikes could be tracked using GPS or Radio Frequency Identification (RFID). Other technologies were also incorporated such as smart cards, electronic docking stations, on-board computers, and telecommunications facilities (DeMaio, 2009). The first third-generation system was at the University of Portsmouth in England in 1996, where students could use smart cards to access bicycles. The first city-level system to use smart cards was “Velo a la Carte” in Rennes, France, in 1998. "Call-a-bike" was launched in Munich (Germany) in 2000 with a rental option based on cell phone calls (DeMaio, 2009).

In 2005, Lyon built the biggest system at the time, with 1,500 bikes. BSS were implemented in other cities in Europe, America, Oceania, and Asia from 2008 onwards, following the successful introduction of the "Velib" system in Paris with 7,000 bikes. At the end of 2008, there were about 92 bike-sharing programs worldwide (Figure 2.1) (DeMaio, 2009).

Finally, a fourth-generation was born in 2010 with demand-responsive multimodal systems (Shaheen et al., 2010). Thanks to new IT technologies, real-time bike tracking and rebalancing were possible, and systems were integrated with other modes of transportation. Today, BSS are wide-spreading in more than 2,000 operating schemes around the world (Figure 2.1) with around 18 million bicycles (Meddin and DeMaio, 2020). Europe and Asia are the continents with the most systems, with China having the world's largest fleet with 6.1 million shared bikes in 2018 (Shaheen et al., 2020). Nowadays, there are mainly six forms of BSS classifications that are summarized in Table 2.1.

Table 2.1: Classification of bike-sharing systems

Classification	Subclassfication	Description
1. Type of Service (Cohen and Shaheen, 2016)	1.1. Roundtrip	Trip starts and ends at the origin.
	1.2. One way	Origin and destination may vary.
2. "Shared economy" concept (Shaheen et al., 2020; Cohen and Shaheen, 2016)	2.1. Platform-economy	Digital platforms are used to rent or return bikes in the public space.
	2.2. Closed-campus	BSS available exclusively university campuses.
	2.3. Access-economy	Bike owners offer a short-term bike rental.
	2.4. Community economy	Bikes are owned and managed by a community. Non-contractual, -monetized, or -hierarchical interaction.
3. Presence or not of stations (Shaheen et al., 2020)	3.1. Station-based (SBBSS)	Bikes are rented or returned in fixed stations.
	3.2. Virtually station-based (VSBBS)	Bikes are rented or returned in virtual stations, which are areas defined by the operator.
	3.3. Free-floating (FFBSS)	Bikes are rented and returned in the public space inside a service area.
	3.4. Hybrid (HBSS)	Bikes are rented or returned either in the public space or at (virtual) stations.
4. Type of bicycles (Shaheen et al., 2020)	4.1. Mechanical	Regular mechanical shifting bicycles
	4.2. Electric or e-bikes	Bikes have an electric motor to reduce physical effort.
(Cohen and Shaheen, 2016)	4.3. Cargo	Bicycles adapted to carry loads.
	4.4. Tandem	Bicycles adapted for two people.
5. Access technology	5.1. Card-based	Renting bikes with card readers. Cards can be "magnet cards, chip cards, credit cards or RFID cards."
(Büttner and Petersen, 2011; Chen et al., 2018)	5.2. Code-based	The user can rent a bicycle by inserting a code provided via a call, an SMS, or smartphone applications.
	5.3. Key-based	The user gets a key to open the lock of a bike from a device or a kiosk.
	5.4. Smartphone-based	Scanning QR codes or using the Bluetooth system with smartphones are used to unlock the bikes.
6. Business model (Shaheen et al., 2014)	6.1. Non-profit 6.2. Privately owned and system operated 6.3. Publicly owned and operated 6.4. Publicly owned and contractor operated	Categorization according to profit orientation and if the system is public or private operated and/or owned

2.1.1 Bike-sharing benefits

BSS have experienced exponential growth from a few schemes in the 2000s, to hundreds in 2010, and now thousands in 2020 (Shaheen et al., 2020; Meddin and DeMaio, 2020). This widespread and growing trend of BSS can be associated with their positive impacts. BSS share the advantages of both access economy and bicycling, including their additional benefits of mobility and sustainability. Therefore, the potential benefits of BSS were classified into four main categories:

1. **Cycling benefits.** Bike-sharing is cycling, therefore the benefits associated with cycling are linked to BSS.

    - *Cycling is convenient.* Cycling can save travel time by avoiding congestion, or detours, or low frequencies in public transportation. Large cities have reported a shift from public transportation to bike-sharing due to cost and travel time savings (Shaheen et al., 2012). Around 73% of study participants agreed that BSS can save travel time in Washington D.C., USA (Buehler et al., 2014). In Beijing, using a shared bike can save about eight minutes of travel time on average per day (Qiu and He, 2018). Moreover, Manca et al. (2019) identified that the strongest motivation of students in London to use BSS is to avoid congestion.
    - *Cycling is an alternative for motorized transport.* In a survey conducted in multiple cities across North America, about half of BSS users reported reduced usage of their private cars, and 5.5% have sold or avoided purchasing a new car (Shaheen et al., 2014). In a similar study in the Netherlands, Ma et al. (2020) identified that around 30% of BSS users decreased the usage of private car/passenger and taxi.
    - *Cycling is healthy.* Cycling has shown to improve cardiorespiratory fitness, enhance psychological well-being, and reduce risks of heart disease, cancer, overweightness, obesity, and diabetes (Oja et al., 2011; Cavill and Davis, 2007). However, when bike-sharing trips replace walking or private cycling trips that have similar health benefits, estimated health benefits can be overstated (Ricci, 2015; de Chardon, 2019; Bauman et al., 2017).
    - *Cycling is fun.* Cyclists have described that riding a bike is "an adventure, an excitement, and an escape" (Daley and Rissel, 2011). In a survey in Washington, 42% of participants stated that “enjoyment" was the main reason for using BSS (Buehler et al., 2014).
    - *Cycling is the way to discover cities and people.* Cycling allows interaction with the surrounding environment and with other cyclists and pedestrians. "The opportunity to stop at any given moment and the freedom to navigate the narrowest of streets challenges a cyclist to interact with their spatial surroundings at an exploratory level." (Brömmelstroet et al., 2017, pg. 8).

2. **Access-economy benefits.** Sharing can be defined as a social exchange of goods without any profit, if sharing is market-mediated and a company acts as an intermediary, it is no longer sharing (Eckhardt and Bardhi, 2015). The sharing economy has been losing the sharing concept and has been developed as an access-economy, which allows short-term access to resources for a charge or fee (Eckhardt and Bardhi, 2016; Acquier et al., 2017).

- *Access on an as-needed basis.* BSS enables cycling when a person does not own a bike, does not have a bike with them, or when their bike is damaged.

  > *"I got a Velo Go membership because my regular bike was breaking down and needed constant maintenance. The main benefit of bike share for me is that I never needed to worry about my bike. Also, my parents came to visit and I threw them on Velo Gos to get around and it was easy."* $@jordobicycles$ posted on Twitter on the 4th Sept. 2018.

- *Access to the underprivileged.* Access-economy has a social contribution, which consists of providing the opportunity to consume goods and services regardless of the person's purchasing power. "People who are currently not able to own or drive their own vehicles to have new access to the benefits they derive" (Lucas, 2019, pg. 3).
- *Monetary savings.* Beyond cycling, BSS allows access to goods excluding purchase, maintenance, parking, and theft costs (Cohen and Shaheen, 2018). Savings in travel costs because of BSS has been perceived, for instance, in Washington, USA (Buehler et al., 2014) and Valencia, Spain (Molina-García et al., 2015).

3. **Mobility benefits.**

- *Greater transit usage.* BSS serve as a "bridge between first and last-mile gaps in transportation networks, encouraging multimodal trips" Cohen and Shaheen (2018). In small North American cities, higher use of public transport has been observed, as BSS provide greater access/egress on the first-last mile connection (Shaheen et al., 2014).
- *Greater cycling population.* BSS can support cycling initiatives, and change attitudes towards cyclists (Bauman et al., 2017). For example, about 60% of Mexican-BSS-users have been cycling more after joining a bike-sharing system. (Shaheen et al., 2014).
- *Promote tourism.* BSS offers tourists the opportunity to cycle and thus experience cities at a slower pace and get to know the local life and activities (Chen and Huang, 2020; Oh et al., 2016).
- *Transport resilience.* BSS have shown to improve the resilience of urban transport systems during cancellation of transit services in the event of service failure, e.g. strikes or lockouts during the COVID-19 pandemic (Teixeira and Lopes, 2020; Manca et al., 2019). In New York, an increase in bikes-sharing usage was reported during the first lockdown in the COVID-19 pandemic (Teixeira and Lopes, 2020).

4. **Sustainability benefits.**

- *Economic development.* In many cities, bike-sharing is an economic activity that can improve employment opportunities (Schoner et al., 2012). Buehler et al. (2014) showed that implementing BSS stations encouraged new riders in areas where new spending and new businesses were opened.
- *Sustainable and modern image of the city.* Bakogiannis et al. (2018) showed that the increment of bicycle and public transport usage caused by BSS leads to an improvement in the image of the city of Piraeus as modern and sustainable.

- *Greater environmental awareness.* Together with the deployment of BSS, campaigns have been carried out to promote environmental awareness (Bakogiannis et al., 2018).
- *Potential reduction of emissions and energy consumption.* In 2016, BSS saved 8,358 tonnes of gasoline and 25,240 tonnes of CO_2 in Shanghai (Zhang and Mi, 2018). In 2012, around 60 tons of CO_2 would have been emitted daily if BSS users in Paris had rather traveled by car (Pucher and Buehler, 2017). However, the environmental effect could also vary according to the strategies for balancing and maintenance of the bicycles (Ricci, 2015).

2.1.2 Bike-sharing challenges

Despite the potential benefits, not all BSS have been deploying successfully. Historical reasons for system failures are: 1) cycling barriers; 2) administrative barriers when stakeholders and policy-makers do not support BSS development; 3) infrastructure barriers, when the design and planning of BSS are not optimal; 4) equity barriers when BSS are not planned to be accessible for all; and 5) environmental barriers when BSS have shown to be inconsistent to the environmental benefits. These barriers are explained as follows:

1. **Cycling barriers**. As BSS is part of the cycling system of a city, a lack of cycling infrastructure can make it less attractive, direct, comfortable, safe, and convenient than other transport modes (Fishman et al., 2012). Other factors against ridership include weather conditions and the physical effort required, especially over long distances and hilly terrain (McNeil et al., 2017; Cantelmo et al., 2020).

   One of the most common cycling barriers is safety concerns (Stöckle et al., 2020; Fishman et al., 2014b; McNeil et al., 2017; Fishman et al., 2012). For example, about 69.2 deaths per million users per year have been reported in Barcelona, while between 3.3 and 10.9 in London(Ricci, 2015).

   Furthermore, there are also cultural barriers against cycling. For instance, in some regions in the global South, cycling is seen as something for disadvantaged populations or only for villagers (Pochet and Cusset, 1999). Furthermore, sexism and concerns about traffic safety can create social/cultural barriers to cycling for women. Since women are traditionally in charge of running the home, their main safety issues are not about getting wounded or killed in an accident, but rather about the consequences for everyday family life. (Van der Kloof, 2015).

2. **Administrative barriers**. Administrative reasons which have made BSS less attractive are: lack of funding and support, overnight closure, mandatory helmet usage, lack of integration into the public transport system, lack of information, and lack of regulations (Small, 2017; Fishman et al., 2014b, 2012; McNeil et al., 2017).

   The lack of regulations allowed start-ups to maximize private utility through over-investment, over-competition, and over-supply of bicycles to meet the (potential) market demand (Ma et al., 2018). For instance, 1.7 million bikes flooded Shanghai from January to August 2017, without any notice in advance. Due to the massive number of bikes in the public space, many bicycles crowded the streets, blocking parking spaces and sidewalks (Ma et al., 2018; Sun, 2018; Haas, 2017). Oversupply, blocking public space, and lack of maintenance and contact to the operators caused some FFBSS to be perceived as a public nuisance and bicycles started getting stolen, and vandalized (Sun, 2018). Examples of companies that went bankrupt for these reasons are Bluegogo in China in 2017, Gobee in France in 2018, and Obike in Munich in 2018 (Berger, 2018).

3. **Infrastructure barriers**. Previously identified barriers of BSS related to the infrastructure are delayed expansion, poor access to infrastructure (Stöckle et al., 2020; Fishman et al., 2014b; McNeil et al., 2017), poor quality and maintenance of bicycles (McNeil et al., 2017; Sun, 2018). Systems have suffered from saturated markets, which have caused conflicts because of the lack of docking stations (Li et al., 2019). For instance, around 28% of respondents in Portland (USA) stated that they do not use BSS because there are no stations where they want to travel (McNeil et al., 2017).

4. **Equity (access-economy) barriers.** BSS image of sustainability have led it to be used to support political parties, and the implemented infrastructure a visualization of their investments in cities, apart from the usability or social benefits (de Chardon, 2019).

   Some BSS have been criticized for being too costly. Around 17% of non-users of BSS in a survey in Munich (Germany) and 10% in a survey in Portland (USA) said they do not use BSS because it is too costly (Stöckle et al., 2020; McNeil et al., 2017). In addition, people expressed dissatisfaction with their inability to use BSS due to the technology's complexity. (Stöckle et al., 2020; McNeil et al., 2017).

   BSS have shown to mainly benefit the privileged population and have contributed to the privatization of public space (de Chardon, 2019). The common user's profile of BSS in the Global North tends to be a young white affluent male, highly educated, already engaged with cycling, and with access to bank accounts and credit cards (Fishman et al., 2015; Ogilvie and Goodman, 2012; McNeil et al., 2017; Stöckle et al., 2020). Historically, the distribution of stations and the service areas have been focused on central (Fishman et al., 2015; Duran-Rodas et al., 2019b; Chen et al., 2019) and densely populated regions with a predominance of young Caucasians, as well as, areas with highly educated people (Chen et al., 2019; Ursaki and Aultman-Hall, 2015; Mooney et al., 2019). Moreover, deprived and low-income areas have reported less access to BSS infrastructure (Ursaki and Aultman-Hall, 2015; Mooney et al., 2019; Ogilvie and Goodman, 2012; Smith et al., 2015), even though some schemes promote themselves as being equitable (Duran-Rodas et al., 2020b).

5. **Environmental barriers**. The sustainability of BSS is questioned when unused bicycles generate massive amounts of waste, and polluting modes of transportation take care of the balancing and maintenance of the bicycles (de Chardon, 2019; Ricci, 2015; Sun, 2018). In China, for example, shared bicycles were piled in areas the size of football fields that caused an estimated 300 tonnes of waste in 2017 (Haas, 2017; Shi et al., 2018).

Moreover, unwanted shared bikes have been destroyed, placed on trees, thrown into water bodies, or even burned (Sun, 2018).

2.2 Bike-sharing planning

According to guidelines in North America and Europe, four "macro" steps are commonly used for planning BSS (Yanocha et al., 2018; Gauthier et al., 2014; Anaya Boig and para la Diversificación y Ahorro de la Energía, 2007; Büttner and Petersen, 2011; Toole Design Group, 2012): I) set goals, II) estimate the potential demand and potential bike-sharing users, III) define the potential location of stations and service area, and IV) fix the locations (Figure 2.2).

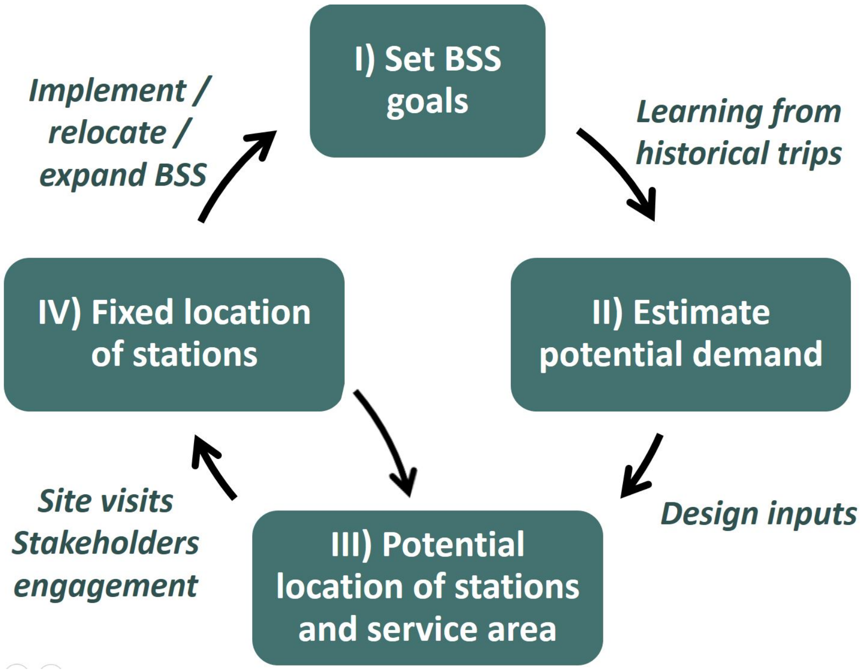

Figure 2.2: Planning cycle for BSS

Commonly, the implementation or expansion of BSS starts by defining the goals of the system. The goals relate to the aimed benefits of the system, such as cycling, access-economy, mobility, or sustainability. Once the goals are defined, the potential demand is estimated based on the historical behavior of comparable existing systems, and design inputs are defined. The design inputs include the available budget, rebalancing method and strategies, and key performance metrics shown in Table 2.2, among others.

Based on the designed inputs and potential demand, the potential location of stations and service areas are determined. BSS guidelines usually recommend that a "first draft" of the allocation should be prepared and confirmed by site visits and stakeholder involvement (Gauthier et al., 2014). If potential sites are not accepted or able to allocate BSS supply, new sites should be sought that are consistent with the existing infrastructure and people involved. Finally, the cycle continues if a system changes its goals or if implementation in a new area, relocation, or expansion is required.

However, if systems are designed based on experience and if past implementation did not focus on the most vulnerable populations, the planning cycle would continue and "reinforce inequity." In other words, Unfair systems could be further shaped by learning from existing unfair systems.

Table 2.2: Bike-sharing key metrics in different design guidelines

Parameter	A	B	C
Bicycles per 10.000 residents	100 - 300	0.1 - 105.8 (14.8)	
Docks per bike	2-2.5	1.0 - 3.2 (1.7)	1.8 - 1.9
Stations density (bikes/km2)	10-16		9 - 18
Stations per 10.000 residents		0.1 - 6.7 (1.5)	
Distance between stations (m)	500	300	800

A= Gauthier et al. (2014), B= Büttner and Petersen (2011), C= Toole Design Group (2012)

2.2.1 Estimation of the potential demand

Estimation of the potential demand is typically conducted by the analysis of spatial factors associated with the historical ridership (Noland et al., 2016). Thus, a high number of studies have examined the spatial factors associated with the ridership of BSS at the origin and destination of the trips. They have focused generally on the built environment, sociodemographic characteristics, and system settings. The most influencing spatial factors found in related work and design guidelines are shown in Table 2.3 and can mainly be classified into six categories: 1) social environment, 2) mobility behavior, 3) regulations, 4) built environment, 5) attitudes and 6) BSS settings. It is worth highlighting that these spatial factors have been associated with BSS usage, however, there is a lack in studying causal relationships among them.

Most studies have analyzed the influencing factors in two scales a) multiple cities, with each city considered as one observation, or b) a single city where one city is analyzed, and the observations are based on areas of influence (Table 2.4). Regarding potential demand prediction, ordinary least squares models are one of the most implemented techniques to build potential demand models and identify the most influencing factors on BSS usage (Duran-Rodas et al., 2019a; Faghih-Imani et al., 2014; El-Assi et al., 2017; Wang et al., 2015; Faghih-Imani et al., 2017; Mattson and Godavarthy, 2017; Zhao et al., 2014). Other approaches have considered robust linear regression (Chardon et al., 2017; Tran et al., 2015) and negative binomial regression (Noland et al., 2016), among others. The logarithm of the number of historical rentals is usually considered as the dependent variable (Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani and Eluru, 2016). Finally, log-likelihood (LL), R^2, and Akaike information criterion (AIC), and Bayesian information criterion (BIC) are mostly used for assessing the fit of models.

If implementing or expanding BSS in new areas is desired, the factors analyzed in only one region may not be sufficient. There is a need to analyze multiple cities, but on a local scale, to identify factors associated with the usage of BSS beyond the geographic boundaries. Moreover, in the literature, there is not a clear comparison of different linear and nonlinear modeling techniques to define which technique fits better BSS usage and their associated spatial factors in multiple cities.

2.2.2 Methods to search the potential location of stations

In terms of finding the potential location of stations, five types of algorithm approaches have been identified in the literature, the first four by Gavalas et al. (2016) and the fifth, which is the equity-

Table 2.3: Factors associated with bike-sharing usage in the literature

Variables			Guideline				Non-spatial studies		Spatial studies			
			a	b	c	d	A	B	I	II	III	IV
Social environment	**Population**	City population	✓	✓	✓				✓			
		Population density	✓	✓		✓				✓	✓	
	Socio-Demography	Employment density				✓			✓		✓	
		Age					✓	✓				
		Gender						✓		✓		
		Household income					✓	✓				
		Household size					✓			✓		
		Education level					✓					
Mobility Behaivor	Mode to commute (work/school)		✓		✓		✓					
	Time / distance to commute						✓					
	Bicycle ownership							✓				
	Cycling propose							✓				
	Driver license ownership							✓				
	Already combine cycling and PT							✓				
Political regulations	**Trans. Reg.**	Traffic calm zones	✓									
	Safety	Bicycle thefts						✓				
Built environment	**Topography**	Slope (max 4%)	✓			✓						
		Altitude							✓	✓		
	Urban Structure	Distance to city center	✓	✓				✓			✓	
		Accessibility		✓	✓			✓				
		Mixed use land use	✓	✓								✓
		Industrial land use		✓								
		Single land use		✓								
		Residential land use										✓
		Commercial activity				✓						
	Transport infrastructure	PT stops	✓	✓	✓	✓						
		Metro									✓	✓
		Railway station							✓			
		Major roads									✓	
		Streets									✓	
		Embankment road							✓			
		Transport POIs								✓		
		Cycling infrastructure	✓	✓	✓	✓					✓	
	POIs	Student residence							✓			
		Cinema							✓			
		Worship POIs								✓		
		Hotel								✓		
		Restaurant							✓	✓	✓	
		Universities	✓			✓					✓	
		Parks		✓								
		Sports Centers	✓									
		Recreation POIs								✓		
		Tourist attractions				✓						
Attitudes	Environmental consciousness						✓					
BSS settings	Capacity		✓	✓	✓	✓			✓	✓	✓	✓
	Density		✓	✓	✓	✓			✓	✓	✓	

a=Ferrando et al. (2007) b=Gauthier et al. (2014) c=Büttner and Petersen (2011) d=Toole Design Group (2012) A=Efthymiou et al. (2013) B=Bachand-Marleau et al. (2012) I=Tran et al. (2015) II= Faghih-Imani et al. (2017) III=Faghih-Imani et al. (2014) IV= (Noland et al., 2016)

Table 2.4: Related work concerning factors influencing Station–Based bike-sharing. Source:(Duran-Rodas et al., 2019a)

Reference	City Name	Spatial Scale	Dependent Variables	Model Type	Model Assessment
Chardon et al. (2017)	75 cities worldwide	City	Log trip/day per bicycle	Robust linear regression	AIC, BIC, R^2, LL
Zhao et al. (2014)	69 cities in China	City	Log Daily use + turnover rate	OLS and partial least squares	R^2
Faghih-Imani and Eluru (2016)	New York	Station	Log arrivals and departures rates	Pooled linear regression & spatial and temporal lagged	AIC, BIC, # parameters, LL
Noland et al. (2016)	New York	Station	Number of trips	Negative binomial regression	AIC, LL, R^2
Wang et al. (2015)	Minneapolis + St. Paul	Station	Log number of trips	OLS	R^2
El-Assi et al. (2017)	Toronto	Station	Log number of trips	OLS	R^2
Faghih-Imani et al. (2014)	Montreal	Station	Hourly arrivels and departures	OLS	LL, BIC
Tran et al. (2015)	Lyon	Station	Arrivals or departures per hour	Robust linear regression	R^2
Faghih-Imani et al. (2017)	Barcelona + Seville	Subcity district	Log arrivals and departures rates	OLS + Auto regressive moving average	LL
Mattson and Godavarthy (2017)	Fargo	Station	Log (rides per day+1)	OLS	R^2
Caulfield et al. (2017)	Cork	Station	Probability trip travel time falls in a category	Logistic regression	R^2

based approach:

1. *Integer programming-based approaches* take into account BSS' historical trips to optimize the level of service and costs (travel, operation, infrastructure) to identify the optimal location of stations (Lin and Yang, 2011; Sun et al., 2019; Caggiani et al., 2018; Reiss and Bogenberger, 2015).

2. *Heuristic approaches* use (meta)heuristic techniques, in which they search for the near-optimal solution. Cintrano et al. (2020) used five meta-heuristic techniques to solve the p-median problem (minimize the distance to stations to all points). Also, Lin et al. (2013) developed a heuristic method for station location based on costs from users and stakeholders.

3. *GIS-based approaches* are developed using geographic information systems tools. For example, García-Palomares et al. (2012) used GIS tools to apply heuristic methods to located stations by minimizing impedance (p-median) and maximizing coverage based on the high density of spatial features associated with BSS usage.

4. *Data mining-based approaches* use data to discover knowledge to plan BSS. Gehrke and Welch (2019) clustered existing stations based on built environment factors. Every candidate station was classified into five different groups being suitable or not to place a station. In a

similar approach, Vogel et al. (2011) proposed to plan BSS by clustering stations based on the temporal pick-ups and drop-offs, and then, correlate them to their most common geographical information.

5. *Equity-based approaches*

   Commonly, when BSS include a goal of equity, access is improved in these two ways: a) reducing barriers to entry into the system, and b) improving physical access to the infrastructure in underprivileged areas. Yanocha et al. (2018) recommended reducing barriers to entry into the system for ensuring equity in BSS, such as higher accessibility for people with different abilities, affordable pricing, or renting mechanisms that do not require smartphones or credit cards. For example, in Philadelphia, fees can be paid with cash at local convenience stores, or in Boston, residents classified as "low-income" only pay an annual fee of 5 U.S. dollars Yanocha et al. (2018). Moreover, system fleets have included adaptive bicycles such as electric bikes and standard trikes for people with less physical abilities (MacArthur et al., 2020). Regarding the access to infrastructure, in Philadelphia, extra stations were placed after considering the income levels and public participation in the planning (Hoe, 2015). In New York, one system has concentrated shared bicycles in low-income communities that have low access to transit (Kodransky and Lewenstein, 2014).

   Only a few studies have incorporated equity-based concepts in the planning process of BSS (Caggiani et al., 2020). Conrow et al. (2018) optimized the distribution of stations based on the minimum distance to access the system in the service area and maximized the potential demand. They called it an equitable approach, however, it does not prioritize the neediest population. Therefore, this study would be in line with the concept of spatial equality. In a similar approach, Caggiani et al. (2020) optimized the location of stations, minimizing walking distances to access the system and distributing a similar number of bicycles in all the districts of a city. To the best of the authors' knowledge, the only study which considers the neediest population for systematically planning BSS is Caggiani et al. (2017). They suggested using the money from cars' toll payments to implement dockless BSS in deprived areas as a compensation measure.

Chapter 3

Research questions

After reviewing the literature, we aim to develop a heuristic fairness-based method for planning BSS that would incorporate spatial fairness criteria as part of the design inputs. Thus, the method employs a mixed approach of heuristics, data-mining, and equity criteria to develop scenarios for the “first draft" of station locations and service area boundaries.

The objectives of this study are achieved by answering the following research questions:

1. What is the public debate about BSS in terms of their benefits, drawbacks, and future on an international level?
2. How the allocation of BSS infrastructure can be assessed based on spatial fairness?
3. Which spatial factors are associated with BSS usage?
4. How can BSS be expanded or implemented based on spatial efficiency, spatial equity, or a balance of both?

The research questions emerged from the problems and needs identified in the research gaps presented in the previous chapter. Figure 3.1 summarizes the links between the research needs and gaps and the research questions in this study. In summary, the urban impacts (social, environmental, economic) of private motorized transport may potentially be mitigated through the development (implementation and expansion) of active transport modes such as BSS. To further develop BSS, their efficiency and design quality should be improved. To improve design, BSS should first be understood in terms of their advantages, disadvantages, unclear future, and social and built environment factors associated with their use (RQ1 & RQ3).

In addition, it has been shown that the planning of BSS is focused on economic efficiency by building infrastructure mainly in privileged areas, which results in unequal use by social groups. Therefore, it is suggested that spatial fairness should be considered in the planning of BSS. Spatial fairness in this study refers to the assessment of whether the distribution of resources follows spatial equity, efficiency, or a balance of both. RQ2 focuses on assessing whether the actual distribution of FVS infrastructure follows equity, and finally RQ4 supports the search for potential sites for BSS based on equity and/or efficiency.

In the following sections, each research question is explained in more detail.

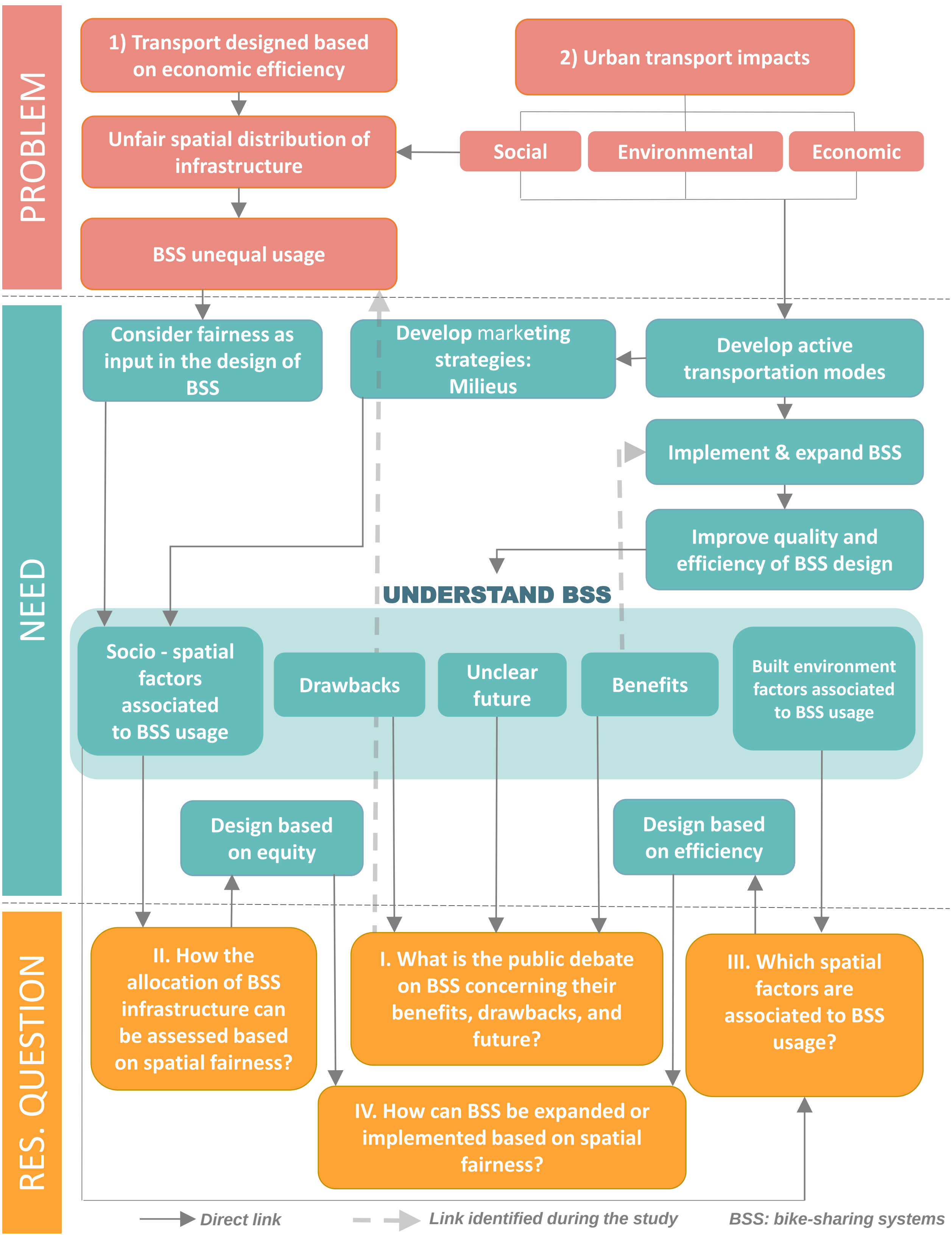

Figure 3.1: Problem definition, needs and research questions framework

3.1 RQ1. What is the public debate about BSS concerning their benefits, drawbacks, and future on an international level?

Based on the benefits and challenges of BSS presented in the previous chapter, there is a dilemma about whether BSS are "good or bad", and also whether BSS will be part of the future of mobility. Since the main goal of this study is to develop a method for designing BSS, an analysis of the public discussion regarding BSS advantages and disadvantages can help to incorporate perceived positives into the design and eliminate or mitigate their drawbacks. Furthermore, the perceived future of the systems can help explore whether it is worthwhile to further develop BSS and how. Finally, an international approach should be considered to have a wider picture of BSS beyond geographical boundaries.

Social media has the potential to reach a wide audience to analyze this public debate at the international level and to explore the relationships between the different actors involved (Shi et al., 2018). Previous studies performed quantitative (Pereira et al., 2013; Das et al., 2019; Rahim Taleqani et al., 2019) and qualitative (Marwick, 2014; Gibbs, 2007; Papacharissi, 2012) methods for transport-related text analysis. Combining both methods is aimed at an approach where quantitative analysis is a starting point for qualitative assessment and helps to generalize its results. On the other hand, the qualitative analysis helps to confirm and understand deeper the topics identified in the quantitative one. One approach informs the other.

Andreotta et al. (2019) proposed a four-step mixed methodological approach that combines the advantages of qualitative and quantitative methods to understand the public debate on climate change in the social media: 1) textual data is collected, 2) contributions are clustered based on quantitative methods, 3) a sample of the most relevant contributions is extracted or the sample is randomly selected, and 4) a qualitative analysis is performed. This methodology can be used for any public discussion, e.g. for the BSS dilemma between benefits, disadvantages, and unclear future. However, to the best of the author's knowledge, this methodology has not been used in public discussions about any transport system.

BSS public opinion has been studied through social media Das et al. (2019); Rahim Taleqani et al. (2019) or interviews (Sun, 2018). For example, Rahim Taleqani et al. (2019) gathered English posts on Twitter worldwide for two and a half months to understand public sentiment and topic clustering regarding FFBSS. However, there is a gap in the literature to a) understand the various issues that are discussed for all types of BSS at the international level and not only FFBSS, b) to identify the positive and negative aspects and future of BSS, and c) to combine qualitative and quantitative social media analysis with interviews for exploring the public discussion on BSS.

The expected outcomes are list of the perceived disadvantages and advantages of bike-sharing. The main expected disadvantage is the conflicts of BSS with other modes of transport, as described in Sun (2018), while the main expected advantages are that BSS are sustainable and should and will remain so in the future because of their economical, environmental, and social benefits (Chapter 2).

Finally, bike-sharing is a relatively new concept that has been called in different ways in informal conversation, social media, conventional media, and scientific language. For example, BSS are referred from "bike-share" to "shared public cycling schemes". To the best of the author's knowledge, there is no previous research that has collected different ways to express BSS in English.

3.2 RQ2. How the allocation of BSS infrastructure can be assessed based on spatial fairness?

To identify the potential location of stations, guidelines suggest estimating the potential demand by learning from historical trips (Yanocha et al., 2018; Toole Design Group, 2012). Unfair systems could be further shaped by learning from existing unfair systems. Hence, before planning BSS and using the aimed method in this study, an assessment is recommended of how fair a system is. Additionally, this assessment can reveal the need for optimization or extension of the infrastructure to build fairer systems. Therefore, a method is required to assess how fair the allocation of the supply of a bike-sharing system is. This method should identify the focus of spatial fairness followed in the distribution of resources, i.e. whether the infrastructure is distributed equally, oriented towards to neediest, or oriented towards those who have the financial means to access the system.

Firstly, to assess how fair the spatial distribution of resources is, the concepts of justice, fairness, and equity are explored. Given the complexity of the concepts and their connections, there is a need to develop a conceptual framework that simplifies them all together so that they can be more easily understood, measured, and applied.

In addition to the existing classification of BSS presented previously, BSS should be also classified according to their infrastructure distribution and who they serve and do not serve. In this study, a quantitative approach is aimed to be elaborated that numerically classifies whether a system follows spatial equity, equality, efficiency, or a mix of them. A quantitative assessment can communicate the fairness criteria adopted in the distribution of people's public resources to achieve greater acceptance and trust in the implementation of a system. Furthermore, data from interviews can complement the results of the quantitative part and determine the perceived focus of spatial fairness on BSS and gain a deeper understatement of the quantitative results.

Moreover, answering this research questions aims to cover what similar previous approaches have not considered: a) assessing spatial equity and equality in hybrid BSS, b) identifying an availability indicator for hybrid BSS, c) estimating an indicator of the underprivileged population considering the social status and accessibility to basic opportunities, and d) categorizing social groups beyond sociodemographic characteristics.

To the best of the author's knowledge, the study by Chen et al. (2019) is one of the few studies that contains an analysis of the spatial equity and equality of hybrid BSS. Therefore, there is a need to study different hybrid BSS in other locations to compare and confirm their results. Moreover, the availability of bicycles in an area is a common indicator of the accessibility of the infrastructure. It has been calculated in different ways, e.g. as the reciprocal of idle time (Mooney et al., 2019) for FFBSS or as the ratio of available bicycles corresponding to station capacity for SBBSS (Reynaud et al., 2018). The inverse of the idle time depends on the time scale that is calculated, e.g. number of bicycles per day in an area. However, multiple bicycles may be only available in a certain period of the day, and they may be missing at other times on the same day. It is therefore necessary to redesign the definition of the availability of bicycles as an indicator of accessibility to BSS infrastructure, especially in free-floating systems.

Furthermore, previous studies have a gap in terms of an index that identifies deprived areas according to access to transportation, land use, and the people's individual components of the concept of accessibility defined in Geurs and Van Wee (2004). In other words, a deprivation index is needed that classifies areas based on the amount of underprivileged population and accessibility to basic opportunities (e.g. education, food, transport).

Finally, sociodemographic characteristics such as income, education, or occupation have often been used as indicators to identify who benefits from a particular service or resource distribution (see Table 1.1). However, there is a research gap in the complimentary usage of values in this analysis. Resources are hypothesized to be distributed according to sociodemographic characteristics and also according to values. Values, lifestyles, and psychographics have been used in market segmentation to prioritize sales for a certain population because of the high predictive ability of consumer behavior (Lesser and Hughes, 1986). Therefore, if monetary efficiency is the goal for resource distribution of BSS and if social status and values are not in line with the market segment, the distribution of transport resources might not serve those with different social status, values, and lifestyles. In sum, there is a gap in research analyzing whether values are parameters that cause unequal distribution of resources.

3.3 RQ3. Which spatial factors are associated with BSS usage?

If efficiency is to be considered in the allocation of BSS infrastructure, estimating potential ridership can provide an idea of where station and coverage area allocations should be prioritized. Identifying spatial factors from the built and social environment that are directly or inversely associated with the usage can help estimate a higher or lower ridership of BSS in an expanded or new area. This research question aims to identify these spatial factors.

Typically, factors associated with the usage of BSS are identified by learning from historical ridership. Furthermore, they can impulse an increase of the performance and ridership of the systems in a region and mitigate possible over-saturation or under-supply issues. As shown in the previous chapter in Table 2.3, multiple studies have focused on searching for these factors. The main spatial factors associated with BSS usage are demography and the built environment represented by the transport infrastructure, points of interest, and land use.

Three sub-questions related to spatial factors associated with BSS use were identified in the literature:

I. What factors studied in one city are associated with usage of BSS in another city or region? The spatial factors associated with the use of BSS in one city, which are also associated with use in other cities, can help transfer knowledge from one region to another. Several methods have been used to estimate usage based on spatial variables in individual cities (Table 2.4). In this study, multiple systems in different cities are modeled as one system to validate the associated spatial factors across geographic boundaries. However, for several cities, which regression method, linear or non-linear, is the most parsimonious and at the same time better fits the dataset?

Therefore, this study builds models in different systems in different cities, countries, and continents (Montreal, Chicago, Hamburg) using linear and non-linear techniques to determine 1) the associated spatial factors across borders, and 2) the regression technique that is most parsimonious while better fitting the dataset.

II. What factors from the social environment are associated with the usage of BSS? A question arises whether an area has the associated built environment factors with the usage of BSS but no ridership. The social environment can help answer these questions, as the lack of ridership can be associated with behavioral or cultural aspects (Deffner et al., 2006). To develop BSS with greater efficiency, it is necessary to know the market sector and the values of potential customers, where they live and work, and the characteristics of their neighborhood.

The transport market is heterogeneous, in which one of the most dominant products is fossil-fueled automobiles (Mögele and Rau, 2020). Heterogeneous markets are usually composed of homogeneous sub-markets, in which customers share the same interest and characteristics (Stöckle et al., 2020; Smith, 1995). The so-called market segmentation helps to identify these homogeneous sub-markets and helps to offer products that meet customers' needs, develop strategies to attract new customers, position branded offers, and identify market gaps (Tynan and Drayton, 1987). Segmentation is typically based on customer attributes, with geographic, demographic, psychographic, behavioral, and attitudinal characteristics being the most common (Stöckle et al., 2020).

Psychographic segmentation is based on lifestyles, values, and social behavior (Töpfer and Bug, 2015). This segmentation helps classify people in terms of interests, attitudes, and behavior patterns beyond demographics (Töpfer and Bug, 2015). Social milieus are a type of psychographic segmentation in which groups of people are clustered based on similar values and life orientations defined by everyday practices and lifestyles and have tended to have similar tastes, communication structures, and living environments (Barth et al., 2017).

The Sinus Milieus® example (Sociovision, 2018) illustrates the benefits of using milieus instead of social characteristics. In this example, two women are 36 years old, married, with two children, and working part-time in marketing. These two women are therefore considered sociodemographic twins. These women were asked to show their "heart of your house" in an interview in their homes. One woman showed a piece of furniture against the wall, under a shelf of liquor bottles. The other woman, on the other hand, showed a wall where the skull of a bull was displayed. Although the two women shared sociodemographic attributes, the differences in their "heart of your house" exhibit that the two women have different lifestyles, values, live orientations, i.e., they belong to a different milieu.

This study considered milieus as an indicator of the social environment for planning BSS because they have advantages over demographics. Therefore, a part of this study aims to search for a spatial association of milieus, as a social categorization based on values and social status (Sociovision, 2018), with BSS usage. They can be used for the spatial market segmentation of BSS. Then, the locations where people of a particular milieu live and travel are identified to prioritize the implementation of a bike-sharing station for planning more efficient systems.

III. Are the previously associated factors causal or indirectly associated with the usage of BSS? Usually, spatial factors associated with the usage are identified without considering the possible relationships that these factors can have among them (Faghih-Imani et al., 2017; Tran et al., 2015; Noland et al., 2016). The exploration of these relations can provide an understanding of which factors are directly or indirectly connected to the usage of BSS. For example, it was found that the use of BSS is higher in densely populated areas (Chardon et al., 2017; Faghih-Imani et al., 2017, 2014). However, people do not travel because an area is densely populated, but because population density attracts more activities that can be performed in the area. There are two methods to explore these relations a) validation of theoretical interactions, b) numerical inferring relationships (e.g. Bayesian networks) (Thakkar, 2020). The first approach was chosen because the interactions of the associated factors have already been validated.

The relationships of the associated factors have been theoretically conceptualized in two different theoretical models: a) interactions of land-use and transport (built environment & transport demand) (Wegener and Fürst, 1999) and b) urban mobility cultures (social environment & transport demand) (Deffner et al., 2006). However, there is the need to combine these two structures to quantify the interactions between the built and social environment, thus understand the ridership of BSS. This combination of theoretical structures can be the basis to build Structural Equation Models (SEM) to a) predict ridership, b) understand the linkages of the predictors, c) validate the theoretical structure, and d) use unobserved variables as predictors (e.g. urban structure, attractiveness). Bringing together these two theoretical structures into one framework is hypothesized to provide a more comprehensive understanding and transferability of the factors associated with BSS use.

3.4 RQ4. How can BSS be expanded or implemented based on spatial fairness?

There is a need for a method for planning BSS that incorporates the concept of spatial fairness, based on what the public, planners, stakeholders, and policymakers believe is fair. In other words, a method that provides the opportunity to design a system efficiently, equitably, or with a balance of them both. Therefore, the goal of this question is to make available a decision-making method that shows different scenarios and what a system would look like if the distribution of resources would not only be prioritized for the most privileged groups of the population without jeopardizing the monetary efficiency of the system.

As shown in the previous chapter, previous planning methods for BSS have not prioritized people's needs in terms of social status or opportunities. There is a lack of a spatial equity criterion in the distribution of BSS infrastructure. Therefore, the development of a spatial fairness-based method is aimed in this study to plan BSS. This method would include the fairness criteria on the distribution of stations and service areas depending on the justice focus desired: deprivation (spatial equity), potential demand (spatial efficiency), or a balance of them. The method will rank zones of analysis based on four heuristic algorithms.

Existing algorithms for the localization of BSS stations are not based on how hybrid BSS work. The stations must be distributed as spread as possible to reach more people, and also as densely as possible for better service and lower compensation costs. Algorithms in the literature do not mix up these two concepts. For example, García-Palomares et al. (2012) considers p-median which is the median of the distance to the facilities, however, the density of them is not considered.

Therefore, different scenarios resulting from the planning method will be assessed based on the coverage area and the density of stations to reduce balancing costs.

Finally, the building of different scenarios is aimed to be as automated as possible to multiple options for decision-making. An automated creation of scenarios could help to collect, process, and analyze large databases, reduce time, human and economic resources, increase reliability, weigh the influencing factors, test multiple systems, spatial levels, and reduce human error (Bonilla et al., 2018).

3.5 Linkage: Research question, research contributions and scientific papers

As stated previously, this study aims to answer four main research questions to develop a method to allocate stations and limit the service area for BSS based on spatial efficiency, equity, or a balance of them. The three first research questions (RQ1, RQ2, RQ3) are about understanding BSS, and they merge to make it possible to answer the final research question (RQ4). Since the goal of the study is developing a method to plan the implementation of BSS, the first step should be to understand them: what people think about them (RQ1), who they serve (RQ1 and RQ2), and what spatial factors are associated with their use (RQ3).

Firstly, we aim to explore people's opinion on the benefits, drawbacks, and future of BSS (RQ1) as part of the literature review to understand the dilemma of BSS between their advantages and disadvantages to incorporate perceived benefits into the design and eliminate or mitigate their drawbacks, and the perceived future of the systems can help explore whether it is worthwhile to further develop BSS. This exploration will be conducted as a mixed-methods approach to understand the public discussion about BSS through qualitative and qualitative analysis on English posts on Twitter and interviews with underprivileged populations, and people in Strasbourg feeling socially excluded in relation to their mobility.

The difference between the method of Andreotta et al. (2019) and this approach is that data is not randomly selected for qualitative analysis but through sentiment analysis and the integration of data from interviews. The expected outcome is a list of the most frequently discussed topics related to the advantages, disadvantages, and future of BSS. As an additional contribution, the most common English terms related to BSS will be collected to fill the research gap and use in the future the term that most users of Twitter relate to BSS.

The next step is to develop a theoretical classification and assessment of BSS based on spatial fairness using quantitative and qualitative techniques (RQ2). Firstly, a conceptual framework will be developed to simplify related fairness concepts. Then, based on a spatial analysis, a system can be classified as spatial efficient, equitable, equal, or a balance of both. This classification can be further understood by interviews about perceptions of how fair BSS are. This assessment will be applied in the hybrid BSS in Munich, Germany, where a new indicator of availability and deprivation will be developed with a social classification based on values and social status. It should be emphasized that the developed deprivation index will serve as an indicator of equity in this study's intended method for planning BSS.

Since the main goal is to locate BSS stations based on spatial efficiency, equity, or a balance of both, and spatial equity can be estimated through the developed deprivation index, spatial efficiency needs to be determined. Potential demand estimation via spatial factors associated with BSS usage will be modeled. Built and social environment factors associated with BSS usage will be identified (RQ3). Built environment factors will be explored at an international level to identify the transferability of the factors and also the regression technique which fits better the data and has the least number of variables. The social environment associated with BSS usage will be identified with regard to milieus which categorize social groups in terms of social status and values. Finally, a theoretical structure will be developed based on urban mobility cultures and the interaction of transport and land use. This structure will include the linkages of the built and social environment with BSS usage to explore the relationships between the factors and those who have a direct connection with BSS usage.

Two approaches were used to answer RQ3: a) multiple cities in Germany (Frankfurt am Main, Stuttgart, Hamburg, Kassel, Darmstadt, Marburg) and multiple cities on an international level (Hamburg, Montreal, Chicago) with observations at the local level to identify factors of the built environment associated with BSS use, and b) a single city (Munich, Germany) that includes factors from the built and social environment as well as relationships from theoretical models of land-use and transport interactions and urban mobility cultures.

Now that the potential demand will be estimated representing spatial efficiency and the deprivation index representing spatial equity, a heuristic method is developed (RQ4) to place stations and limit the service area of BSS. First, areas are ranked according to estimated potential need, deprivation index, or a mixture of both. Heuristic algorithms are developed to place stations in the ranked areas. These algorithms allow different scenarios to be created in the most automated way possible, and finally, the scenarios are assessed based on station coverage and density.

In summary, this research project is based on four scientific papers linked to the four research questions of the study. For each research question, there are theoretical, methodological, and practical contributions. Table 3.1 summarizes the links to the scientific papers and the level of the contributions of the research questions. The following four chapters belong to each of the four scientific papers. Each paper contains a literature review, methodology, application, discussion, and conclusions.

Table 3.1: Linkage: Thesis contributions + research questions + scientific papers

			PaperI	PaperII	PaperIII	PaperIV
Research question	**Research contribution**	**Type**	**Ch.4**	**Ch.5**	**Ch 6**	**Ch.7**
RQ1. What is the public debate on BSS concerning their benefits, drawbacks and future?	– English terms referring to BSS.	**T**	✓			
	– Mixed methods approach for understanding a public discussion for transportation systems in social media and interviews	**M**	✓			
	– Topics related to the public discussion on BSS benefits, drawbacks and future in social media and interviews	**P**	✓	✓		
RQ2. How to assess how	– Conceptual framework and BSS classification according to spatial fairness.	**T**		✓		
	– Availability of bicycles and Deprivation index: indicators for the quantitative assessment	**T**		✓		
	– Method to asses qualitatively and quantitatively spatial fairness in BSS	**M**		✓		
	– Application of the quantitative and qualitative spatial fairness assessment.	**P**		✓		
	– Using values and social status as a social categorizations to assess spatial fairness.	**P**		✓		
RQ3. Which spatial factors are associated to BSS usage?	– Theoretical framework of the interactions between actors associated to BSS usage combining the theories of land-use and transport interactions and urban mobility cultures.	**T**				✓
	– Potential usage estimation of BSS using Structural Equation Models and actors from the theories of land-use and transport interactions and urban mobility cultures.	**M**				✓
	– Identification of spatial factors associated to BSS usage beyond geographical boundaries.	**M**			✓	
	– Social and built environment factors associated to BSS usage in Munich, Germany	**P**		✓		✓
	– Built environment factors associated to BSS usage beyond geographic boundaries	**P**			✓	
	– Regression method to associate BSS usage with built environment factors beyond geographic boundaries.	**P**			✓	
RQ4. How can BSS be expanded or implemented based on spatial fairness?	– Heuristic Method to Plan BSS based on spatial efficiency, spatial equity or a balance of them	**M**				✓
	– Algorithms for positioning stations based on the ranking of the analysis zones.	**M**				✓
	– Method to assess different allocation scenarios.	**M**				✓
	– Application of the method in a city and its periphery	**P**				✓

T= Theoretical, **M**=Methodological, **P**=Practical/Applied

Part II

Scientific papers

Chapter 4

Bike-sharing: the good, the bad, and the future

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Due to the dilemma of bike-sharing concerning its benefits and drawbacks, and its unclear future, we focused on a mixed-methods approach to analyze this public discussion through posts or "tweets" from the social media channel Twitter. We collected around 12,000 tweets in English around the world related to bike-sharing for a period of about six months. We considered two approaches, including topic clustering and sentiment analysis in tweets including: a) bike-sharing related terms and b) "future" and bike-sharing related terms. Strongly positive tweets promote bike-sharing and its benefits such as being convenient, well-performing, and sustainable. Additionally, there is a tendency to write that public, electric, and dockless are better, together with scooters. In contrast, the complaints on bike-sharing focused on inequity, rentals and safety issues, critique on authorities and laws, and poor performance especially of dockless Asian bike-sharing start-ups with low-quality bikes. Around 50% of the tweets that included the terms "future" and "bike–sharing" stated that bike-sharing is going to be part of the future of mobility as an electric dockless version together with other shared modes. The hesitant statements towards bike-sharing being part of the future referred mainly to the systems with poor bikes' quality. Politicians and stakeholders can use this information to enhance bike-sharing or consider the implementation of certain types of bike-sharing in their cities. To the best of the authors' knowledge, this study would be one of the first that analysis the public discussion on social media about a transportation system and its future using a mixed-methods approach. Future studies should aim at identifying and comparing the public opinion of different emerging transportation technologies.

4.1 Introduction

Bike-sharing systems (BSS) have experienced exponential worldwide growth from one hundred programs in 2010 (Shaheen et al., 2010) to around two thousand schemes in 2019 (Meddin and DeMaio, 2020). This growth can be explained because BSS, beyond the benefits of cycling, offer the advantages of the sharing economy, and also, they have a relatively low purchasing and operating cost (Buckley et al., 2014) giving "sustainable" image to a city and supporting tourism (Ricci, 2015).

As part of the cycling benefits, BSS can help to increase public health, environmental awareness, and it can lessen the negative environmental effects of the usage of polluting transport means (Shaheen et al., 2012; Shaheen and Chan, 2015; DeMaio, 2009; Fishman, 2016). Moreover, cycling can increase the leisure time of riders while commuting (Qiu and He, 2018) and allow riders to interact with others and the surrounding environment (Brömmelstroet et al., 2017). Some systems have adapted electric bicycles which help riders to avoid perspiring, to extend traveling distance, to cycle in heterogeneous topography, and to enable cycling for riders with physical difficulties (Shaheen and Chan, 2015).

Beyond cycling benefits, BSS foster cycling access to those who might not use bikes otherwise (Shaheen and Cohen, 2019). BSS, as enlargers of the cycling population (DeMaio, 2009; Fishman, 2016), allow riders to have access to a bicycle if they do not own one of their bicycles are not available, or even if users want to cycle for a one-way trip. Users do not have to worry about bike theft or maintenance (Bachand-Marleau et al., 2012), storage, and parking in the case of docked-systems (Shaheen and Cohen, 2019). Moreover, BSS have shown to bridge the first mile-last mile connection to public transport stations (DeMaio, 2009; Shaheen and Cohen, 2019). BSS's trips have been reported to reduce mobility costs in comparison with other payment-based transport modes. For example, in Beijing, users of BSS reported a 58% reduction in travel budget (Sun, 2018).

Even with their potential benefits, some BSS have been misused, vandalized, and perceived as a public nuisance (Hamann et al., 2019). Vandals brake bicycles, setting them on fire, or place them in unreachable places such as trees (Sun, 2018). Moreover, when private companies exit the market, they leave their bikes in the public space causing significant waste (Sun, 2018). Oversupply, low support of authorities and law, saturated markets and low-quality bicycles, disorderly parking, and safety of BSS are some historical reasons for these system failures (Hamann et al., 2019; Sun, 2018). "Oversupply has led to graveyards of bikes, and deep concerns about quality control, maintenance, and management of these systems" (Sun, 2018). In a survey in Beijing, 35% of respondents complained about the bikes' poor quality. Therefore, Sun (2018) states that dockless systems start-ups are worried about increasing territory and not providing a good service. In contrast, other systems suffer saturated markets, which have caused conflicts because of the lack of docking stations (Li et al., 2019).

Furthermore, bicycles are bought and stations are placed based on demand usually, then, the sharing concept is lost (Shaheen and Cohen, 2019). These systems have reported, especially in the global north, an unequal degree of infrastructure location and usage. The common user's profile is male, young, white, high income, high education, already engaged with cycling and with access to credit card and bank account (Buck, 2013; Fishman et al., 2015; Murphy and Usher, 2011; Ogilvie and Goodman, 2012; Shaheen and Cohen, 2019; Ursaki and Aultman-Hall, 2015). Traditionally less privileged people have also less access to BSS (Ursaki and Aultman-Hall, 2015). In London specifically, "women and those living in deprived areas are less likely to register to use the scheme" (Ogilvie and Goodman, 2012).

Because of the dilemma of BSS being "good or bad", i.e. the conflict between benefits and drawbacks, we aim to explore the public discussion about this dilemma and BSS being part of the future of mobility. Our goals are 1) to identify and interpret patterns and themes in the narrative about this public discussion, and 2) to describe and categorize common words, and phrases. For this research, public discussion means the themes, ideas, opinions, facts, debates, complaints, advertising from institutions, news, researchers, riders, individuals, the general public, etc.

To get a sample of the "public" concerning this topic, we explored the public discussion from posts on social media, specifically on Twitter. This approach helps to explore the BSS dilemma across multiple cities in a cost-efficient, and anonymous way, and also, the posts came from a context from the real world, in a naturalistic way. Even though Twitter might not represent society as a whole, the results of this study can support understanding the public discussion of a sample of society. Politicians and stakeholders can use this information to enhance BSS or consider the implementation of certain types of BSS in their cities.

The remainder of this paper includes a literature review about bike-sharing, twitter, and transport-related studies using Twitter data. Then, a three-step methodology is presented including data collection, data cleaning and classification, and a mixed-methods approach for the data analysis. The results are presented in two parts: public discussion of a) the BSS dilemma and b) BSS's future. After discussing the methodology and the results, we conclude the paper with recommendations to politicians and stakeholders.

4.2 Literature review

4.2.1 Bike-sharing systems

BSS allow users to rent a bicycle offered in the public space for a short period and on an "as-needed basis" (Büttner and Petersen, 2011; Shaheen et al., 2015). According to the availability of stations, BSS are classified mainly into three categories: a) docked-based, in which bikes are picked-up and dropped-off at fixed stations, b) dockless, where bikes are picked-up and dropped-off in the public space within a service area, and c) hybrid, in which bike can either be picked-up and dropped-off at stations or in the public space (Shaheen et al., 2019).

BSS are not a new form of mobility. They started as a free service in Amsterdam in 1965 (DeMaio, 2009). After the system collapsed mainly because of vandalism and appropriation of the bicycles, the next generation, born in 1993 in Denmark, allowed a coin deposit and bike pick-up and drop-off in specific locations. Within the evolution of technology, BSS developed ICT based systems, starting in 1996 in England and 1998 in France. Users could rent bikes in stations with identification cards (DeMaio, 2009) and bikes could be tracked (Shaheen et al., 2012). After the success in Paris with 23,600 bikes in the city, BSS started being implemented around the world, arising to 120 programs in 2010 (Shaheen et al., 2010).

Finally, a fourth-generation emerged allowing a demand-responsive system, renting bikes with mobile devices, real-time integration with other transport modes, GPS tracking, and dockless systems (Shaheen et al., 2012). Nowadays, electric BSS are rapidly emerging in China and Northern Europe (Pucher and Buehler, 2017), in which e-bikes (electric bikes) reduce the physical effort of the rider (Shaheen et al., 2016).

4.2.2 Twitter

Twitter (http://www.twitter.com) is a social media platform with a stronger emphasis on conversations based on microblogging (Chaniotakis et al., 2016). It does not require a reciprocate access permission -as is the case of Facebook - between the user who posts and their follower (a person who checks posts from another user). These posts are called "tweets", which can have a maximum size of 280 characters. Additionally, on Twitter, there is a retweet mechanism that allows followers to spread another person's original tweet (Kwak et al., 2010).

According to (STATISTA, 2020), Twitter registered 386 million active users around the globe in April 2020. It occupied the 14th position on social networks with the most number of users. Around a third of the users enter Twitter several times a day. The United States, Japan, Russia, and the United Kingdom are the countries with the most users. In the world, around 85% of users are younger than 50 years old and 60% are male. Twitter was the fourth most popular social media app in the United States by reach and also by monthly users in September 2019.

Tweets are publically available to software developers and users throughout the Application programming interfaces (APIs). Users can access tweets by registering in the application and they will be provided an API access key, a token, and a consumer. Tweets can be collected after searching for specific keywords or posts from specific accounts (Roesler et al., 2020). There is a limit of 100,000 requests per day and 75 requests per 15-min window in a 7-day limit for standard users (developer.twitter.com).

4.2.3 Twitter data and transportation systems

public engagement and b) real-time or historical data collection and mining (Chaniotakis et al., 2016). Regarding data, the most common types used in transport are geotagged information of tweets and the text used in the posts. Twitter allows public transport agencies to interact directly with users by retweeting, and also, to communicate different news as delays, events, or disasters (Casas and Delmelle, 2017). After a survey of public transport agencies in the U.S.A., Bregman (2012) identified that Twitter is the most preferred social network used by transit authorities, followed by Facebook and YouTube. Twitter is preferred for agency news, service alerts (real-time), and press releases and statements. However, agencies reported that social media was not useful for increasing ridership, save money, and recruit and keep staff. However, transit agencies reported that social media is not a good way to reach the elderly and minorities.

– Quantitative data analysis on Twitter – Real-time data has been used to estimate predictions, disruptions, and events (Chaniotakis et al., 2016). Transit agencies use real-time data from Twitter as a traffic sensor. However, it has been reported not to be reliable because people perceive congestion in different ways and the combination of the words to express "congestion" is enormous (Wojtowicz and Wallace, 2016). Another way of taking advantage of real-time tweets is to locate traffic incidents (Gu et al., 2016; Li et al., 2012; Schulz et al., 2013; Zhang et al., 2018). For example, Gu et al. (2016) developed a methodology for real-time incidents' detection and they validated them with official data.

Regarding historical geotagged data, Steiger et al. (2015) correlated tweets' locations with census data in the United Kingdon. Chaniotakis and Antoniou (2015) identified in Athens, Greece a significant correlation between tweets' density with high-income areas and leisure or transport-related areas. Another transport-related application is the estimation of origins and destinations of trips (Yang et al., 2014). Moreover, Chaniotakis et al. (2016) correlated geolocated tweets with the conventional travel survey in Thessaloniki, Greece.

Historical text data has been used to identify points of view of transport projects, implementations, or policies. Text relevant to the policy have been categorized in a) need to travel b) transport network state or event, and c) opinion about a transport service (Gal-Tzur et al., 2014). To collect transport-relevant information and understand the public opinion of transport systems, Gal-Tzur et al. (2014) filtered messages from authorities and individuals. Around 45% of the messages in the dataset were labelled as originating from individuals. They identified that individual messages are around 45% of the times and they include mostly terms as "I" or "we" and informal terms as "lol". Also, Twitter has helped to identify numerous trips and socio-demographics in a cost-efficient manner (Grant-Muller et al., 2014; Liu et al., 2012) built a method using Twitter data to identify "the gender breakdown of different types of commuter populations"

Schweitzer (2014) used text mining, sentiment analysis, and machine learning techniques to examine the content related to public transport and compared it with other public services on Twitter. Public agencies were shown to influence the comments with their engagement in social media. Those agencies who chatted with their users have more significantly positive sentiments in their posts. Collins et al. (2013) evaluated rider satisfaction in transit usage in Chicago, U.S.A., using sentiment analysis on Twitter. In different situations, transit riders showed a prevalence of negative sentiments rather than positive.

Most studies concerning BSS and social media have dealt with text analysis or sentiment-based analysis. For instance, Das et al. (2019) collected tweets including the term "bikeshare" in Washington DC for nine months to show a methodological approach for sentiment analysis. Rahim Taleqani et al. (2019) collected English worldwide posts on Twitter for two and a half months to understand public sentiment and topic clustering regarding dockless BSS. The posts included the hashtags “dockless”, “bike sharing”, and “bike share”. They carried out a word clustering approach using latent Dirichlet allocation (LDA) method and discovered seven clusters of words association. They highlighted the high relationship of BSS with the word “scooter” and negative sentiment towards the shared bicycles blocking sidewalks.

– Qualitative data analysis on Twitter – Qualitative methods allow analyzing text data beyond their literal description (Marwick, 2014). Because of Twitter’s great amount of data and users, qualitative methods can be labor-intensive. Nevertheless, they might overcome the disadvantage of quantitative methods of not describing messages between the lines, or not identifying typos, sarcasm, or abbreviations (Gu et al., 2016; Marwick, 2014). Then, qualitative methods can reveal social norms, concerns, practices, and also complement the exploration and arguments of the quantitative methods (Marwick, 2014).

Qualitative research on Twitter has been focused on interviews, ethnography research, and textual interpretation (Marwick, 2014). Interviews can be carried about by asking users quick questions. Marwick and Boyd (2011) carried out a snowball method in which they posted questions to their followers about their experiences, opinions and feeling about using Twitter. Then, their followers retweeted the question or questioned their followers. Ethnography research includes observing or participating in a particular online group to understand the interactions between people (Marwick, 2014). For instance, Chretien et al. (2015) used digital ethnography to investigate IT professionals and their usage of Twitter in shaping communities.

Textual analysis and discourse analysis of individual tweets are typically collected in an automated way using keywords, and then, the individual analysis of each tweet is carried out from a selected subset (Marwick, 2014). In this approach, each tweet is assigned to one or multiple “codes”. “Coding is a way of indexing or categorizing the text to establish a framework of thematic ideas about it” (Gibbs, 2007). For instance, Papacharissi (2012) coded 1,798 tweets manually for content and discourse analysis to investigate the presentations of the self. The sample was selected based according to a different conversation of trending topics.

Andreotta et al. (2019) proposed a four-steps mixed-methods approach combining the advantages of qualitative and quantitative methods to understand the public discussion on climate change. The four steps are: 1) text data are collected, 2) posts are clustered based on quantitative methods 3) extract a sample of most relevant posts or select the sample randomly, and 4) perform qualitative analysis. To the best of the authors’ knowledge, this study would be one of the first that analyzes the public discussion in social media about a transportation system and its future using a mixed-methods approach.

4.3 Methodology

We performed a three-step methodology to explore the language usage and to identify patterns and themes about the public discussion on the BSS dilemma and their future. The main three steps are 1) data collection, 2) data cleaning and classification, and 3) mixed-methods approach for data analysis

4.3.1 Data collection

We collected tweets in English related to “bike–sharing” and related terms for all the possible combinations that represent BSS on Twitter over a determined period by using the package “twitteR” (Gentry, 2015) from the “R” programming language. The first challenge was to identify the different terms that people use to refer to BSS in social media, conventional media, and scientific articles. Si et al. (2019) searched for different terms used in scientific papers referring to BSS including “bike sharing”, “bicycle sharing”, “bike share”, “shared bicycle”, “bikesharing”, “shared bike”, “public bicycle”, “public bike”.

For this research, three different types of combinations of the term “bike-sharing” were identified in newspapers and scientific papers. They are composed of root terms (i.e. mandatory words) and complimentary terms (i.e. optional words to complement the root). Four common complements were identified concerning bike-sharing: “system”, “service”, “scheme”, and “program”. Figure 4.1 shows the three different types of BSS-related terms and their potential combinations. As an example, Type I includes: “public bike”, “public bicycle service”; Type II terms are, for instance: “bike-share”, “shared bike”, “public bicycle sharing system”; and finally, Type III can present the composition of the words: “bikesharing”, “bikeshare program”.

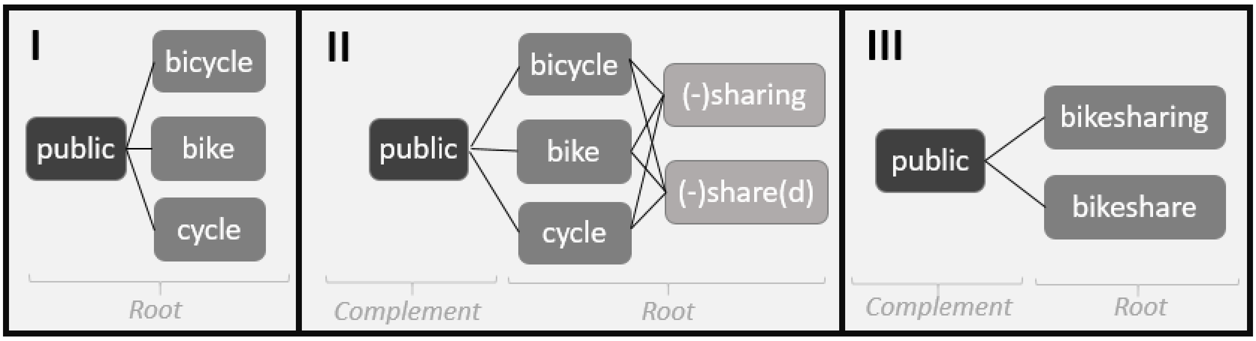


Figure 4.1: Terms combinations referring to BSS in the literature

4.3.2 Data cleaning and classification

We wanted to focus on the collection of only original ideas, based on original tweets. Original tweets represent the opinion of individual users and not the chain of an idea through retweets. Retweets are a fast way to spread opinions and they can give an idea of the post’s significance. However, their frequency is correlated to the number of followers that a poster has. Therefore, neither retweets, as in Rahim Taleqani et al. (2019), nor very similar tweets are included in the study. Thus, a cleaning process is carried out to discard all the tweets that have more than 70% of identical words. A sensitivity analysis was carried out considering 90%, 80%, 70%, and 60%. Tweets with a similar idea but not original were discarded after considering 70% as a threshold. Finally, only one tweet per user and category was selected, to avoid the bias opinion of only highly active people on Twitter.

We carried out two analyses of tweets to understand the public discussion on BSS: a) Highly positive and highly negative tweets including “bike–sharing” and its related terms to understand the current situation of BSS, and b) tweets including the terms “future” and “will” to understand the discussion regarding the future of BSS.

a) Strongly positive and Strongly negative posts. To identify the dilemma of BSS being good or bad, we classified the tweets into “strongly negative” and “strongly positive”. We assumed that tweets with negative words will contain the BSS disadvantages and tweets with positive words the advantages. We did not include neutral tweets assuming that they are not part of the discussion of the BSS dilemma.

Therefore, first, we classified the tweets on “positive”, “neutral” or “negative” by sentiment analysis. Sentiment analysis is a text mining technique that evaluates sentiments from written language (Liu, 2012). We used a polarity lexicon-based method, which assigns a combination of words of a text to a respective sentiment, such as positive, neutral, and negative. We implemented lexicon-based methods because we aim to have a score of the frequency of either positive or negative terms, which we expect are related to benefits and drawbacks respectively. We preferred lexicon-based methods over supervised machine learning techniques because they required labeled data to train the models (Ribeiro et al., 2016).

In lexicon-based methods, every word is compared to a dictionary to be classified as positive or negative. Then, a polarity score is calculated per tweet, which is defined as the algebraic sum of terms classified as positive or negative, divided by the total number of words of the tweet (Hu and Liu, 2004). If a word in a tweet is included in the dictionary, it is classified as negative, positive, or neutral. Tweets are classified as "positive" (score $>$ 0), "neutral" (score = 0) or "negative" (score $<$ 0). Shifter words such as negators (e.g. not), amplifiers (e.g. very), and deamplifiers (e.g. barely) were also considered in the estimation.

In this study, we used the "vader" package in R for polarity analysis (Gilbert and Hutto, 2014). This package uses the vader dictionary with 7515 words. Vader dictionary was developed using tweets, movie reviews, among others. It includes 5 heuristics: 1) punctuation (e.g. !!!), 2) capitalization (e.g. We LOVE it), 3) shifters, 4) amplifiers, and 5) trigramms identification (Ribeiro et al., 2016). We chose vader dictionary because it is one of the newest dictionaries based on tweets, and also, after the comparison between several dictionaries, Ribeiro et al. (2016) showed that vader is one of the dictionaries that perform better sentiment analysis with tweets.

After assigning a polarity score to each tweet, we wanted to be on the "safe side" and have a high probability of choosing real positive or negative tweets including "bike–sharing" and its related terms. Therefore, we selected tweets between a range of 0.5 and -0.5, i.e. tweets were subset into strongly positive (e.g. $>$ 0.5) and strongly negative (e.g. $>$ -0.5). We considered this threshold appropriate after testing by reading part of the tweets and verifying the content.

b) Post including the term "future". We create a subset of tweets including the terms "future" and "will" in the intent of exploring the public discussion on the future of BSS.

4.3.3 Mixed-methods approach data analysis

After the tweets were classified into the three categories (strongly positive, strongly negative, and future-related), we carried out a mixed-methods approach for text analysis, in which, we take the advantages of quantitative and qualitative methods. Both methods should not substitute each other but complement. Quantitative methods help to describe the big dataset at a macro-level, while the qualitative approach provides detailed information and explanation of the macro-level (Kelle, 2006).

First, we counted the most repetitive terms in each category for evaluation and comparison. The frequencies helped us to have an idea of the language used and gave us an idea of the possible themes for each category. Then, we performed topic clustering, i.e. we assigned a category, theme, or topic to every tweet. We followed one quantitative and one qualitative method for topic clustering. In this research, we used the information about the results of the quantitative approach as a starting point for the qualitative one. As the qualitative analysis can be subjective to the authors, the quantitative approach helped to corroborate the impartiality of the results.

Quantitative clustering method. Clustering is carried out quantitatively by Reinert textual clustering method (Reinert, 1987, 1983) based on descending hierarchical classification with the open-source software IRAMUTEQ (Camargo and Justo, 2013). The selected tweets are treated as a single corpus, whereby each tweet is considered to be one paragraph. The process has mainly four steps: 1) reduction of the sparse corpus, 2) lemmatization (extracting root form words), 3) creation of units of context by classifying the words into active terms (verbs, adjectives, substantives, adverbs), and supplementary terms (prepositions, pronouns, and frequent adverbs, adjectives, etc.), 4) descending hierarchical clustering based on the frequency of the root of the words, the maximum number of clusters to be computed, and the minimum number of forms in each (Ruiz Bueno, 2017; Villeneuve, 2020). The number of clusters was set by 1) minimizing the number of tweets that do not belong to any category, 2) logical topic separation between clusters, and 3) considering a minimum distance between clusters.

Qualitative clustering method. Tweets were clustered manually (qualitatively). After reading and analyzing every tweet, each one is assigned one or more categories or "codes" based on the literal text or the meaning "between lines". For instance: the tweet "They're the best bikesharing around because you can actually move around town fast and are affordable" had the following codes:

- They're the best bike-sharing around: BSS perform well
- you can actually move around town: BSS good for mobility
- fast: BSS are convenient
- affordable: BSS are sustainable: Socioeconomic

We used the results of the quantitative clustering approach and terms frequency as a starting point of possible codes in our dataset. Then, those with similar codes were aggregated. If a code was identified only one time, the tweet was not included in the clustering.

4.4 Results

Tweets including all the possible combinations of the term "bike-sharing" were collected from 18.08.18 to 12.02.19. In total, 12,498 tweets in English were collected and cleaned with a mean of 109.6 tweets per day. A peak of around 500 tweets per day was identified on 4-7 September during the conference of the North American Bike Sharing association. Usually, there were around half of the number of tweets on the weekends than on working days. The most common terms associated with bike-sharing were "bike share", "bike sharing", "bike-sharing", and "bikesharing" (Figure 4.2). Together, these four terms served to collect around 70% of the total tweets. After deleting very similar tweets, the sample included 5.403 tweets.

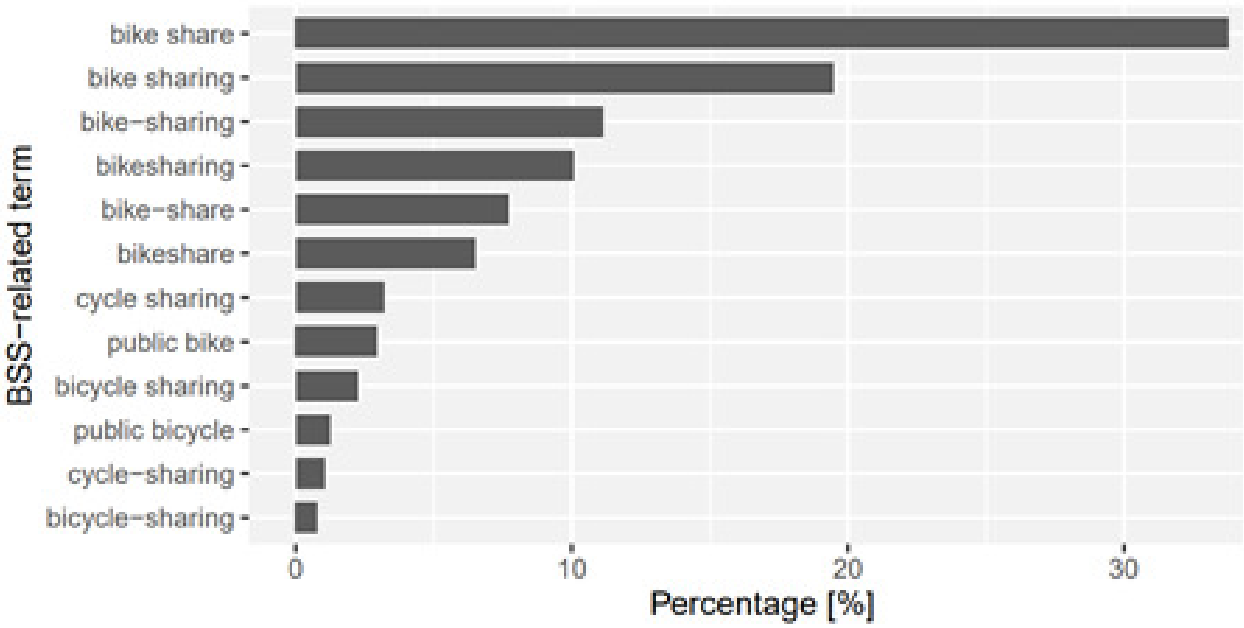


Figure 4.2: Relative frequencies of BSS-related terms in the collected tweets

4.4.1 Public discussion on BSS dilemma

The polarity evaluation showed a mean score of 0.36, where 73% of the tweets were classified as positive, 13% as neutral, and 14% as negative (Figure 4.3). For the analysis, strongly positive tweets were selected as those having a polarity score greater than 0.5 (n=3070) and strongly negative tweets with a score of less than -0.5 (n=682). After estimating the relative frequencies of the words' roots used in tweets in both sentiments (Figure 4.4), positive tweets presented a higher association with, for example, the stems terms "public", "city", "ride", "electric", "station", and “e-bike”, while the negative tweets were associated with “Manchester”, “mobike”, “Chinese”, “start-up”, “million”, “lot”, “space” and others. In the middle line of being used in either positive or negative tweets, we found the words “dockless”, “uber”, “lime”, “new”, “launch”, “city”, and others.

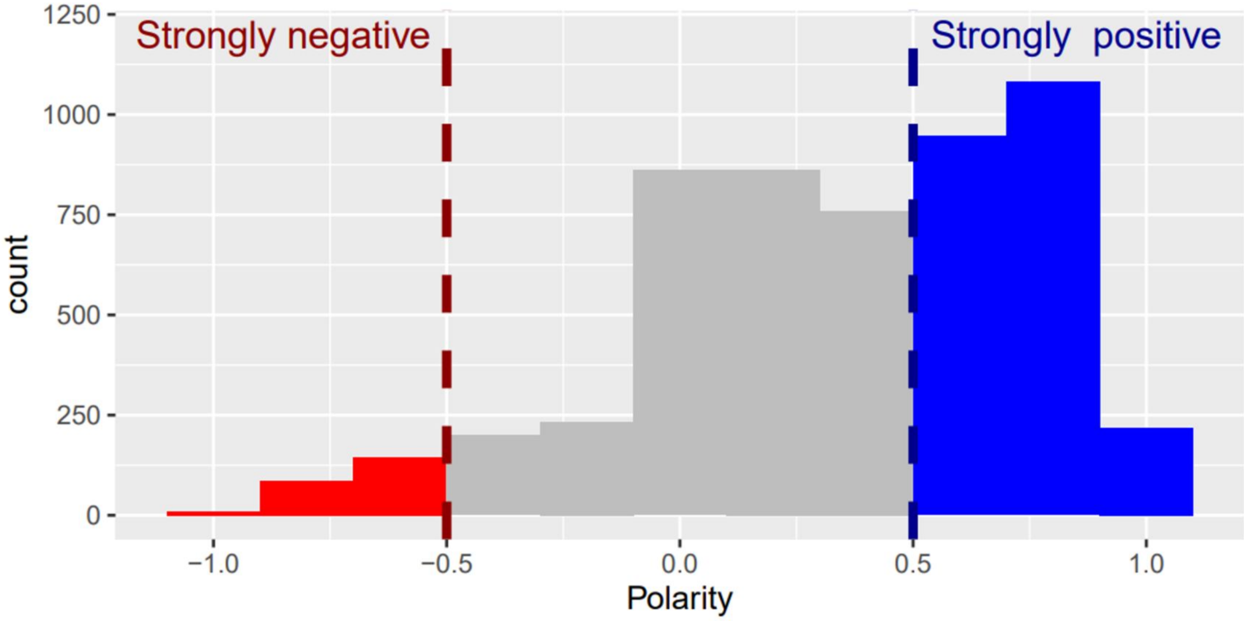


Figure 4.3: Polarity scores for tweets including BSS-related terms

– Bike-sharing: The good – On the other hand, 91.04% of the strongly positive tweets were clustered into four clusters following a decreasing hierarchical clustering technique using Reinert’s method (Reinert, 1987, 1983). From the clustered tweets, the majority, 63.8%, were in the category “BSS are good” and the remaining in “BSS marketing” (Figure 4.5). Around half of the tweets in the category of “BSS is good” are related to BSS being good for mobility. We can corroborate this after the most associated words in this cluster are “transport”, “public transport”, “mobility”, “solution”. The remaining tweets talked about other reasons why BSS are good, e.g. when they are “dockless”, “electric” and they complement with “scooter” sharing systems.

For the qualitative topic clustering, we subset the 150 tweets with the highest positive score. We identified mainly 7 categories (Figure 4.6, Table 4.1) in 89% of the selected tweets. Three of these categories were identified in the quantitative approach. The categories were as follows:

1. BSS are sustainable (25%). BSS are claimed to be good for the environment (6%) and the socioeconomy (19%). The environmental part is justified after stating that BSS help to reduce car usage, and replace cars and therefore, fewer emissions. The socioeconomic part is highlighted in statements that BSS are affordable and cheap, support the local economy and community empowerment, increase mobility inclusivity and equity, and also they are good for health.
2. BSS are good for mobility (17%). BSS are promoted to be good when a person does not own a bike, good for the lat-mile connection with public transport, and good to explore the city. Finally, some stated that BSS are better than car or scooter sharing.
3. BSS expansion and opening (11%). Positive tweets about a system’s expansion or a system that is going to be implemented.
4. BSS marketing (11%). Posts mainly from entities promoting the usage of BSS
5. BSS perform well (10%). Tweets explaining how well a system performs. Also, this theme includes satisfied people with the service and people supporting BSS.
6. BSS are convenient (10%). This category includes the reasons why BSS are convenient: BSS are fast, fun, easy to use, riders dot not have to worry about bike thefts.

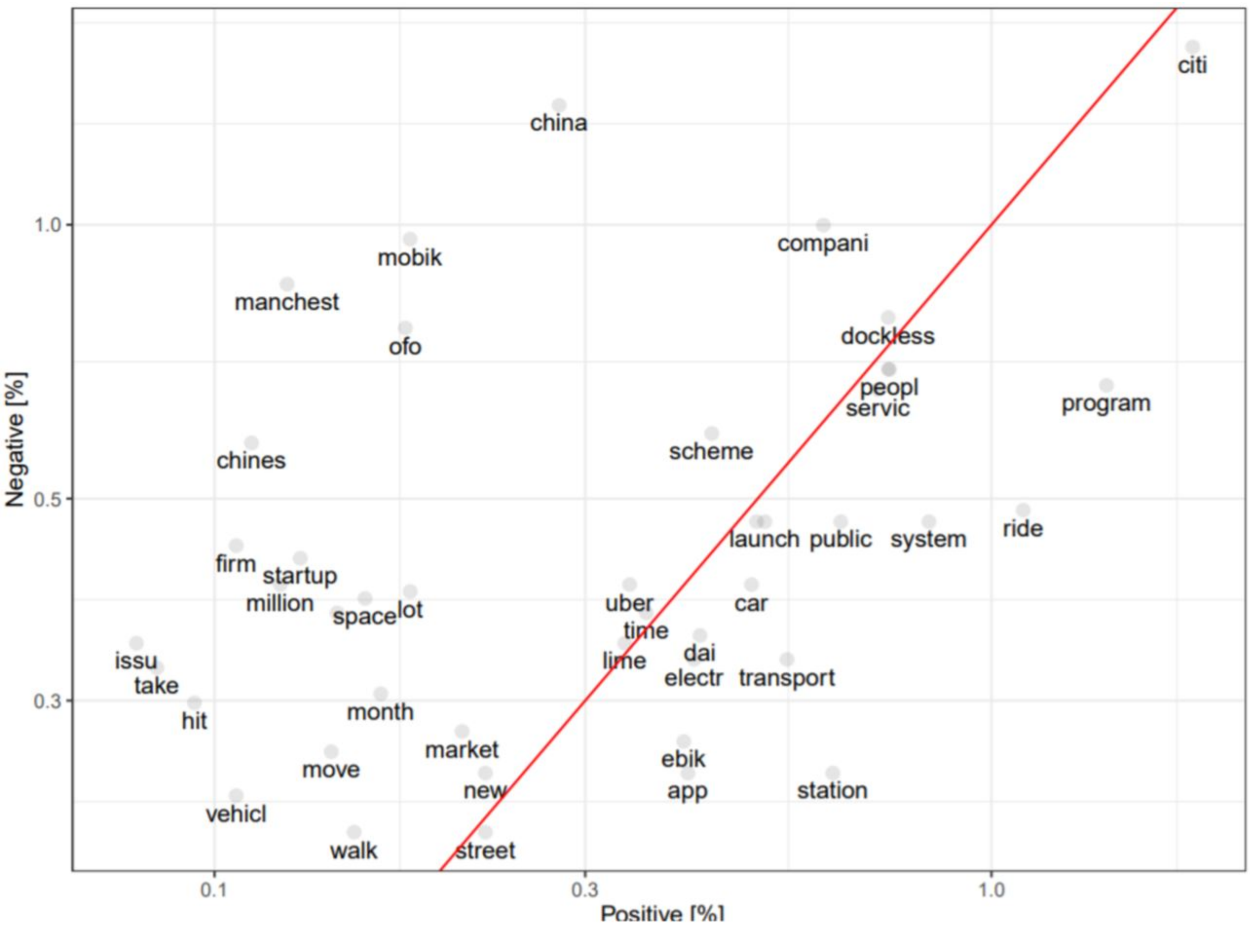


Figure 4.4: Words' roots relative frequencies of positive and negative tweets

7. When better? Dockless and electric (5%). The opinion of people and entities stating that they like BSS with an electric and dockless scheme.

Finally, around 2% of the tweets were classified as sarcasm, for example:

> *"More free median parking, less bike share, zerp eScooter = more freedom for me and my mostly empty car! Thanks @EdReiskin @stma_muni !" [@Bob_Gunderson 30.08.2018]*

– Bike-sharing: The bad – Four main topics were identified quantitatively from 95% of the tweets classified as strongly negative (Figure 4.7). Around half of the strongly negative tweets were classified as bad performances of BSS. The other topics were related to BSS oversupply especially of bikes' graveyards in China, vandalism of bikes, and cycling being not safe. According to the qualitative topic clustering, 150 strongly negative tweets were clustered into 8 categories (Figure 4.8). The categories determined in the quantitative part (Figure 4.7) were a subset of these 8 categories. Moreover, 23 tweets did not belong to any category or they were wrongly classified due to sarcasm (around 2%). An example of a wrongly classified tweet due to sarcasm is:

> *"E-bikes represent a real danger" says NYC mayor. Look at the picture. Who's more dangerous: The e-cyclist who goes 30 km/h or the two-ton metal boxes that move around the city at 60 km/h?" [@LiorSteinberg, 12.03.2018]*

Around 24% of the negative tweets were related to Asian start-ups of dockless systems, and specifically to the companies "ofo" and "mobike". The predominant cluster (28.9%) was related to

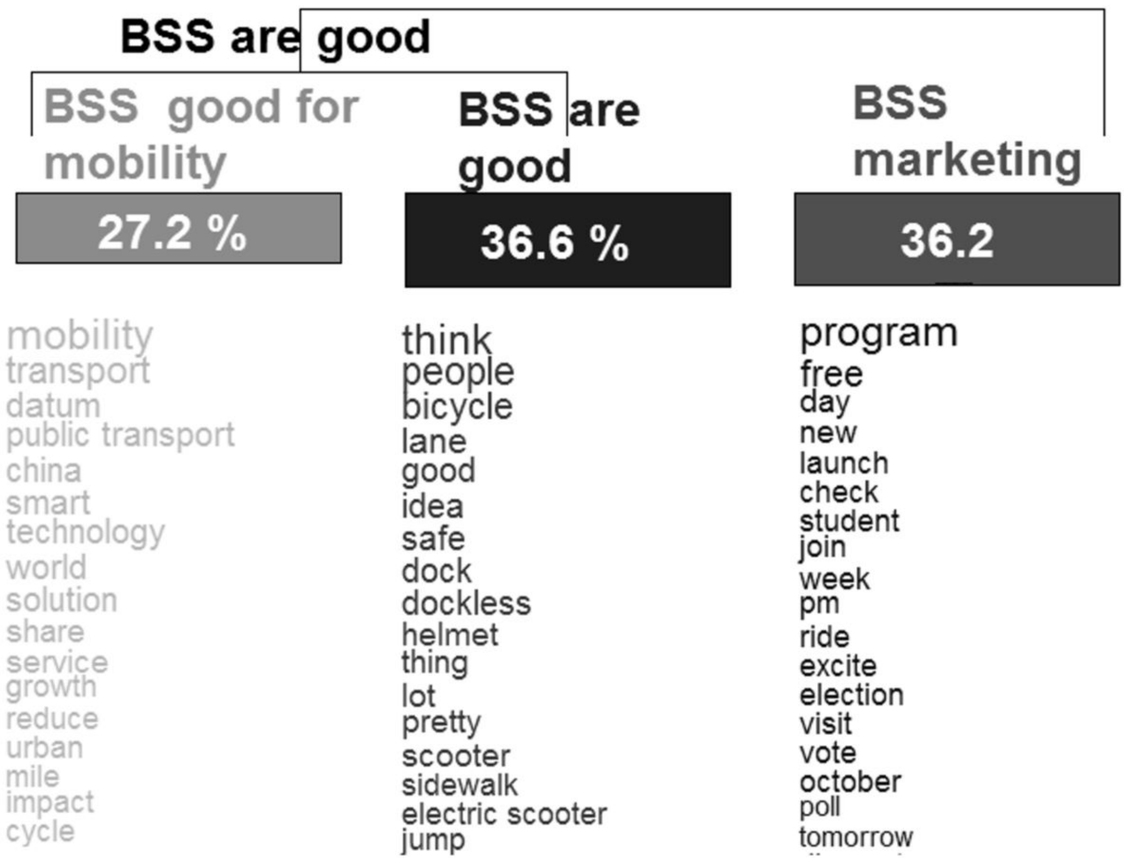


Figure 4.5: Quantitative topic clustering on strongly positive tweets

tweets describing BSS that have experienced poor performance or that have been pulled out from a city. The other main categories are related to vandalism issues to the bike-sharing infrastructure, mainly bicycles, and also complaints about the oversupply of some systems and the bicycle graveyards. Another cluster included the unsatisfactory deployment of the system, even approaching equity issues, issues by using or renting bicycles, and safety issues. Finally, the least frequent clusters dealt with complaints to public authorities and the lack of BSS in their cities. Table 4.2 shows examples of the strongly negative tweets per cluster.

4.4.2 Public discussion on the future of BSS

The word “future” or “will” and “bike-sharing” related terms were included in 426 tweets. After the quantitative topic clustering, 81% of the selected tweets were classified into 3 categories (Figure 4.9). Around two-thirds were categorized that the future of BSS is electric, dockless and together with scooter. The other third is related to BSS marketing offering futuristic expansions, rides, and the benefits of BSS.

For the qualitative approach, we selected the tweets including the word future (n=149) to avoid tweets associated with marketing, in which 123 tweets were clustered in 9 topics (Figure 4.10). Because of the language used and the availability of the tweet poster’s username, while performing the qualitative clustering, we realized that several tweets selected belonged to scientists, activists, politicians, municipalities, BSS companies, and media. Table 4.3 shows examples of the different topics of tweets including “future” and BSS-related terms.

Around 50% of the tweets stated that BSS are included in the future of mobility. Highlights are towards the future of BSS being electric and the future of mobility including other shared modes e.g. scooters and cars. On the other hand, 11.9% of the tweets stated that BSS is probably going

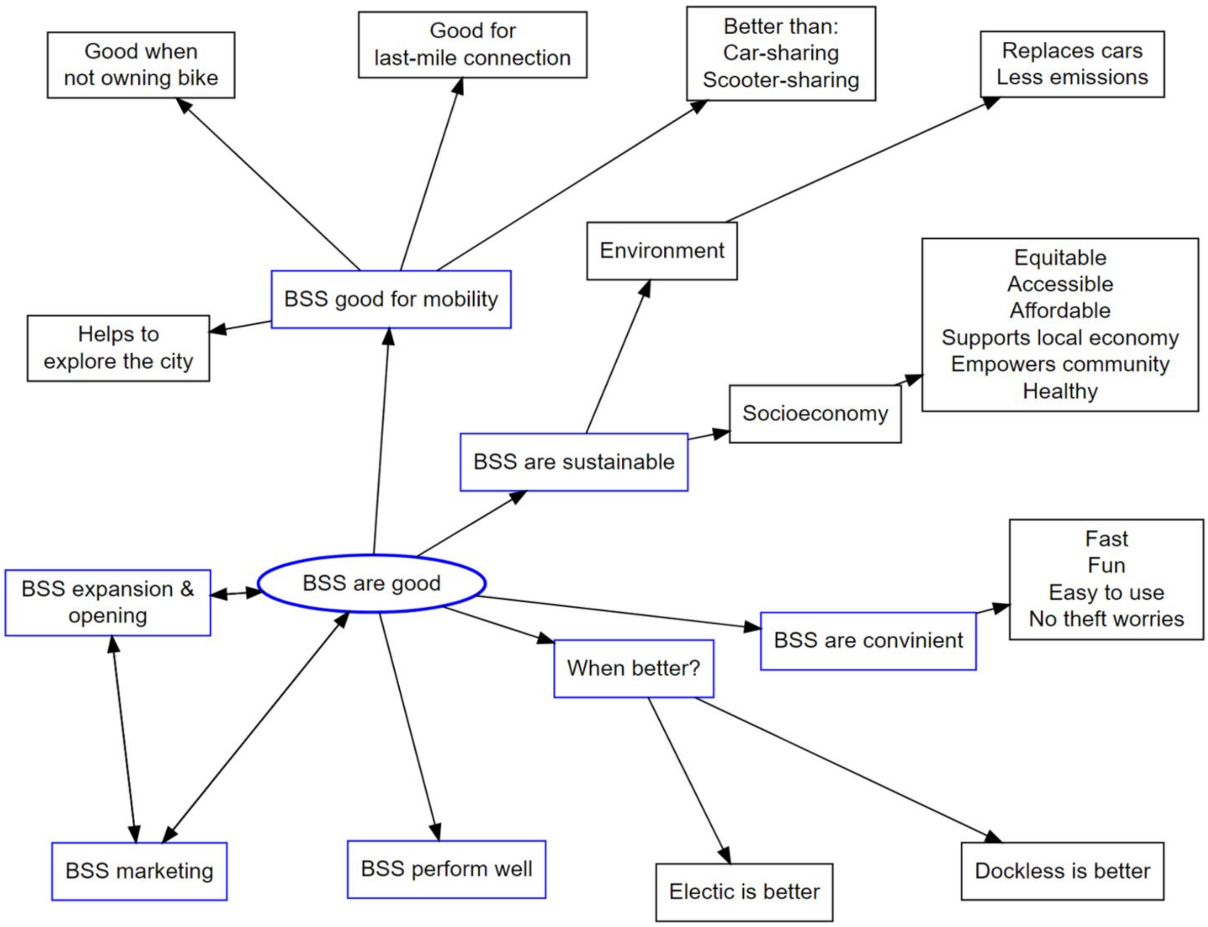


Figure 4.6: Qualitative topic clustering on strongly positive tweets

to collapse. It is worth mentioning, that around 50% of these statements specifically refer to Asian dockless BSS start-ups.

4.5 Discussion

Tweets including BSS-related terms were 3.7 times more often classified as positive than negative. These results are comparable to Rahim Taleqani et al. (2019), who collected 2.8 times more positive than negative tweets regarding dockless BSS. The number of tweets collected over a relatively long period of time helped us to understand that the public discussion of BSS-related terms tends to be more positive than negative.

Strongly positive tweets presented a higher frequency of the word "e-bike" and "city", which showed the high acceptance of BSS using electric bikes. There was a debate between terms "new" and "dockless", in which some talk positively about them and others negatively. Therefore, we assumed that the debate or dilemma is towards new BSS entering a city and dockless systems. On the other hand, there was a tendency among negative tweets to include the words "Manchester", due to the vandalism problem in this city of bicycles with the company "mobike". This negative tendency also included terms such as "ofo" or "China", which show higher negativity towards dockless Asian BSS start-ups with low-quality bikes. Furthermore, "space" and "million" gave us an idea of complaint about the oversupply and their space consumption. Also, we could see that "start-up" was associated with negative and "public" to positive. This result gives us the idea that public systems are preferred than private start-ups.

Strongly positive tweets promoted BSS and their benefits such as convenience, good perfor-

Table 4.1: Examples of strongly positive tweets per cluster

Cluster	Example	Poster & Date
BSS are sustainable	“Bike share in Africa; good for the economy , good for health , good for the environment , Good for air quality , good for job access ... what are we waiting for ?”	*@GilboCarly 14.10.2018*
BSS are good for mobility	Last year I was the only one in my apt that biked, now all four of us do. Very cool. Thanks @RideBluebikes! Bike share rocks.	*@CodyPajic 13.09.2018*
BSS expansion & opening	Good news for cyclists in New Orleans: 485 new bike racks are coming, and bike-share rentals are now cheaper	*@CurbedNOLA 12.10.2018*
BSS marketing	“Did someone say FREE?! Yup! FREE Metro Bike Share monthly pass!!”	*@JenMaradiagaMPH 16.10.2018*
BSS perform well	“Rode a Lime bike from the ferry to @factionbrewing with @AttemptedChem and let me tell you something about bike sharing... folks, it’s good. It’s very good.”	*@rich_roberts 01.09.2018*
BSS are convenient	“Just tried Metro Bike Share for the first time in DTLA. Great experience! I actually like the feel of the bike better than @BreezeBikeShare! Both are great; Metro bikes are lighter, smoother, faster, less clunky. Breeze has better connectivity and better docks/system locations.”	*@sean_baba 08.10.2018*
Dockless is better	“There are definite benefits to going dockless, particularly in New York, where NIMBY-led fights over docking stations can hold up the placement of new bikes.”	*@ReginaRyan_NYC 14.09.2018*
Electric is better	“Marlon Boarnet on Twitter: "How e-bikes are game changers, and why we should welcome them. . . . Light duty e-mobility has great prospects for sustainability and equity. . . ”	*@SteveAuterman 05.12.2018*

mance, and sustainability. Additionally, there is a tendency to write that electric and dockless are better, together with scooters. On the other hand, most of the strongly negative tweets were related to poor performance, vandalism, and oversupply, in which most of the complaints were related to dockless Asian BSS start-ups with low-quality bikes. We also discovered complaints related to safety and cycling, which were identified as a barrier with regard to taking out a BSS membership in Melbourne and Brisbane (Fishman et al., 2015).

Strongly negative tweets were posted more frequently from private individuals rather than institutions or media. In contrast to strongly negative tweets and based on topic clustering around a third of the strongly positive tweets were related to marketing and promoting BSS by media and companies which provide the service rather than private individual sharing experiences or opinions. Some posters commented on the inequitable usage and distribution of the allocation of the infrastructure of BSS, and also they complained about the high usage costs. This means that not only in scientific studies (Lucas, 2019; Ogilvie and Goodman, 2012) but also, BSS users and citizens are perceiving BSS as inequitable (see Table 4.2), even though BSS are promoted to be equitable, affordable and accessible.

Regarding the future of BSS, such tweets were posted by users who were mainly scientists, practitioners, and media more than common people, commenting on their thoughts. However, these posts gave us the impression that BSS are part of the future of mobility, especially as an electric version, and developed together with other shared modes such as scooters. On the other hand, it is doubtful that Asian dockless systems are seen as being part of the future of mobility, mainly due to oversupply and low acceptance among the public, which was shown in their posts commenting theft and vandalism.

The quantitative clustering approach helped us for automatic analysis of a big number of tweets, while the qualitative approach provided more help in understanding the problem better,

Table 4.2: Examples of strongly negative tweets per cluster

Cluster	Example	Poster & Date
BSS poor performance	“Bike-sharing firm Ofo’s dramatic fall from grace a warning to China’s tech investors”	*@rothwell_scott 27.12.2018*
Vandalism issues	“Dockless bike-sharing company pulls out of Manchester due to "theft and vandalism”	*@snebq 07.09.2018*
BSS oversupply	“Huge piles of impounded and broken bicycles lie in a rubbish dump after dozens of bike-sharing companies went bankrupt last year in Nanjing, China on January 10, 2019.”	*@Joopjadieja 19.01.2019*
BSS are unsatisfactory	“The bike share touted as being “for poor people” was too expensive. Shocking.”	*@ineedja_kadeeja 03.10.2018*
Renting issues	“So I lost more than 30 minutes and 5$ for nothing, no replies at all. #Useless #bikesharing #app #bikers #danger #mobike #scam”	*@braisontour 29.01.2019*
Safety issues	An 18-year-old went to the hospital last night after the brakes reportedly failed on the bike share bike he was riding. @komonews says they found a Lime bike with its brakes slashed at the scene of the crash.	*@davidlgutman 11.09.2018*
Authority/laws complaints	Lack of infrastructure, regulations killing bike-sharing services	*@TMReserve 22.11.2018*
Lack of a BSS	“It never stops being mind blowing that Aberdeen has no air pollution plan. The most toxic air of a city this size in the UK, has little cycle ways, no public bike hire, our local suttle buses are the most expensive in scotland, no car pool lanes 1 person per car is just selfish.”	*@soozstewart 11.02.2019*

Table 4.3: Examples of tweets referring to the future of BSS

Cluster	Example	Poster & Date
The future of mobility includes BSS	“The future of #bikeshare programs is bright, To counter congestion and pollution worldwide, bike share will surely go in high gear. #Cycle2work #future #green #Mobility #made #easy”	*@mobycy 17.10.2018*
The future of mobility does not include BSS	“Google "bicycle graveyards China" to see a glimpse of the future of bikeshare and scootershare strategies. Should the profit makers bear responsibility?”	*@JosephHsuMD 08.09.2018*
The future of BSS is electric	“As mayor of one giant hill, electric bike sharing is the future.”	*@JeromeMayaud 07.01.0218*
BSS future is unclear	The @CDPHPCycle bike-share program has provided 15,000 rides this year, with three months left in the season. But future is uncertain...	*@gazettesteve 08.09.2018*
Shared and intermodal mobility are the future	“The future of #transportation is #multimodal. The shift is rapidly happening from vehicle ownership to #ridesharing, #bikesharing, #scootersharing, and #AutonomousVehicles. Urban cities are seeing lower demand for #parkinglots. . . ”	*@Lucky_Sandhu, 19.11.2018*
Literature about the future of BSS	“From my colleague Nicole, her Monocle article on the future of bikesharing.”	*@LongBranchMike 30.08.2018*
The future of mobility includes (e)scooters and BSS	“Have you rode on an E-bike or scooter in your town yet? These could be the future of #urbancommuting! Will E-Bike Sharing Platforms Revolutionize Urban Commuting?”	*@MMAMidAtlantic 04.02.2019.*
Uber wants to be involved the future of BSS	“Uber wants to drive the future of bike-sharing. #Sustainability #SharingEconomy #Auto”	*@TheFutureLab 30.08.2018*
The future of mobility car-sharing and BSS	“1$ to start., car sharing, just like bike share is the future of transit in large cities. — at Ballard Farmers Market”	*@joseph_procella 27.11.2018*

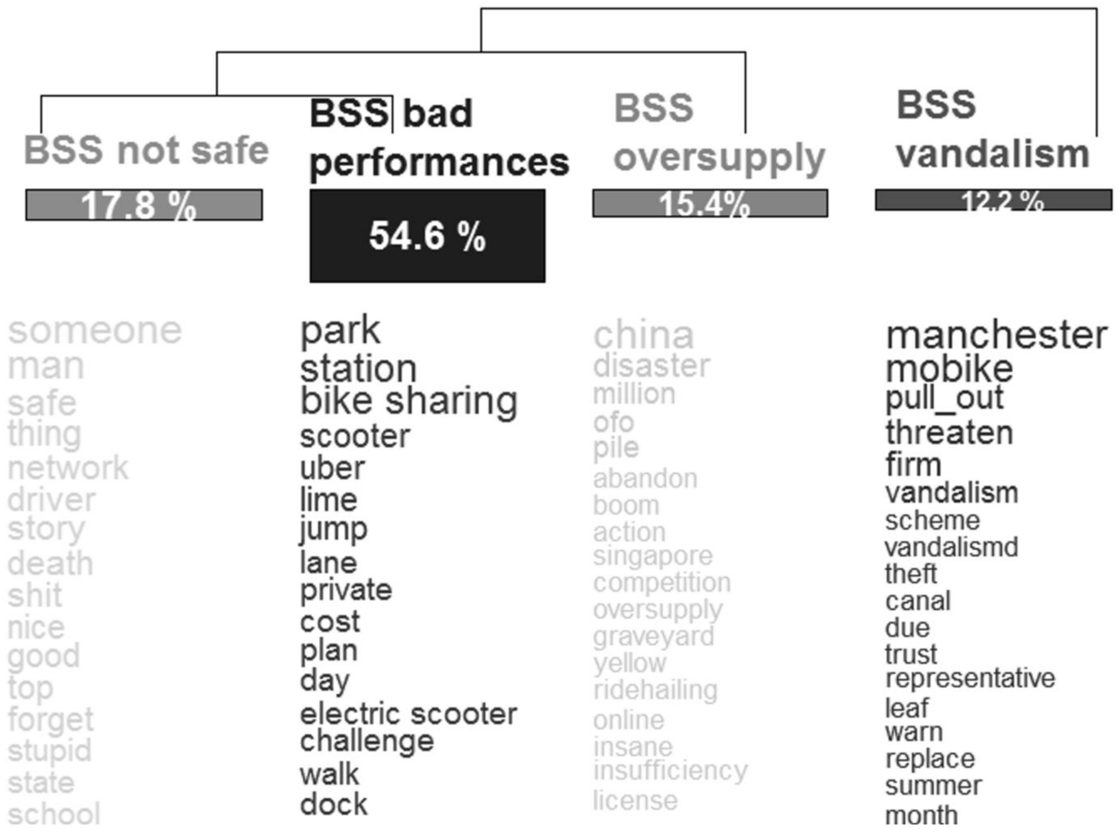


Figure 4.7: Quantitative topic clustering on strongly negative tweets

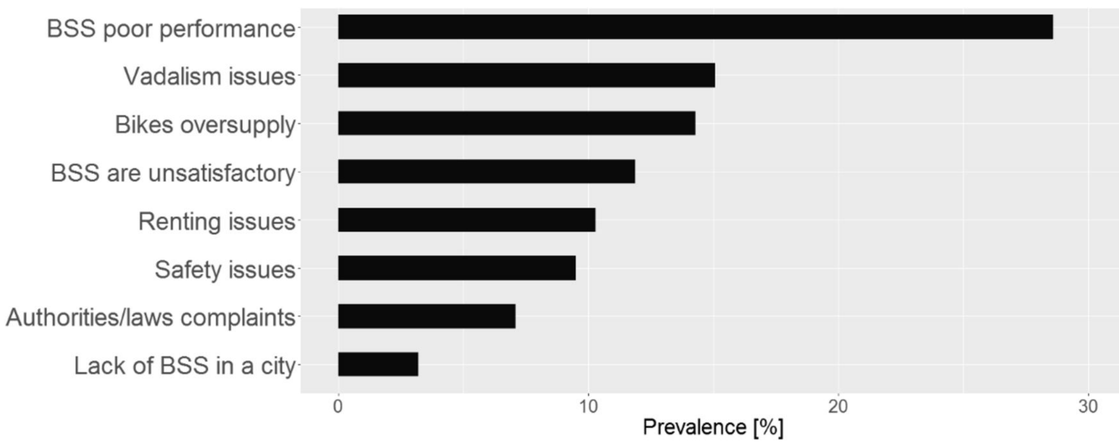


Figure 4.8: Qualitative topic clusters according to the strongly negative tweets (n=150)

having fine-tuned categories, and diagnosing sarcasm and wrongly classified tweets. The categories from the qualitative approach were mainly the most frequent topics. Therefore, the quantitative approach helped as a starting point for the qualitative analysis. Also, if a macro approach is required the quantitative approach is a good approximation about the public discussion.

Qualitative methods are blamed to be subjective, and not generalizable. Thanks to the quantitative approach and the frequency of the terms, the subjectivity in this research is reduced, however, this approach was labor-intensive. On the contrary, quantitative methods are less laborious but their results are at a macro level and dependent on the dictionary implemented and include sarcasm which could not be detected. Nevertheless, in the qualitative clustering approach, we identified the same categories as in the quantitative approach and also, around 2% of sarcasm. In

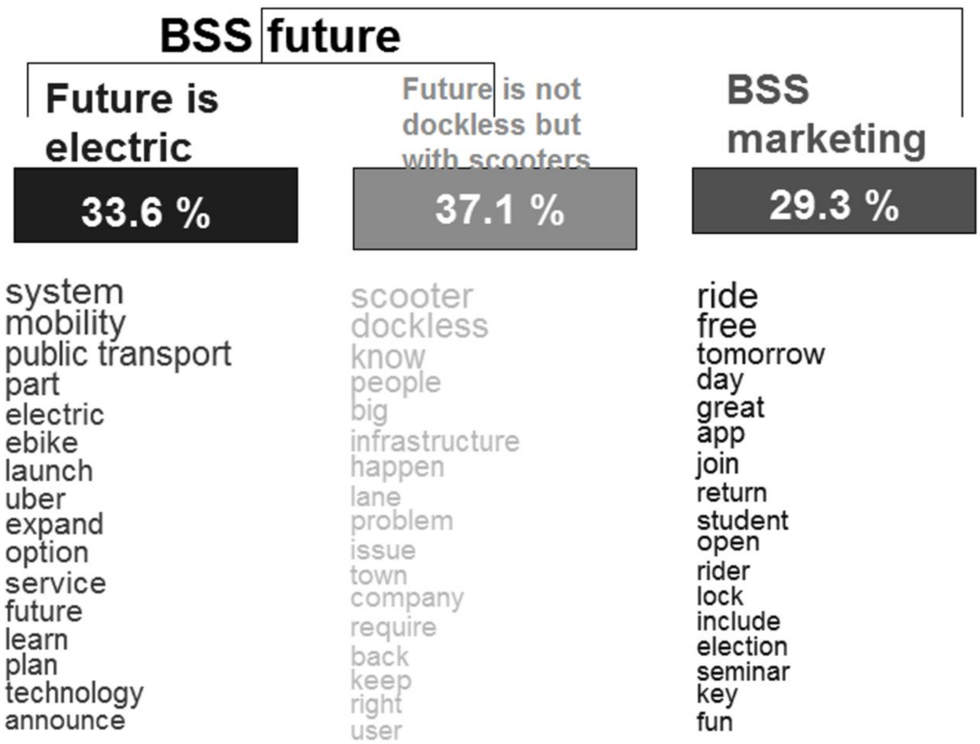


Figure 4.9: Quantitative topic clustering on tweets including the terms "future or "will"

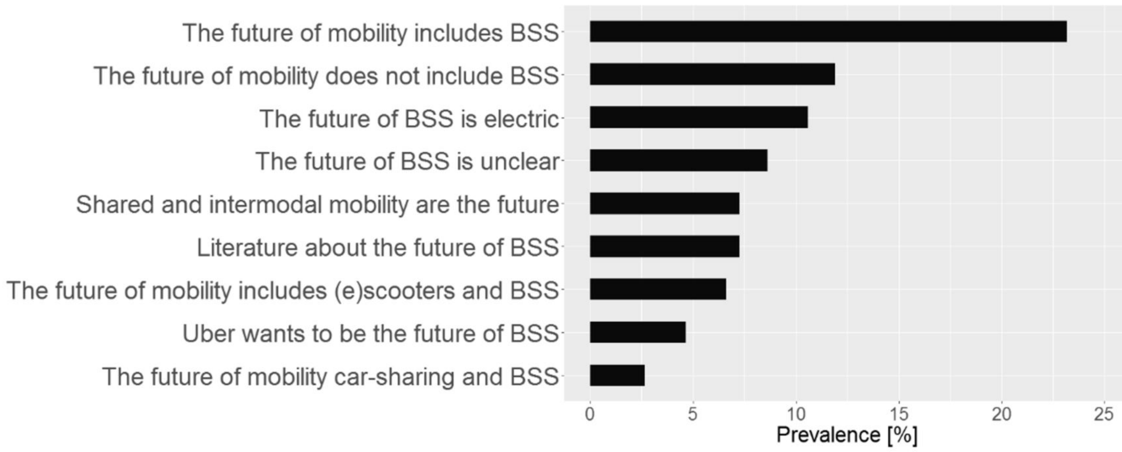


Figure 4.10: Qualitative topic clustering on tweets including the terms "future or "will" (n=142)

conclusion, the qualitative approach helped to understand the quantitative results. Furthermore, let's not forget the frequency of the term, which collaborated not only with the language usage but also helped to identify where are the conflicts in the public discussion. This approach helped us as a starting point of the debate of dockless systems and also start-ups vs public.

This study presented some limitations. Lexicon-based approaches alone do not have the ability to infer the polarity of a tweet at a sentence level (Ribeiro et al., 2016). However, the dictionary used was created and validated using tweets (Ribeiro et al., 2016; Gilbert and Hutto, 2014). According to the sentiment analysis, photos, videos, and URLs were excluded. Furthermore, strongly negative posts might be "trolling", i.e. posts in which their "real intention(s) is/are to cause disruption and/or to trigger or exacerbate conflict" for their amusement (Hardaker, 2010). In order to avoid the inclusion of trolling, further research can select the users of the tweets who have an account for more than 2 months and have more than a minimum number of followers.

The public discussion on BSS does not reflect the ideas, comments, or complaints of people who do not use Twitter, and neither of Twitter users who did not post in English. However, Twitter allowed us to collect opinions, thoughts, or ideas from the news, activists, pessimists, people from different cities and nationalities, etc. Strongly positive and strongly negative tweets might not reflect an individual opinion. However, this study aimed to understand different components of the public discussion, and therefore, news, marketing, ideas, comments, and opinions were included in the analysis. Further research can explore the individual opinion with segregating methods, for instance, those presented in Gal-Tzur et al. (2014).

Moreover, we did not search for commercial names of BSS, in which we might have missed the collection of potential tweets related to BSS. We wanted to get the general public discussion on BSS and by searching for specific names, the information could have been biased to a specific system. Even though, we did not search for commercial names, mainly Asian dockless companies where included in the posts and also the BSS company "Lime" due to their high implementation in English-speaking countries.

In summary, we were able to identify the general public discussion as expressed on Twitter and a tendency of an emerging transportation system within a relatively short period of time while using few resources. However, we want to highlight that this approach would not replace approaches that involve interviewing, observing, or surveying people. Further research might be oriented on interviews related to understanding deeper the main topic cluster and debates such as dockless systems, and equity issues.

4.6 Conclusions

There were 3.7 times more original tweets including the term "bike–sharing" classified as positive than negative. The benefits and drawbacks of BSS could be identified by counting the most frequent terms and qualitative and quantitative topic clustering methods. Strongly positive tweets promote BSS and their benefits such as BSS being convenient, well-performing, and sustainable. Additionally, there is a tendency to write that public, electric, and dockless are better, together with scooters. Strongly negative tweets focused on poor performance, vandalism, theft, and oversupply of BSS, especially with regard to dockless Asian BSS start-ups with low-quality bikes. Around 50% of the tweets including "future" and BSS-related terms stated that BSS are going to be part of the future of mobility in an electric version together with other shared modes. Around half of the statements that were hesitant towards BSS as being part of the future, refer to the dockless BSS start-ups.

We want to conclude by highlighting some policy recommendations and how we could make bike-sharing better for cities based on the public discussion. BSS are highly probable to be part of the future of mobility because of the benefits discussed above. These systems are higher accepted when they are public, inclusive, affordable (or even free), keep communication with clients, and their design and allocation are based on public participation and people's needs (equity). The most accepted designs are when the systems are hybrid systems (dockless + docked), electric, and integrated with public transport in terms of infrastructure and price. On the contrary, start-ups are less accepted by the public, especially if they do not have communication with users and have placed an excessive amount of low-quality bicycles in a dockless format that blocks other transport modes.

Finally, we recommend politicians and stakeholders sponsor these active modes using terms from posted benefits of BSS. They can use these terms in their marketing efforts if the arguments match their systems: convenient, healthy, fast, fun, cheap, easy to use, inclusive, environmentally friendly, no theft worries, help to explore the city, connected to public transport.

Further research might include the comparison of tweets regarding BSS to other shared modes such as car-sharing, scooter or ride-sharing. Also, interviews can be carried out with different people that posted about the future of BSS to gain a deeper understanding of their opinion. Finally, public discussion related to equity and shared systems can be further studied.

Chapter 5

How fair is the allocation of bike-sharing infrastructure?

This chapter has been published in Duran-Rodas, D., Villeneuve, D., Pereira, F. C., & Wulfhorst, G. (2020). How fair is the allocation of bike-sharing infrastructure? Framework for a qualitative and quantitative spatial fairness assessment. Transportation Research Part A: Policy and Practice, 140, 299-319. https://doi.org/10.1016/j.tra.2020.08.007

How fair is the allocation of the infrastructure of a bike-sharing system (BSS)? Design guidelines for BSS focus on optimizing the demand but not on who is served who is not. Areas where mainly young Caucasians, highly educated people live, and that have high access to community resources, presented greater access to BSS. Based on the concept of spatial fairness and its subjectivity, we developed a framework for a qualitative and quantitative assessment to help decision-makers and the general public evaluate the allocation of BSS infrastructure. First, from the general concept of justice, we developed our definition of spatial fairness assessment based on the rules of spatial equity, equality, and efficiency. Then, we developed a qualitative and quantitative spatial fairness assessment of BSS. The qualitative assessment aims to understand how underprivileged people perceived the spatial fairness of BSS taking as case study non-motorized households in Strasbourg feeling socially excluded. The quantitative assessment helps to numerically determine which distribution rule (equity, equality, efficiency) the infrastructure of a BSS follows. This assessment was applied in residential blocks inside the service area of the hybrid BSS in Munich, Germany. We developed a concept of availability as an accessibility indicator. As social indicators, we considered social milieus, access to other opportunities (e.g. health, education), and developed an deprivation index that is a combination of those two. As a result of the qualitative assessment, non-motorized individuals who felt socially excluded were less likely to talk about BSS at all. Furthermore, bicycles' availability in the bike-sharing system in Munich matched the efficiency and equity rule, although lower availability of bikes correlates to residential blocks where traditional-oriented social groups live. Policy makers, stakeholders, urban and transport planners, and the general public have now available 1) the perception of a group of the underprivileged population about BSS, and 2) a quantitative methodology to identify which distribution rule(s) the infrastructure of a bike-sharing system follows and which social groups are spatially advantaged or disadvantaged by it. Further research may be oriented to apply the approach in the same city or applying them to more case studies.

5.1 Introduction

How should resources be allocated? The allocation problem is universal and impacts all social groups (Leventhal, 1980). If allocation follows distribution rules related to justice, this problem is solved based on an assessment of fairness (Leventhal, 1976). Fairness in resource allocation should be considered in decision-making because the attitude and behavioral responses of the people affected by the decision can affect the satisfaction and effectiveness of the allocation (Leventhal, 1980; Cropanzano et al., 2015). The allocation of public resources not only affects people's economic and social opportunities but also influences their well-being (Fainstein, 2009). Opportunities can improve and benefit disadvantaged groups, but conversely, a low level of justice leads to resistance towards the allocation, low project consent (Wüstenhagen et al., 2007), and low political acceptance due to low trust and perceived corruption (Ariely and Uslaner, 2017).

In terms of transportation infrastructure, we ask: how fair are investments allocated? For example, do they meet the specific needs of the most vulnerable population, such as those without access to a private car? Soja (2009) argues that these problems are related to spatial fairness, especially when considering the spatial distribution of urban resources. A new question arises regarding shared mobility services (e.g. car-, bike-, scooter-, ride-sharing). Specifically, if these services use public resources, how fair is the distribution of their supply? Who is afforded, and who is excluded from, access to the new shared mobility options? According to Lucas (2019), there are mainly two equally split perspectives: a) optimists, who believe that these technologies increase access and opportunities for people who cannot afford to own a vehicle; and b) pessimists, who state that these systems will mainly benefit the privileged population.

In this study, we focused on bike-sharing systems (BSS), which offer short-term rental of a bike provided in the public space where riders usually have to pay a fee and have a membership (Büttner and Petersen, 2011). BSS have emerged in the major cities around the world, most through publicly-owned companies (Shaheen et al., 2020). They have presented a significant growth of approximately 800 programs around the world with a fleet of more than 900,000 bicycles in 2015 (Fishman, 2016) to 1,600 systems and 18.7 million bicycles in 2018 (Shaheen et al., 2020).

BSS have existed in four different forms since their initial introduction in 1965 (Shaheen et al., 2012). The first generation of BSS were free systems for public use. Theft and vandalism plagued these early systems and led to the implementation of dock-based systems requiring a coin deposit for use. This implementation did not completely reduce these issues mainly because of user anonymity. IT developments helped to manage this problem and the third generation of BSS tracked the location of bicycles in a docked-based system. Finally, the fourth generation of BSS is demand-responsive and self-balancing both included dock-free options and integration with the public transportation network. These BSS's use on-board computers, the internet, and GPS for real-time tracking of the bicycles (Shaheen et al., 2012), in which big data enables real-time optimization of the bicycle fleet (Chen et al., 2018).

BSS use different types of bicycles such as, among others, mechanical, electric, or cargo (Moon-Miklaucic et al., 2018). Furthermore, according to the presence or absence of dock-based stations, they can be categorized into station-based (SBBSS), free-floating (FFBSS), or hybrid (HBSS), a combination of both (Schönberg et al., 2018; Shaheen et al., 2020). FFBSS's bikes can be locked to the bike frame anywhere in public space, without the need for fixed stations. In contrast with SBBSS, FFBSS avoid the cost of docking stations. Using GPS, bicycles can be tracked in real-time allowing smart management and reduced probabilities of bicycles' theft. FFBSS is more convenient for users than SBBSS because the average walking distance from the bike to their destination is shorter and they do not have to worry about storing the bike at a docking station (Pal and Zhang, 2017).

BSS provides cycling-related benefits, including but not limited to improving health, reducing congestion and creating environmental awareness (Shaheen et al., 2010; Fishman et al., 2014a; Fishman, 2016; Ricci, 2015; Buck, 2013). In addition to these benefits, BSS avoid the maintenance, parking and security issues of privately owning a bike. Riders can take spontaneous bicycle trips, which has been shown to increase the population who cycle (Shaheen et al., 2014). These systems support a first- or last-mile connection to public transportation, allowing the potential increase of inter-modal trips (Shaheen et al., 2012, 2010). Also, implementing BSS in a new city seems to enhance the city's "sustainability image", where tourists can experience a new city on bicycles without owning one (Ricci, 2015). Moreover, Shaheen and Chan (2015) reported 5.5% of BSS users postponing buying a car or selling their cars and Shaheen et al. (2014) showed a 50% reduction on private car usage. Due to the reduction of private car usage, BSS are actually associated with emission reduction. However, rebalancing bikes by truck can backfire in terms of emissions (Shaheen et al., 2014).

These benefits have been unevenly distributed among different social groups. Previous work on BSS showed that their typical user's profile is male, young, and white, with high income, a high education, is already engaged in cycling, and has access to a bank account, credit card, and smart-phone (Murphy and Usher, 2015; Ogilvie and Goodman, 2012; Fishman et al., 2015; Buck, 2013; Goodman and Cheshire, 2014; Winters et al., 2019; McNeil et al., 2018; Nickkar et al., 2019; Shaheen et al., 2012). Spatially, relevant research showed that poorer/deprived areas are less likely to have access to BSS infrastructure (Ogilvie and Goodman, 2012; Goodman and Cheshire, 2014; Ursaki and Aultman-Hall, 2015; Hosford and Winters, 2018; Smith et al., 2015; Mooney et al., 2019). In contrast, areas where mainly young Caucasians, highly educated people live (Smith et al., 2015; Ursaki and Aultman-Hall, 2015; Chen et al., 2019), and that have high access to community resources, presented greater access to BSS (Mooney et al., 2019).

We identified an efficiency focus in terms of design and operation in BSS. Design guidelines for BSS show a focus on the demand as an indicator for where to implement new infrastructure (Gauthier et al., 2014; Büttner and Petersen, 2011) and Mooney et al. (2019) found that the demand is highly correlated with the rebalancing destinations. Some systems focus their services in central (Fishman et al., 2015; Chen et al., 2019) and denser (Ursaki and Aultman-Hall, 2015) areas. Ursaki and Aultman-Hall (2015) showed that the location of stations in denser areas attracted more users (efficiency focus) but limited access to disadvantaged populations.

So how fair is it to plan BSS based on potential demand and not serve every area equally or not primarily serve underprivileged people who cannot afford another type of mobility? To support policy makers, transport planners and the general public in answering this subjective question, this study focuses on developing a quantitative and qualitative conceptual framework and method for assessing the spatial fairness of accessibility to the infrastructure (stations and bicycles) of bike-sharing systems (BSS). First, our goal is to develop a conceptual framework regarding spatial fairness, which synthesizes the concepts of justice, social and spatial fairness, and distribution rules. Then, we aim to qualitatively understand how underprivileged people perceive the spatial fairness of a local bike-sharing system. Due to the availability of pre-existing data, we considered the case of non-motorized households feeling socially excluded in Strasbourg, France. Finally, our third objective is to develop and apply a method to quantitatively identify which distribution rule, or a combination of rules, is or are present in the supply distribution of a bike-sharing system. Because of a lack of fairness assessment in HBSS in the literature and data availability, we applied the methodology in the city of Munich, Germany. Thus, is the distribution of the supply of the bike-sharing system in Munich according to the demand, to those that contribute the most, to those who need it the most, is it equally spread, a mixture of them or none of them?

The following section discusses the conceptual framework of spatial justice assessment, which is the theoretical core of this study, including a literature review of previous work on assessing spatial fairness on BSS's supply. In the third and fourth sections, respectively, qualitative and quantitative assessments of the fairness of BSS, including an explanation of the methods used in and results yielded from these two methodological approaches. This paper then concludes with a discussion of the results and future applications of both assessments.

5.2 Conceptual framework on spatial fairness assessment

To introduce the terminology used in the paper, we developed a conceptual framework for defining spatial fairness assessment inspired by the justice judgment theory. Justice judgment theory explains how individuals perform a fairness assessment based on justice rules (Leventhal, 1980). Justice and fairness are two different concepts, although in some literature they are considered to be the same (Goldman and Cropanzano, 2015), and in some languages (e.g. Spanish, and French) have only one term to describe both. According to Goldman and Cropanzano (2015), justice involves morally required rules, which tend to be shared by different groups of people, with some considered to be universal (e.g. human rights) and others may vary depending on the cultural or circumstantial context (Leventhal, 1980). Fairness is a subjective assessment of whether or not justice rules are implemented in a morally worthy way (Goldman and Cropanzano, 2015). What is fair for one person, however, might not be fair for others.

Cropanzano et al. (2015) classified justice rules into four categories: a) distribution rules; b) procedural rules; c)interpersonal rules; and d) informational rules. In this research, we focus on distribution rules, which are defined as “the individual's belief that it is fair and appropriate when rewards, punishments, or resources are distributed in accordance with certain criteria" (Leventhal, 1980). There are multiple distribution rules and this paper focuses on the three most commonly applied in literature, which are equity, equality and efficiency (Talen, 1998; Leventhal, 1980). These three rules are defined as follows:

I) Equity or vertical equity or needs rule. In this rule, resources are distributed according to the people's needs, therefore, following a broad justice focus. It has also been defined as an “equal treatment for equals and unequal treatment for unequals" (Leventhal, 1980; Talen, 1998).

   Two categories of needs can be assessed under the equity rule: 1) abilities and 2) social and economic opportunities (Litman, 1999). Social and economic opportunities take into account, for example, sociodemographic attributes (e.g. gender, age, race, migration background, language, income, education, values, social status, occupation, milieu, etc.), and accessibility to opportunities (e.g. jobs, education, health, social and recreational facilities, public transport, vehicle ownership, information, technology) (Geurs and Van Wee, 2004).

II) Equality or horizontal equity. This rule involves the equal distribution of resources, regardless of the different needs or abilities of people (Leventhal, 1980; Talen, 1998). “No agent is privileged over any other agent" (Varian, 1975), and “no agent prefers any other agent's bundle to his own" (Varian, 1974). It follows an intermediate justice focus. Examples of equity include human rights and laws equally applied to all people in a given area.

III) Efficiency or contributions rule. Resources are distributed according to people's contributions (Leventhal, 1980). In other words, the allocation is according to the usage and therefore, willingness and ability to pay (Leventhal, 1980; Talen, 1998). Then, this rule presents a narrow justice focus.

Hirsch et al. (2019) classifies these rules into social or spatial categories. In this study, social fairness assessment refers to who gets the resources and who does not, and spatial fairness is related to whom and where the resources are being allocated. Thus, a spatial fairness assessment determines if the spatial allocation of resources follows a rule of spatial equity, equality, efficiency, or a mix of the three (Figure 5.1). This concept may help to estimate the acceptance of the allocation. Additionally, distributors may have a conceptual tool to assess which rule(s) the allocation of resources follow and whether the distributors, or the people affected by the distribution, consider it to be fair, or not.

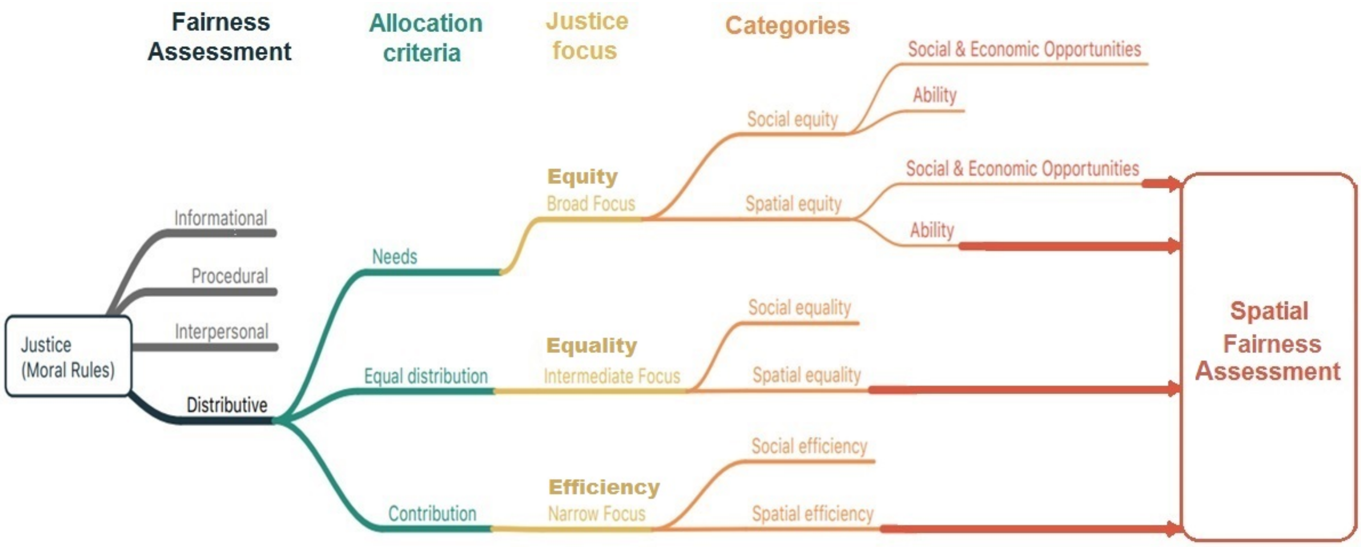


Figure 5.1: Conceptual framework on spatial fairness assessment. Inspired in: (Leventhal, 1980; Goldman and Cropanzano, 2015; Talen, 1998; Lucy, 1981; Cropanzano et al., 2015; Geurs and Van Wee, 2004; Hirsch et al., 2019)

5.2.1 Conceptual framework on spatial fairness assessment applied on BSS's infrastructure

Gössling (2016) classified urban transportation resources to be distributed in terms of exposure, space and time. He defines space as having three components: area used, infrastructure, and access. In this paper, we focus on assessing the fairness of spatial distribution in terms of infrastructure and accessibility.

In this section, we describe five hypothetical cases of distribution rules on BSS infrastructure in a service area related to two extreme conditions: 1) privileged area and 2) underprivileged area (see Figure 5.2). For allocation, we refer to which distribution rule (spatial equity, equality, efficiency, or a mix of the three) are followed in the location of infrastructure, including stations and/or availability of bicycles. Therefore, this exemplification can represent all types of BSS, regardless of whether they are SBBSS, FFBSS, and HBSS.

We distinguished five hypothetical of BSS infrastructure following the above-mentioned distribution rules (see Figure 5.2). In the case of spatial equity (I), most of the infrastructure would be allocated in underprivileged areas, while for spatial efficiency (III) most of the infrastructure would be allocated in privileged areas. Spatial equality (II) would allocate the infrastructure equally throughout the service area. Now the question arises of whether more than one rule can occur at the same time. The hypothetical case would be in a service area without a clear distinction between privileged and underprivileged areas. For example, spatial efficiency and spatial equity rules (IV) would be present at the same time when the infrastructure is not equally spread in the service area and there is not a clear distinction between privileged and underprivileged areas. This case may also occur whether those who contributed the most (efficiency) are the underprivileged (equity). Finally, the three rules would be present (V) in the hypothetical case where there is no clear distinction between privileged and underprivileged areas and the infrastructure would be equally spread throughout the service area.

In the next sections, we use the conceptual framework to qualitatively and quantitatively identify which distribution rules our case studies follow.

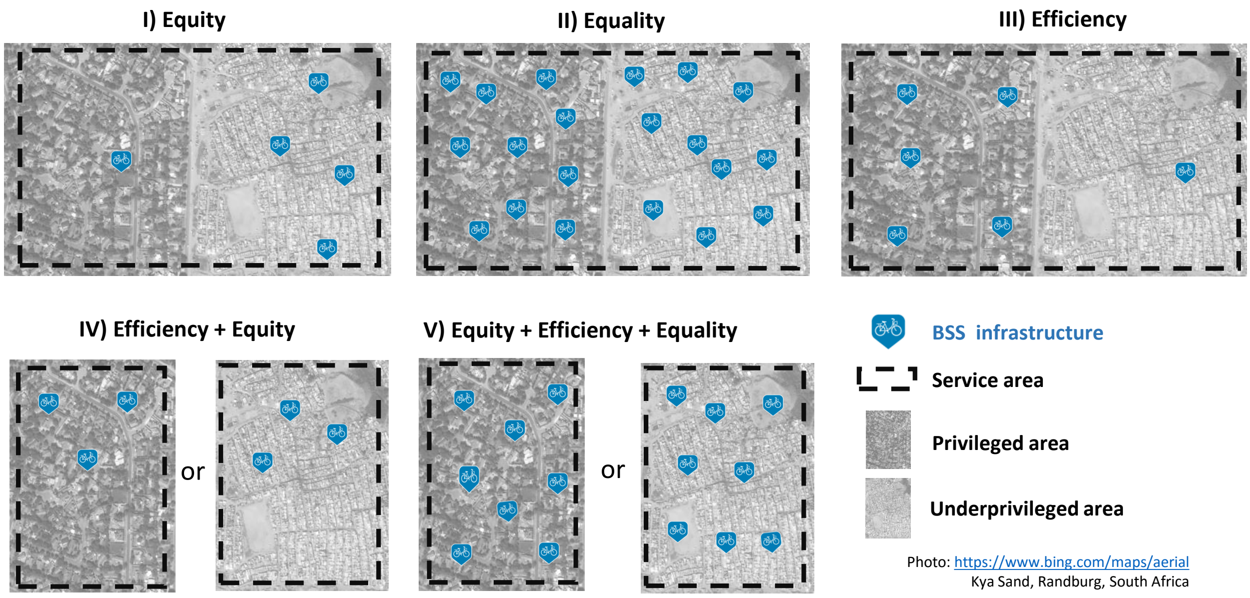


Figure 5.2: Hypothetical cases of BSS infrastructure following different distribution rules

5.3 Qualitative assessment

The qualitative assessment aims to understand what is the spatial fairness perception of underprivileged people. We chose the city of Strasbourg in France as a case study based on data available from interviews with individuals from non-motorized households (NMH). We included variables linked to spatial fairness aspects in a lexicometric (content) and traditional qualitative data analysis. The focus on non-car-owning households in the case of spatial justice as it relates to mobility reflects the fact that "[. . .] there is a disconnect between the mobility needs of low-income, non-car owning citizens to move and act freely within compact and walkable cities and the development trend for segregated, gated, car-friendly and gentrified settings, which correspond with the lifestyle preferences of middle and higher class populations (Barter, 1999; Soja, 2010)" cited by Lucas et al. (2016).

There is also a compelling aspect related to sustainability since by not possessing a private car, these households' lifestyle is more sustainable from a mobility perspective by relying on less carbon-intensive transport modes (including cycling). This decrease in energy use is observed in multiple aspects of life as Tabbone (2017) found that in France, NMH use on average 9% less energy than their motorized counterparts (calculated on the energy usage of households only when at home, in order to exclude any mobility-related energy savings). The qualitative assessment also integrated comparative investigation between participants feeling socially excluded as it related to mobility and those who do not. Social exclusion is a phenomenon linked to the unequal participation of individuals in society, which we consider as the opposite of social inclusion. This part of the work focuses on the role that mobility and transport play in social exclusion, so we refer to mobility-related social exclusion. Schönfelder and Axhausen (2003) linked social exclusion and mobility by claiming that transportation systems can help to perpetuate social exclusion through exorbitant costs in time or money for vulnerable groups. According to them, adding the issue of transport to social exclusion allows a better consideration of the spatial aspect of the exclusion related to activity areas (Schönfelder and Axhausen, 2003). According to McCray and Brais (2007), social exclusion occurs when portions of the population are prevented from participating in activities that affect their quality of life. They warn that this "isolation may be created by a lack of transportation, and/or housing policies that isolate the poor, elderly, and disabled from activities in space and time" (McCray and Brais, 2007).

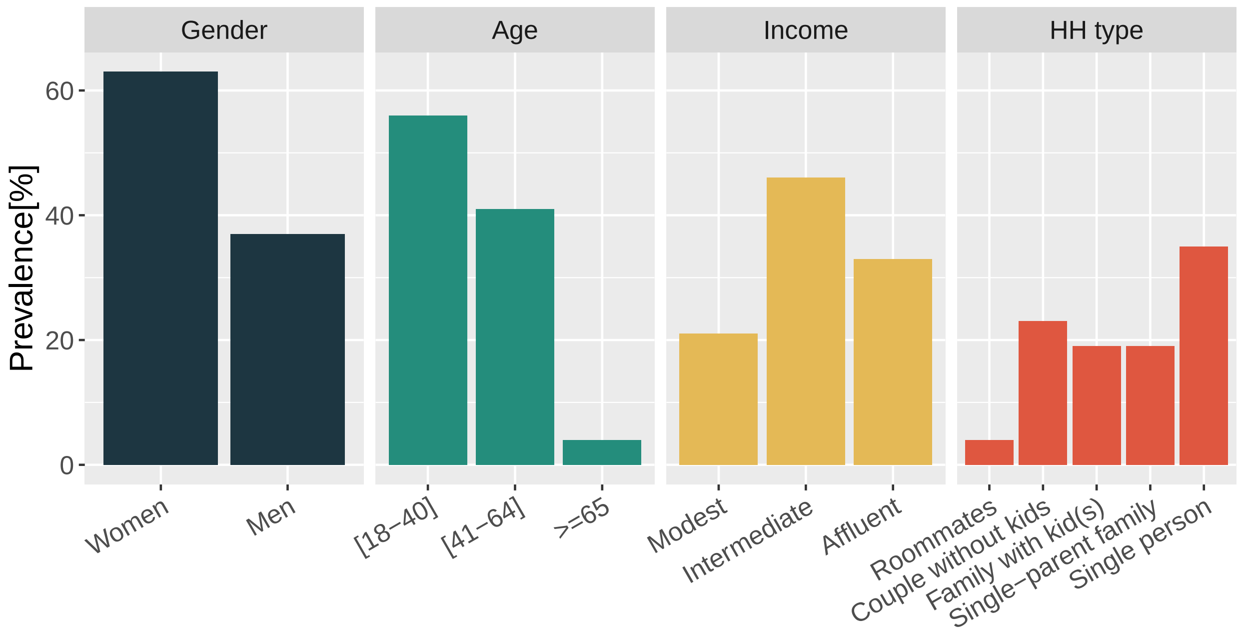


Figure 5.3: Composition of the sample for interviews

5.3.1 Methods

This part of the research is based on empirical work consisting of 27 interviews with representatives from non-motorized households in Strasbourg, France (Villeneuve, 2017). The interviews focused on the daily mobility behavior, accessibility and perceptions of being socially excluded according to mobility. The participants were drawn up at random combining recruitment techniques (social networks, interest groups, banners, and snowball method) while looking for a variety of attributes: household types, income levels, and gender to gather different perspectives. Figure 5.3 shows attributes of the sample by gender, household types, age of participant and income level, attesting to sample diversity.

Since in this paper we focused on issues of spatial fairness, our analysis included variables linked to social and economic aspects of spatial equity. This included age, gender, income level, possession of a driver's license, membership in a car-sharing system, possession of a monthly public transit pass, household type, ownership status of the residence, residential location and socially excluded feeling as it relates to mobility.

We combined conventional qualitative data analysis and a lexicometric analysis to understand the position of the interviewees on BSS. Only the portion of the interview related to bike-sharing was included in the analysis. The qualitative data analysis was performed using the RQDA software (Huang, 2016) with inductive coding. The conventional method of qualitative data analysis provided information directly from participants without imposing preconceived categories (Hsieh and Shannon, 2005).

The lexicometric analysis was performed by using the software IRaMuTeQ (Ratinaud, 2009). This open-source software uses the method known as ALCESTE (co-occurring lexemes analysis in simple statements of a text) developed by Reinert, 1983 (Reinert, 1983). In order to perform this analysis, we transcribed the entire contents of the 27 interviews. The content of the interviews was structured by characterizing the speech with sociodemographic variables and the specific question of the interview guide. For example, the answers to a specific question are grouped into a single body of "statements" which is then analyzed with the software and each response is associated with multiple variables, including the age, gender, income level, etc. of the individual who responded. This part of the analysis took place on the entire group of participants, allowing to compare the statements of those feeling socially excluded about their mobility and those who do not.

5.3.2 Results

– Lexicometric analysis – In our empirical investigation of the perception of non-motorized participants about BSS in Strasbourg, we used a lexicometric analysis to compare the statements of the participants based on various socio-demographic variables. We found significant variance with three variables: the feeling of being socially excluded as it relates to mobility, the income level and gender. We found that the participants that felt socially excluded were less likely to discuss cycling in general (-1.3 times) and bike-sharing (-2.4 times) than those who did not express that feeling. It shows that for that group, cycling and bike-sharing, in particular, don't appear as viable mobility alternatives. When comparing the statements of the three income levels, we noticed that those with an intermediate income level were more likely to discuss bike-sharing (+2.1 times) and those with modest income were the least likely to discuss it (-0.6 times). This indicates that for the modest income group, BSS was less considered as a mobility alternative. Finally, we compared the statements of women and men and found that women were less likely to mention bike-sharing (-1.6 times) than men. This could imply that BSS is answering the needs of men more than those of women.

– Qualitative Data Analysis – Figure 5.4 shows the coding structure that resulted from our analysis. The main topics discussed by the participants revealed by our inductive coding were the users of BSS, their structural aspects of BSS, the positive and negative aspects of BSS and their usage of BSS. We also coded the material using our deductive codes of the types of fairness criteria discussed by the participants.

The Users of BSS The participants often mention whom they think is the target of BSS, who is using it. We found that they didn't think BSS was meant for them. Rather the participants said that BSS was for rich people, tourists or students. They said it was certainly not for the poor and not targeted at those who need it the most. For example, Sabine said:

> *"It's mostly for students"* Woman, 28 years old - Strasbourg area (Neudorf) - Income: affluent - Household size 2 people, car-sharing member, feels socially excluded.

Structural Aspects of BSS Participants discussed certain structural aspects of BSS. Regarding funding BSS, the participants would rely on public authorities subsidies, potentially using gas tax for this purpose. They also mentioned some aspects regarding the usefulness of combining BSS and public transport. The analysis reveals that some NMH in Strasbourg would like to see BSS encouraged. Finally, they mentioned that BSS have an impact on the number and usage of privately-owned bicycles.

Positive and Negative Aspects of BSS The participants who mentioned BSS also discussed some positive aspects. They said the system was successful, practical and simple to use. The analysis shows that some NMH in Strasbourg think that BSS could reduce the problem of bike theft in their city. They specifically referred to the actual bicycles which were described to be better than private bikes; requiring no maintenance and in the long run, being cheaper than owning a bicycle. For example, Samuel said:

> *"There is no maintenance constraint"* Men, 24 years old - Strasbourg area (Contade) - Income level: Intermediate - Household type: Couple - Household size: 2 people - Car sharing: No - Doesn't feel socially excluded.

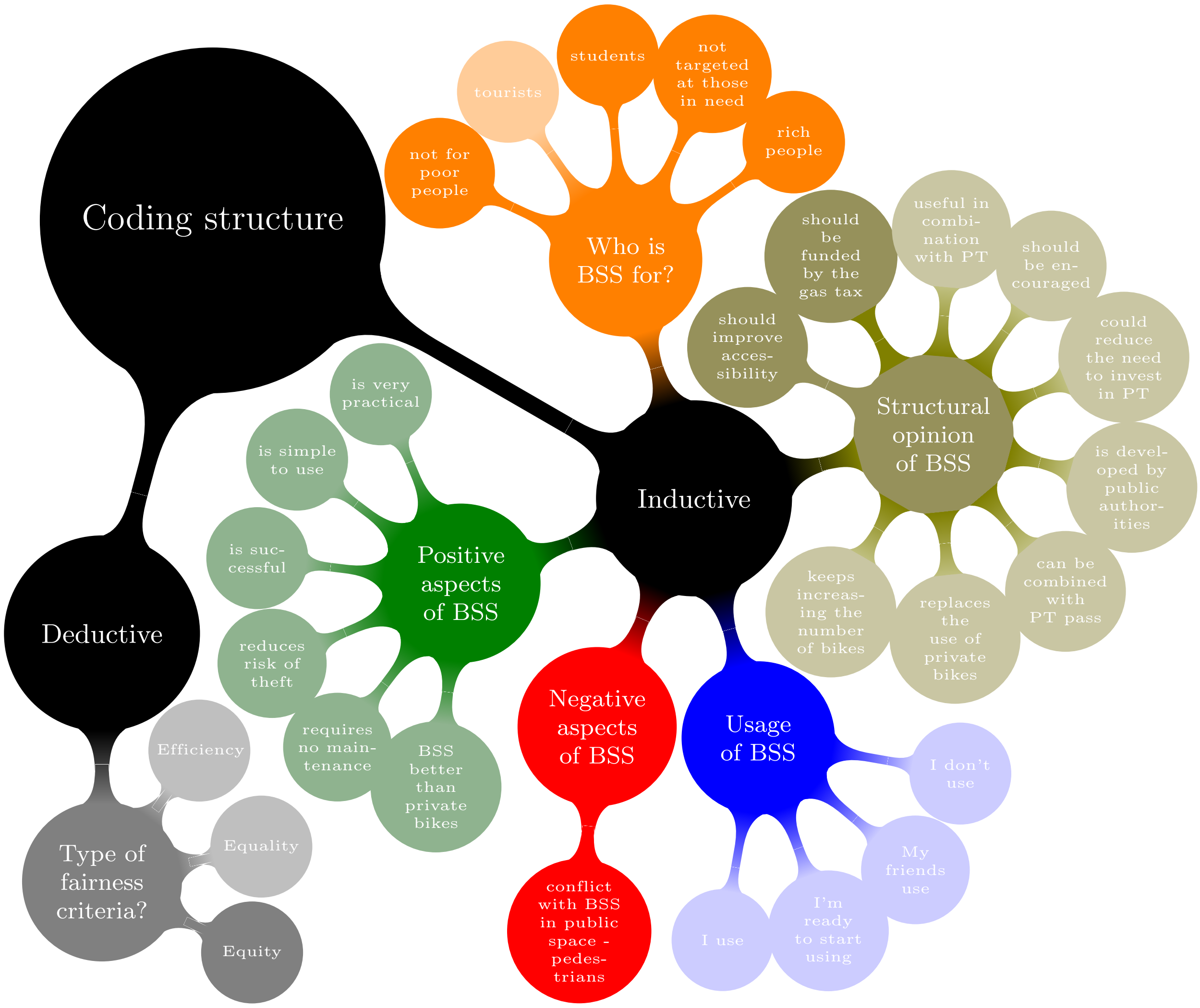


Figure 5.4: Qualitative data analysis

The participants also described one negative aspect of BSS as they thought it might raise the risk of conflicts between riders and pedestrians who are sharing the same space.

Own Usage of BSS Although many participants discussed BSS, not all of them were active users of the system, for example, Naomi said:

> *"So I've never used BSS, it is not bad, but I think it's for tourists, for people who visit [. . .] but I personally do not use it."* Women, 38 years old - Strasbourg area (Wihrel) - Income level: Intermediate - Household type: Single-parent family - Household size: 3 persons - Car sharing: Yes - Feels socially excluded.

Fairness Aspects Since none of the participants commented on the type of fairness assessment associated with BSS in Strasbourg and this was not a specific topic of discussion we cannot state their perception of the distribution rules of the BSS as implemented. However, the equity distribution rule of spatial fairness was the only rule discussed. Some of the participants discussed a negative opinion on fairness and equity aspects without being prompted by the interviewer. For example, Sabine relates that:

> *"I don't know if there are a lot of people in the disadvantaged neighborhoods who have a BSS subscription which is more like students and people like me so it may not be for the right audience"* Women, 28 years old - Strasbourg area (Neudorf) Income level: Affluent - Household type: Couple - Household size: 2 people- Car-sharing: Yes member - Feels socially excluded.

We can summarize that even though BSS had an overall positive image, the participants felt that the system might end up being inequitable when using a broad focus of justice as they might not be targeting the most disadvantaged population.

5.4 Quantitative assessment

In this section, we describe the method used to identify which rule(s) (spatial equity, equality, efficiency) are reflected by the distribution of the bike-sharing system infrastructure (stations and bicycles). First, we discuss how fairness in BSS has been assessed in existing research. Then, we present a methodological framework and show how we apply this framework to assess a HBSS in Munich, Germany.

5.4.1 Previous work on quantitative spatial fairness assessment on BSS

In the literature, spatial fairness in BSS has been quantitatively assessed primarily based on spatial equality and spatial equity. Commonly, fairness in BSS is not assessed in terms of spatial efficiency, but rather efficiency as a strategy for optimizing the location of stations (García-Palomares et al., 2012; Büttner and Petersen, 2011; Frade and Ribeiro, 2015) and balancing strategies (Liu et al., 2015; Contardo et al., 2012).

In previous research, spatial equality and spatial equity have mainly been assessed using four accessibility indicators: a) observed demand, b) bikes availability, c) proximity to or density of the infrastructure, and d) "walking-cycling-walking" accessibility to activity locations (Chen et al., 2019). The concept of accessibility helps to assess access to certain mobility systems for different social groups in terms of users' abilities as well as social and economic opportunities. There are multiple definitions for accessibility (Geurs and Van Wee, 2004). In this paper, we will consider accessibility as "the extent to which land-use and transport systems enable individuals to reach activities or destinations employing a combination of transport modes" (Geurs and Van Wee, 2004).

Table 5.1: Representative studies related to spatial equity assessment in BSS

		Reference											
		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
BSS Type	SBBSS				✓	✓	✓	✓	✓	✓	✓	✓	✓
	FFBSS		✓	✓	✓								
	HBSS	✓											
Assessment method	Descriptive statistics / tests	✓	✓				✓	✓	✓	✓	✓		✓
	Correlation			✓									
	Regression				✓	✓						✓	
	Plot and/or maps	✓	✓						✓	✓	✓	✓	
Accessibility indicator	Observed demand			✓	✓	✓							
	Availability		✓										
	Proximity / density						✓	✓	✓	✓	✓	✓	✓
	Accessibility to location	✓											
Attributes	Sociodemograp		✓	✓	✓	✓	✓	✓			✓		✓
	Deprivation index	✓							✓	✓		✓	
Spatial unit	Neighborhood		✓										
	Census block group							✓	✓	✓			
	Census tract				✓		✓				✓	✓	
	Postal zone					✓							
	Individual level - Synthetic pop.	✓											
Country	USA	✓	✓	✓	✓			✓	✓			✓	
	Canada						✓			✓			
	UK					✓					✓		
	Brazil												✓

I: Chen et al. (2019), II:Mooney et al. (2019), III: Yan and Howe (2019), IV:Couch and Smalley (2019), V: Ogilvie and Goodman (2012), VI: Fuller et al. (2011), VII:Ursaki and Aultman-Hall (2015), VIII: Bhuyan et al. (2019), IX: Hosford and Winters (2018), X: Clark and Curl (2016), XI: Smith et al. (2015), XII: Duran et al. (2018)

Studies addressing spatial equality and accessibility often use the Gini coefficient and Lorenz curve for their assessment (Van Wee and Geurs, 2011; Chen et al., 2019). The Lorenz curve is a cumulative line of the prevalence of the population versus the cumulative prevalence of a certain resource or attribute. The Gini coefficient is the ratio of the area between the Lorenz curve and the 45-degree line, and the total area under the 45-degree line. A Gini coefficient of 0 means perfect equality (everyone gets the same amount of resources) and a value of 1 means perfect inequality (only one agent gets all resources) (Gini, 1936).

Table 5.1 presents an overview of existing research on spatial equity of BSS, including the assessment methods, accessibility indicators, attributes, spatial units, and study areas used in the research. Commonly, the spatial equity assessment determines which social groups living in a spatial unit of analysis are higher correlated to a certain accessibility indicator to BSS's supply (e.g. availability). Most of the literature studied SBBSS in English-speaking countries, especially in the United States. The most common spatial unit is census blocks or tracts, and most assess proximity or density of the infrastructure with sociodemographic attributes using descriptive statistics and statistical tests.

Generally, the four most commonly used methods in existing research to assess spatial equity include: a) descriptive statistics and statistical tests, e.g., Student t-test (Ursaki and Aultman-Hall,

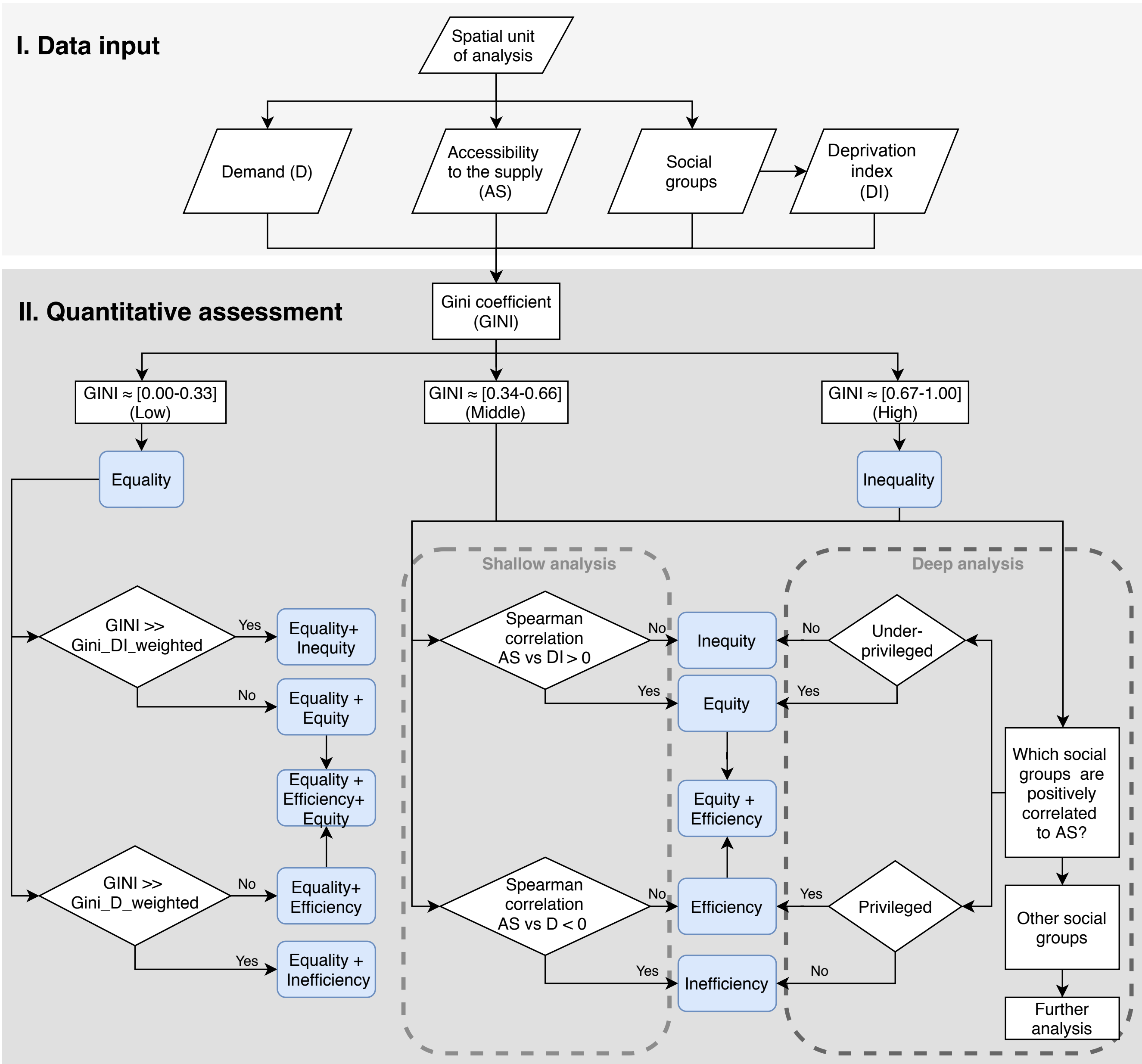


Figure 5.5: Quantitative spatial fairness assessment framework

2015) and Analysis of Variance (ANOVA) (Chen et al., 2019), b) correlation, e.g. Spearman correlation (Yan and Howe, 2019), c) regression, e.g. linear regression (Ogilvie and Goodman, 2012), poisson regression (Couch and Smalley, 2019; Fuller et al., 2011), multivariate logistic regression (Winters et al., 2019), and spatial regression (Smith et al., 2015)), and d) maps & plots (Chen et al., 2019). Finally, the social attributes mainly used in existing research are sociodemographic or spatial deprivation indexes, such as the subgroup in equity index (Stuart et al., 2009), Bike Equity Index (BEI) (Prelog, 2015), economic hardship index (Montiel et al., 2004)), Pampalon Deprivation Index (Pampalon et al., 2012), vulnerability index (Deboosere and El-Geneidy, 2018), among others.

5.4.2 Methods

After selecting a bike-sharing system as a case study, the first step in the quantitative assessment method (see Figure 5.5) is selecting and collecting the input data: a) a spatial analysis unit, b) a unit representing accessibility to supply, c) a unit representing demand, d) the social attributes representing the privileged and underprivileged populations, and e) a unit representing the amount of underprivileged population living within a given spatial analysis unit. We call this metric deprivation index (DI).

The process continues by calculating the Gini coefficient of the supply accessibility unit in the spatial analysis units. When the Gini coefficient is low, we assume that the system follows the spatial equality rule. Otherwise, if the Gini coefficient is high, we assume that the distribution has an unequal allocation of infrastructure. To analyze the possibility of multiple distribution rules, we multiply the accessibility of the supply by the DI, and then we recalculate the Gini coefficient (Gini_DI_weighted). If the Gini coefficient is similar to the Gini_DI_weighted, we assume that the distribution follows an equity rule additionally to the equality rule. Because the Gini coefficient remains constant after the weighting, this means that underprivileged people live equally spread in the area of study. Similarly, we calculate Gini_D_weighted by multiplying Gini with demand and if it remains similar to the Gini coefficient, we assume that the supply also is distributed according to an efficiency rule. Finally, when Gini_DI_weighted is similar to Gini_D_weighted, it can be deduced that the distribution follows the three rules.

On the other hand, when the Gini coefficient is high, we proceed to evaluate spatial equity and efficiency instead of equality. We propose a high-level analysis as well as a deeper one. The shallow analysis aims to carry out a Spearman's correlation test (Spearman, 1904) for DI and demand with the supply accessibility. We performed a Spearman's rank correlation test due to the possibility of outliers, extreme values, and non-normal distribution. If the monotonic relationship is positive between DI and the supply accessibility, we assume that the distribution rule is spatial equity because the supply is aimed at the underprivileged, otherwise if the supply is aimed at the privileged the distribution follows an inequality rule. Similarly, if demand is positively correlated with supply accessibility, the system is spatially efficient, i.e. there is greater accessibility to the supply where people who can contribute monetarily to the system. Therefore, if accessibility to supply does not correlate positively with demand, the system is inefficient because it cannot sustain itself over time without external financing.

The deeper analysis focuses on exploring which social groups live in areas where there is greater supply accessibility. If privileged groups have greater access to the supply, we assume the distribution follows a spatial efficiency rule. However, if underprivileged groups live in areas with greater supply accessibility, we assume that spatial equity is the distribution rule.

Referring to Table 5.1, we evaluated the social groups living in areas with greater supply accessibility in three ways:

1. Visual comparison between heat maps of demand, being the accessibility to the supply and DI.

2. Spearman's correlation test, It is used to analyze which social groups live in areas that positively correlate with accessibility to supply.

3. Feature selection and regression. They are performed to explore which social groups (independent variable) have a higher positive or negative association with supply accessibility (dependent variable I) and to the demand (dependent variable II). This helps us to understand who has access to the system and who uses it. If those who have access and use the system are the same social groups, the distribution is oriented to the efficiency rule. We consider Ordinary Least Squares (OLS) with a transformation (e.g. logarithmic or square root) of the dependent variable in case of heteroscedasticity issues as the regression method. We assume that multiple social groups might be correlated with each other. Therefore, we apply the LASSO (Least Absolute Shrinkage and Selection Operator) method (Tibshirani, 1996) for feature selection to avoid multicollinearity issues and to explore the social groups most associated to the supply accessibility and to the demand. The LASSO technique shrinks the coefficients of the regression, both increasing stability and retaining the variables with the highest association to the outcome. In other words, LASSO does variable selection and shrinkage. The selection of the shrinkage coefficient λ is critical in this technique because the number of variables considered for the model depends on this value. Therefore, we have to calculate the cross-validation error for each value of λ and select the λ with the smallest error (James et al., 2013).

4. Mann-Whitney U test for non-parametric data (Mann and Whitney, 1947). It is used to evaluate if two groups differ in a single continuous variable. The continuous variable would be the percentage of different social groups living in the spatial unit of analysis. These percentages are compared according to four different groups of spatial analysis units that are divided according to the median of the demand and accessibility to supply:

   - Type I. Low accessibility to supply and low demand. The first case of these areas may have a lack of supply because there is no (potential) demand. It can, however, be a lack of demand due to a lack of supply.
   - Type II. Low accessibility to supply and high demand. These areas are critical, where there is demand, but where there is not enough accessibility to supply. They may be potential places for locating stations and focusing re-balancing strategies to bring more bikes to these areas.
   - Type III. High accessibility to supply and low demand. These areas present an over-supply, where potential bikes dropped-off in these areas are used or re-balanced after a long time.
   - Type IV. High accessibility to supply and high demand. The system performs efficiently in these areas.

   The alternative hypothesis for the test is whether the percentage of social groups living in type I, II and III areas are significantly different from living in type IV areas. Thus, the critical situation are social groups that live significantly less in type IV areas than in type I or type III, or primarily in type II areas.

Finally, spatial equity and efficiency would be present simultaneously if DI and demand are positively correlated with accessibility to supply, meaning that privileged and disadvantaged groups both live in areas with greater accessibility to supply. In these cases, there may be an unequal distribution of accessibility to the supply among social groups that are not defined by wealth (e.g. in terms of the social milieus discussed in the next section). The same procedure would apply to assess other levels of conflict.

5.4.3 Application of the method

We carried out a quantitative spatial fairness assessment of the HBSS introduced in the City of Munich in 2015. In 2017, the system included around 90,000 members with access to 1,200 bicycles and 118 stations (Rube, 2018). Users can pick-up and drop-off a bicycle either at stations or anywhere in the public realm. If a bicycle is returned to a station, the user gets a discount of 10 minutes to be applied to a future trip. The use of a bike cost 0.08 euros per minute or 0.05 euros per min for students. Users pay a maximum of 12 euros to use a bike for the whole day. There are also packages in which, for 48 euros per half-year, one can use a bike for up to 30 minutes every day. This half-year subscription costs only 12 euros for students (MVG Rad, 2019).

The data available for this system include the bicycles' position every five minutes and the location of the stations from mid-March until mid-April 2017 (Transit.robbi5, 2019). We used the density of bikes' drop-offs as an indicator for demand, aggregated at the residential block level in the study period. It is assumed that the end of a trip, which we refer to as the bike drop-off, is when a bike "appears" in a new area. Bikes used longer than 150 minutes (approx. time to cross the whole service area) and traveling less than 100 meters (min. distance to be considered a trip) are excluded from the study. Bike drop-off points were used in the study, rather than bike pick-up points because the location of the drop-off is assumed to be closer to the user's final destination than the location of the pick-up to the trip origin. Our approach was exclusively on a residential level to analyze who lives in the areas where the system is serving mots accessible. The spatial unit of analysis was 2,300 residential blocks with a predominant land use categorized as residential from the ATKIS database (Vermessungsverwaltung, 2014).

– Availability of bicycles as an indicator for accessibility to the supply – Availability of bicycles as an indicator of accessibility to the supply can be calculated in different ways, such as the inverse of the idle time (number of bikes per day in an area) (Mooney et al., 2019) for FFBSS, or the "ratio of [the] number of bicycles available to [the] station capacity (ranging from 0 to 1 - empty through full)" for SBSS (Reynaud et al., 2018).

In this study, we developed an innovative concept defining the availability of bicycles as the time rate in which there is at least one bike available in a buffer of distance "d" from a point where a user is willing to walk to access a bike-sharing system. The algorithm for the estimation of the availability starts with assigning every bike drop-off to a spatial unit. We intersected the time intervals between the bikes' drop-offs and the next pick-up per spatial unit. Finally, the availability indicator per spatial unit is the rate between the intersection of the time intervals and the complete period of time evaluated in the study.

Previous research studies have used distances ranging from 250 to 500 meters to calculate a buffer of distance "d" to represent access to the systems (or service areas) or as a distance in which a user is willing to walk to access BSS (Fishman et al., 2015; Fuller et al., 2011; Clark and Curl, 2016; Smith et al., 2015; Winters et al., 2019; Ogilvie and Goodman, 2012; Ursaki and Aultman-Hall, 2015; Hosford and Winters, 2018; Winters et al., 2019; Duran et al., 2018). Therefore, to be on the conservative side, and taking the recommended distance of BSS design guidelines (Yanocha et al., 2018), we considered a distance d of 300 meters.

– Social milieus as social attributes – We wanted to assess spatial fairness by crossing the barriers of traditional sociodemographics by using social milieus as social attributes. Therefore, we used Sinus-Geo-Milieus information, which was provided by the marketing company Microm. This data included the dominant milieu and number of inhabitants per address in Munich for 2014.

Social milieus are groups of people with similar values and life orientations defined by everyday practices and lifestyles and have tended to have similar tastes, communication structures, and living environments (Barth et al., 2017). To explain the advantages of using social milieus, rather than sociodemographic attributes, we use the example from Sinus-Milieus® (Sociovision, 2018). In this example, we have two women who both are 36 years old, married with two children, and

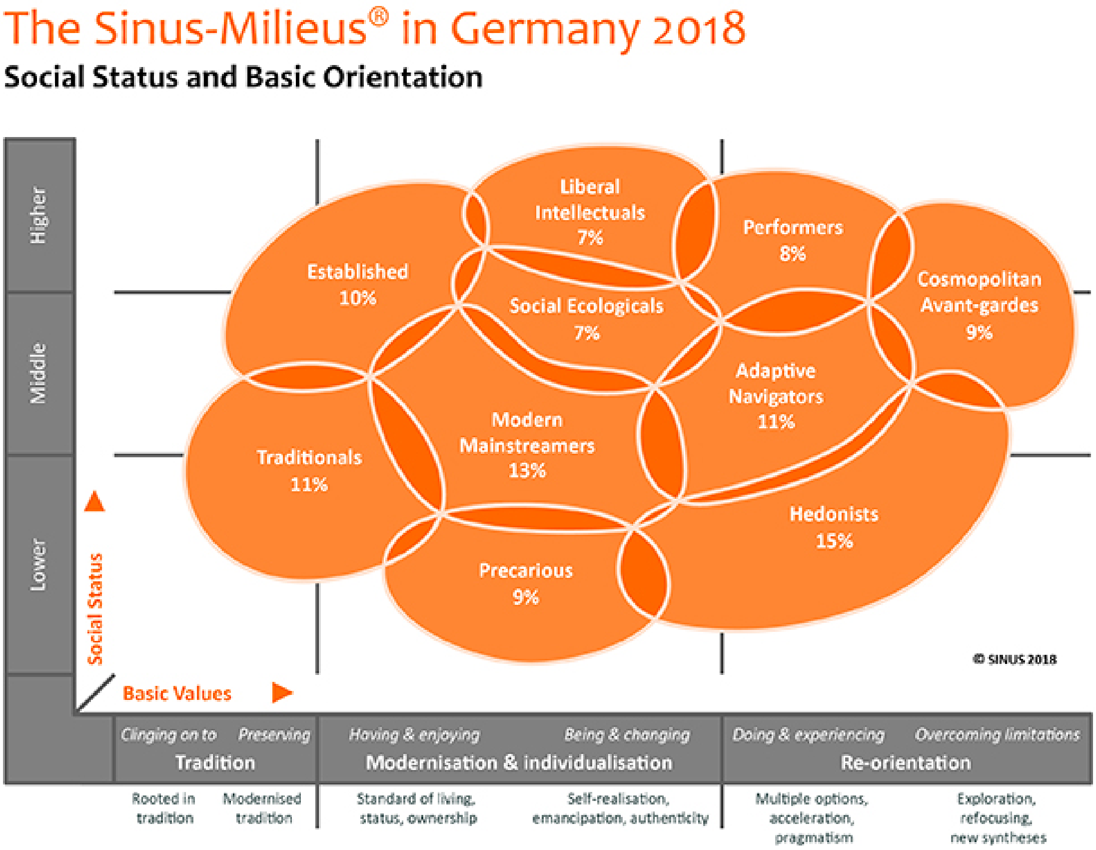


Figure 5.6: The Sinus-Milieus® in Germany 2018. Source: Sociovision (2018)

working part-time in the marketing sector, therefore, they are considered to be sociodemographic twins. These women were asked to show their “domestic altar" in an interview in their homes. One woman showed a piece of furniture against the wall, under a shelf of liquor bottles. The other woman, however, showed a wall where the skull of a bull was displayed. Although the two women shared sociodemographic attributes, the differences in their “domestic altar" exhibit that the two women have different lifestyles, values, live orientations, and that they belong to a different milieu.

The marketing company Sinus Sociovision has developed the Sinus-Milieus® approach, which is one of the leading lifestyles approaches in marketing in Europe (Sociovision, 2018). Every milieu is differentiated in terms of social-status and basic values (Figure 5.6). They clustered the German population into ten different milieus) by using a questionnaire based on 40 questions (Schwarz and Ernst, 2009) and around 24.000 interviews (Küppers, 2018). These were constructed from the so-called “information packages", which included aspects from life orientations to sociodemographics, and values (Barth et al., 2017).

Sinus-Milieus® have been used in research, for example, to conduct agent-based modeling (Schwarz and Ernst, 2009; Jensen et al., 2016), multi-agent simulation (Soboll et al., 2011), marketing research (Diaz-Bone, 2004), as well as for understanding social changes (Manderscheid and Tröndle, 2008) and mobility preferences (Von Jens, 2018; Sinus Markt und Sozialforschung GmbH, 2019). Sinus-Milieus® on a spatial scale are called Sinus-Geo-Milieus and are defined as the probability of every address in Germany to belong to a certain milieu group (Küppers, 2018). Sinus-Geo-Milieus use data from the interviews from Sinus-Milieus®, official national survey data and data collected from the marketing company Microm (`https://www.microm.de/`) and applied a multinomial regression model using the addresses in Germany to calculate the probability of each house in Germany to belong to one of the ten milieus (Küppers, 2018).

We extended the analysis by aggregating the different Sinus-Geo-Milieus groups by residential area according to low (traditionalists, precarious, hedonists), middle (modern mainstreamers, adaptive navigators and social ecologists) and high (established, liberal intellectuals, performers, cosmopolitan avant-gardes) social status, as well as traditional orientation (established, liberal intellectuals, modern mainstreamers, traditionalists, precarious) and progressive orientation (performers, cosmopolitan avant-gardes, adaptive navigators, social ecologist, hedonists).

– Deprivation index – The Deprivation index DI in the spatial unit j defined as the rate of the prevalence of low social-status milieus in spatial unit j with the average of the accessibility defined by Geurs and Van Wee (2004) to the opportunities to basic needs, such as healthcare, social and recreational facilities, education, transport, and proximity to the city center.

$$DI_j = \frac{Milieu_{low\ status}}{1/n \sum_{i=1}^{n} \alpha_1 * e^{-\propto_2 * Di}} \tag{5.1}$$

where D_i is the distance from the spatial unit to the built environment opportunity i, n is the total number of opportunities in the study and α_1 and α_2 are parameters of the decay function of willingness to walk. As Chen et al. (2019) did, we used $\alpha_1 = 1.0126$ and $\alpha_2 = 0.0013$, from Zhao et al. (2003), who measured the decay function for walking to public transport in feet, therefore, we converted distances to feet. It is worth mentioning that accessibility to opportunities can vary depending on the units of the chosen model parameters. For a comparison between different DI, they should have the same metric units.

The indicator for the accessibility to basic needs was calculated as the distance of the spatial unit to the following opportunities: town hall, main train stations, universities, supermarkets, playgrounds, schools, pharmacies, kindergartens, hospitals, sports centers, cycle-ways, and public transport stations. Built environment data was downloaded from OpenStreeMaps (OpenStreetMap-contributors, 2017).

– Feature selection and regression – We carried out two regressions, one with the availability of bicycles as the outcome and other using density of the drop-offs as the outcome. As independent variables, we included the percentage of each social group in every residential area. Also, after a recommendation of Bhuyan et al. (2019) in considering “residential population density, land use, facilities, attractions, origin-destination trips, etc" in similar research, we add population density and the walking accessibility to basic opportunities, which help to analyze whether a residential block does not have access to BSS, to which other opportunities would not have access too. We calculated walking accessibility similarly to the calculation of the denominator of DI (see Equation 1). Accessibility to the city center was the exception because walking accessibility would not make sense because of the commonly great distance. Therefore, we considered the straight-line distance from the centroid of the residential block to the town hall. To overcome heteroscedasticity issues, the square root was calculated for the availability and the logarithm for the bikes drop-offs. The independent variables were the groups of milieus, access to opportunities, and population density. The logarithm of the independent variables was taken, in case the variables were not normally distributed, as was the case of all the variables but for the distance to the town hall. Lastly, the independent variable was log-scale because of the prominent skewness, and the independent variables were normalized and due to the different units.

The entire analysis has been carried out using the R programming language (R Core Team, 2014).

5.4.4 Results

The quantitative assessment was carried out in residential blocks inside the service area of a HBSS in Munich. Table 5.2 shows the descriptive statistics of the variables used in the assessment.

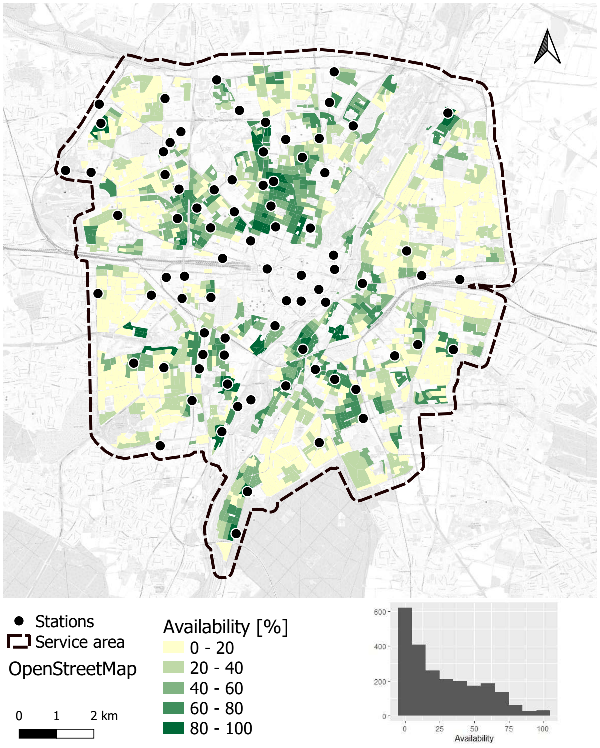
Heat maps Figure 5.7a, 5.7b, and 5.7c show the spatial distribution of the availability, bikes drop-offs and the Deprivation index in the residential blocks inside the service area. Availability is higher in residential blocks closer to the city center, especially in the north and northwest, where the main universities are located, and in the southeast areas close to the main river. On the other hand, availability is lower in the west, and northeast, which are areas with better rapid transit connections. Drop-offs were also greater in areas close to the center and north of the city, but there is a lower demand closer to the border of the service area. Because there is greater availability of bikes and more drop-offs in the center and north, we can assume the supply of the system follows an **efficient** rule in these areas. The DI is higher in the north and south. Therefore, the system is partially available for the underprivileged in the southern part, and reflects that this distribution is based on the **equity** rule. However, overall the system does not reflect a clearly defined distribution principle but rather a mix of rules (**equity + efficiency**) with a predominance of **efficiency**.

GINI coefficients. Figure 5.8 shows the Lorenz curves and Gini coefficients. The Gini coefficient for the distribution of availability is 0.525. When weighted with the DI, GINI_DI_weighted is 0.470, and finally, when weighted with the observed demand GINI_D_weighted is 0.311. Since the Gini coefficient is in the middle range, we cannot assume that the system is spatial equal or unequal. In this case, the other coefficients do not give us relevant information, but a possible tendency to equity and efficiency since the Gini coefficient decreases after weighting it with the DI and demand.

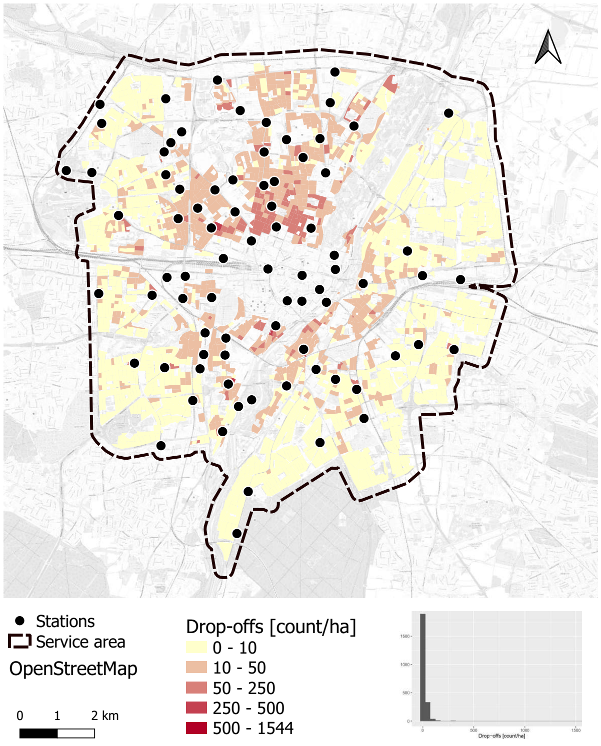
Spearman’s correlation. Figure 5.9 shows the Spearman’s correlation matrix between the variables in the study. We can see a positive correlation between availability and the bikes drop-offs (0.54) but also a weaker correlation between availability and DI (0.19). From the shallow analysis, we assume that the distribution follows the rules of **“equity + efficiency"**. However, the tendency is towards **efficiency** because the correlation is much higher. In the deep analysis, we observe

Table 5.2: Descriptive statistics

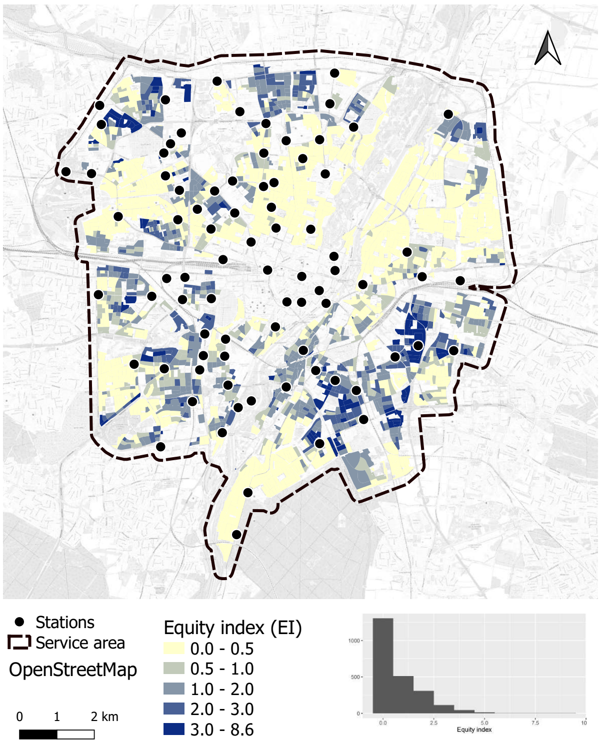
Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Availability [%]	27.33	25.95	0.00	3.92	47.16	98.99
Drop-offs [count/ha]	16.84	56.12	0.00	1.54	17.46	1,544.49
Population density [inh./ha]	90.84	66.73	0.78	34.00	138.14	421.61
Established [%]	0.17	0.23	0.00	0.00	0.28	1.00
Liberal Intelectuals[%]	0.17	0.21	0.00	0.00	0.3	1.00
Performers[%]	0.11	0.15	0.00	0.00	0.18	1.00
Cosmopolitan Avant-gardes [%]	0.12	0.16	0.00	0.00	0.18	1.00
Modern mainstreamers [%]	0.07	0.11	0.00	0.00	0.1	1.00
Adaptive navigators [%]	0.09	0.12	0.00	0.00	0.13	1.00
Social ecologicals [%]	0.05	0.08	0.00	0.00	0.07	1.00
Traditionals [%]	0.08	0.12	0.00	0.00	0.12	1.00
Precarious [%]	0.03	0.08	0.00	0.00	0.02	1.00
Hedonists [%]	0.09	0.15	0.00	0.00	0.13	1.00
BSS station [acc.]	0.16	0.17	0.00	0.03	0.24	0.97
Town hall [km]	4.05	1.32	0.98	3.03	5.10	7.52
Public transport station [acc.]	0.48	0.17	0.07	0.37	0.60	0.99
Cycleway [acc.]	0.65	0.19	0.07	0.51	0.81	1.02
Supermarket [acc.]	0.31	0.23	0.00	0.11	0.47	1.01
Pharmacy [acc.]	0.31	0.22	0.0001	0.12	0.46	0.97
Playground [acc.]	0.30	0.25	0.001	0.10	0.46	1.02
Bakery [acc.]	0.36	0.24	0.0002	0.15	0.55	0.98
Organic store [acc.]	0.13	0.18	0.00	0.01	0.18	0.92
School [acc.]	0.06	0.14	0.00	0.0001	0.05	0.90
Kindergarten [acc.]	0.22	0.22	0.0001	0.04	0.34	0.98
Hospital [acc.]	0.03	0.10	0.00	0.00	0.01	0.87
Sports Centre [acc.]	0.08	0.15	0.00	0.001	0.09	0.94
Community Centre [acc.]	0.04	0.11	0.00	0.0001	0.02	0.86
Low social status [%]	0.20	0.26	0.00	0.00	0.33	1.00
High Social status [%]	0.57	0.34	0.00	0.25	0.90	1.00
Middle social status [%]	0.21	0.19	0.00	0.05	0.33	1.00
Traditional orientation [%]	0.51	0.28	0.00	0.28	0.75	1.00
Progressive orientation [%]	0.47	0.28	0.00	0.23	0.70	1.00
DI	0.78	1.04	0.00	0.00	1.28	8.66



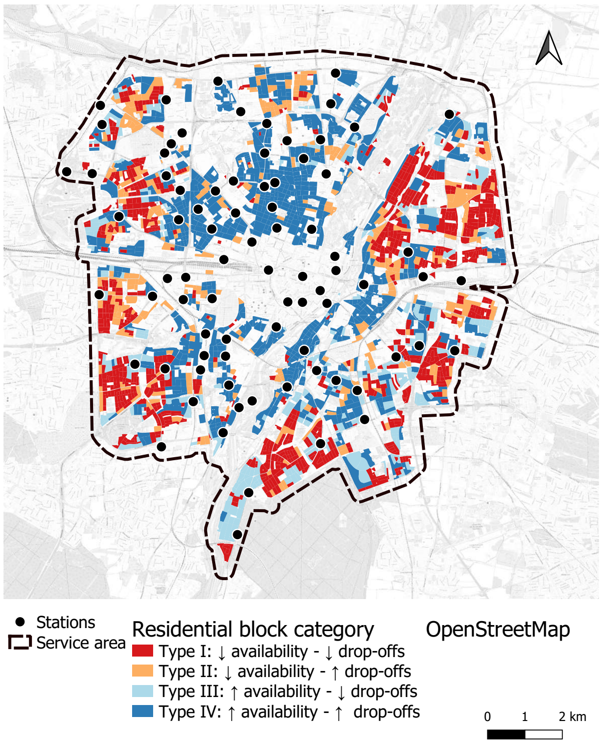
(a) Availability per residential block



(b) Drop-offs per residential block



(c) Dquity index per residential block



(d) Block types: Availability vs drop-offs

Figure 5.7: The average and standard deviation of critical parameters: Region R4

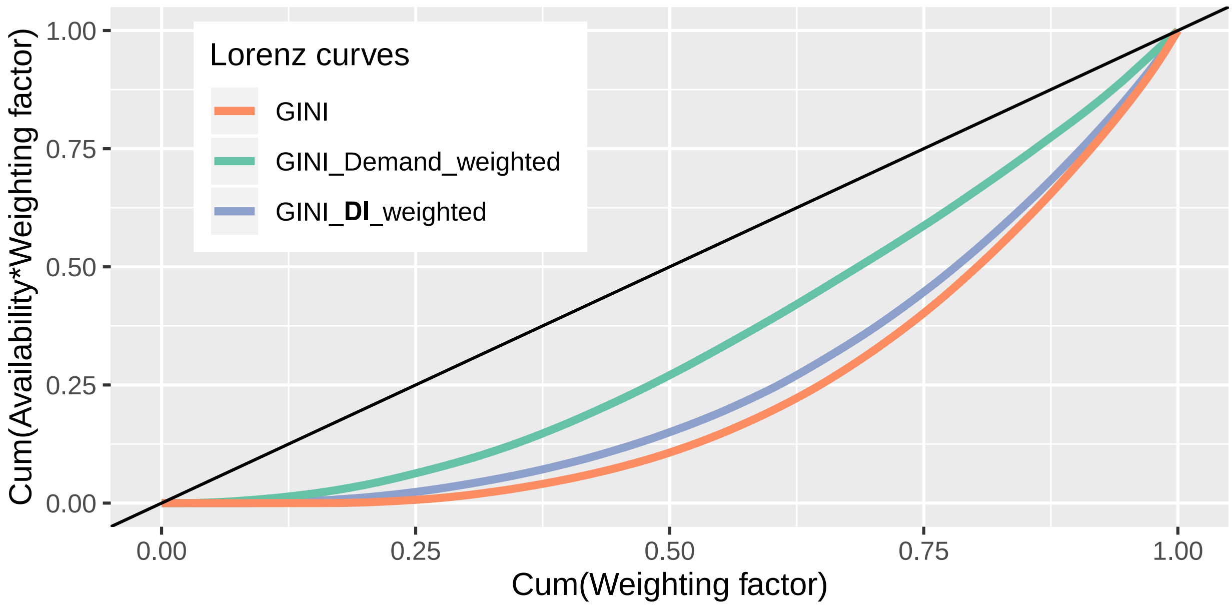


Figure 5.8: Lorenz curves

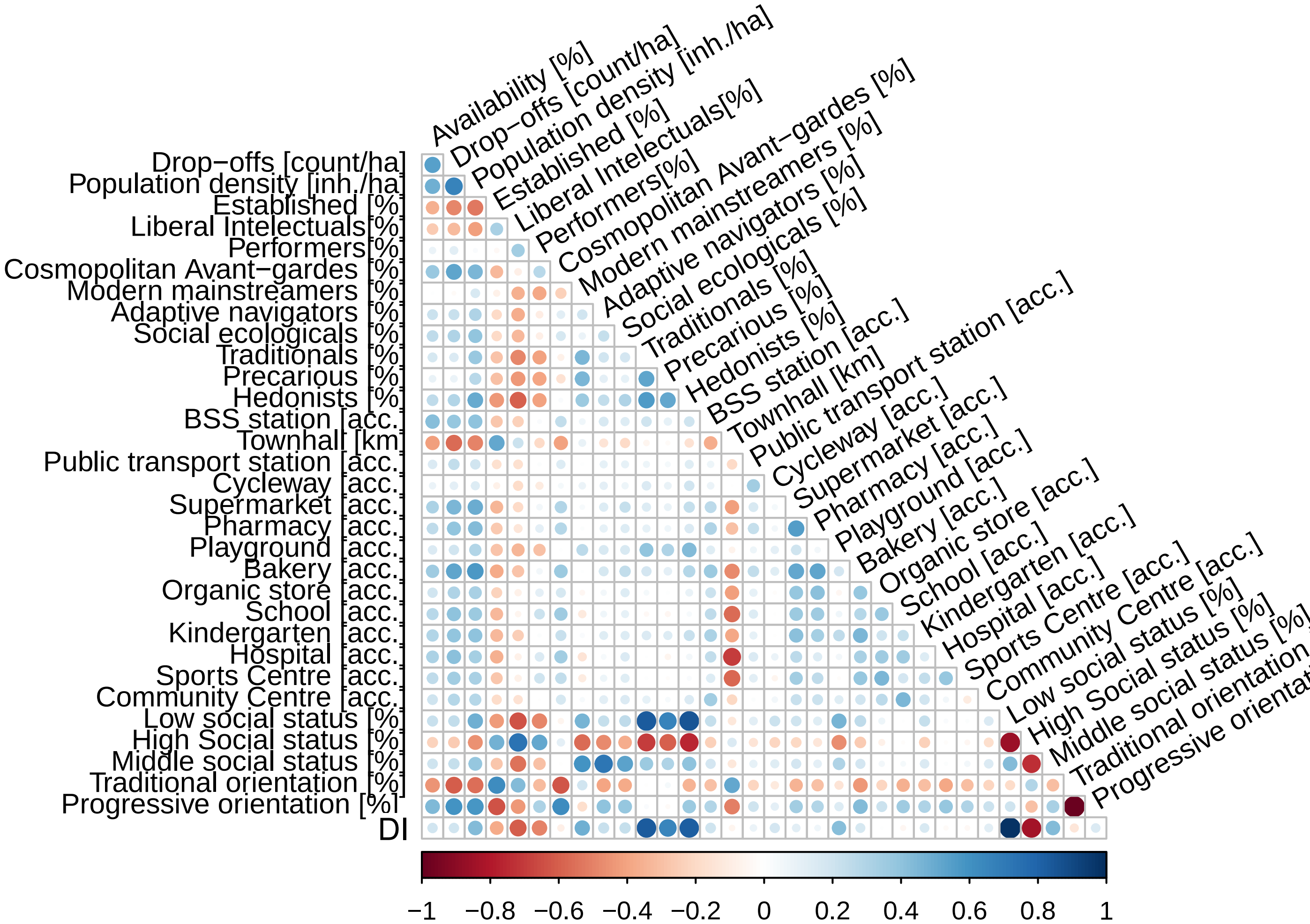


Figure 5.9: Correlation matrix of the studies variables

that the milieus of the established (-0.35) and liberal intellectuals (-0.25) have a negative correlation with availability, while the other milieus a positive correlation. The highest positive correlation is with the cosmopolitan avant-gardes (0.37), followed by hedonists (0.25). If we do the same assessment aggregating the social milieus in terms of social status low (0.22), middle (0.207), high (-0.22), we assume the distribution is **inefficient** because of the negative correlation to the high social status. However, all the social groups have similar "sign" in the correlation with the drop-offs and availability, which means that where there is higher demand there is also higher availability, therefore, we assume that the distribution follows an **efficiency** rule. Furthermore, we found that the highest correlation with availability was based on basic values, traditional orientation (-0.44) vs progressive orientation (0.44), and not with social status.

Table 5.3: Feature selection and OLS regression Results

	Dependent variable:	
	Availability [sqrt(%)]	Drop-offs [log(count/ha)]
	(1)	(2)
Population density [log(inh./ha)]	0.626*** (0.531, 0.720)	0.434*** (0.392, 0.475)
BSS station [log(acc.)]	0.704*** (0.614, 0.794)	0.128*** (0.088, 0.167)
Town hall [km]	−0.309*** (−0.437, −0.181)	−0.236*** (−0.286, −0.187)
Hospital [log(acc.)]	0.189*** (0.076, 0.301)	
Public transport station [log(acc.)]		0.072*** (0.038, 0.107)
Supermarket [log(acc.)]		0.061** (0.017, 0.106)
Bakery [log(acc.)]		0.093*** (0.046, 0.140)
School [log(acc.)]		0.075*** (0.030, 0.120)
Kindergarten [log(acc.)]		0.077*** (0.036, 0.118)
Traditional orientation [sqrt(%)]	−0.503*** (−0.599, −0.407)	−0.370*** (−0.410, −0.330)
Constant	4.369*** (4.289, 4.450)	1.757*** (1.724, 1.790)
Observations	2,300	2,300
R^2	0.335	0.551
Adjusted R^2	0.333	0.549
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5.4: Comparison of the prevalence of milieus in blocks Type IV with blocks Type I, II and III

	Type I	Type II	Type III	Type IV
Availability	*Low*	*Low*	*High*	*High*
Drop-offs	*Low*	*High*	*Low*	*High*
Milieu group				
Established	**29.11%***	**12.23%***	**18.53%***	5.44%
Liberal Intellectual	**24.65%***	12.95%	**17.99%***	10.06%
Performers	**9.95%**	**10.16%**	**10.52%**	13.68%
Cosmopolitan	**5.35%**	**12.42%**	**7.85%**	20.62%
Main Streamers	6.29%	**8.11%***	7.64%	5.54%
Adaptive Navigators	**7.18%**	**8.97%**	**9.86%**	11.14%
Social ecologists	**2.89%**	**5.48%**	**3.67%**	7.57%
Traditionalists	**5.31%**	9.73%	9.32%	8.49%
Precarious	**2.68%**	**4.24%***	3.48%	2.93%
Hedonists	**4.89%**	13.05%	**8.99%**	12.15%

Bold: significantly different than Type IV ($p < 0.05$)
** Significantly less addresses than in Type IV ($p < 0.05$)*

In conclusion, the system seems to be distributed under the **"equity+efficiency"** rules in the shallow analysis because the system is serving both privileged and underprivileged groups (shown in the deeper analysis). In addition, the system is socially **inefficient** by not serving the majority of the high-status population but spatially **efficient** because the supply is more accessible where there is more (observed) demand.

According to the other variables, areas with higher availability have a higher population density (0.48) and are closer to the town hall (-0.41). With regard to the accessibility to walking opportunities, the highest correlations are the accessibility to bakeries (0.35), supermarkets (0.31), hospitals (0.31) and schools (0.28). It is worth noting that the DI correlates negatively with the walking accessibility to schools (-0.04), hospitals (-0.02) and sports centers (-0.03).

Feature selection and regression results. Table 5.3 shows the results of the two linear regressions. The model, including the drop-offs, fits the data set better with a R^2 of 0.55, including 9 variables. On the other hand, the model, including availability, fits worse with a R^2 of 0.33 and 6 variables. The population density, walking accessibility to the bike-sharing stations, and distance to the town hall were parameters that are most associated with the dependent variables in both models. According to social milieus, the traditional orientation group was the only social group that was significantly selected by the LASSO selection technique and presented a negative association. Since both models are negatively associated with the same population, we assume that the system presents an **efficient** distribution because the availability is oriented to the demand. Since variables related to the social status were not selected by the LASSO selection technique, the assessment could not be evaluated in terms of serving the underprivileged and privileged population. Finally, the model including the drop-offs presented as well a high correlation with walking accessibility to public transport stations, and points of interest such as supermarkets, bakeries, schools, kindergartens.

Mann-Whitney U test results. We have classified the residential blocks into four types based on the availability and bikes drop-offs (see Figure 5.7d). Table 5.4 shows that established, mainstreamers and precarious live significantly more in Type II areas than in Type IV areas, and established and liberal intellectuals live more in Type I areas and Type III areas than in Type IV areas. Established and liberal intellectuals do not seem to use the system because even if they have a high level of availability in their residential areas, there are still low bicycle drop-offs (Type III areas). We found that mainstreamers and precarious milieus live significantly more in Type II areas than in Type IV areas. We, therefore, assume that they are potential users of the system, but have little access. We have found once more that social status is not a factor highly associated with the usage of BSS, but the basic values are. In view of the underprivileged population, for example, accessibility is higher where hedonists live (progress orientation), but there is no offer in areas where precarious people (traditional orientation) live. We observed that social groups with basic values oriented to the progress live more in Type IV areas. In summary, we cannot adopt a distribution rule of the system based on social status, but the distribution falls in the case of **efficiency** in that those who do not use the system have less access to the supply.

5.5 Discussion

Distribution rules are harder to choose when resources are limited. However, this is often the case and can start arguments over social versus economic sustainability. By economically sustainable, we mean that monetary resources to maintain the system would be readily available. By socially sustainable, we mean that the people most in need can access the system easily. When the spatial equity rule is applied, more resources are needed to make BSS as economically and physically accessible as possible in underprivileged areas. Also, the neediest people (with lower economic resources) have better access to the system, which makes it socially sustainable but probably less profitable. Spatial equality rule can be more profitable than spatial equity but higher resources are required to build and balance a system in such a way that every area has equal availability. Spatial efficiency is the most profitable distribution rule and the system can be economically sustainable. However, those who might benefit the most from access to the system might not have access.

Cases reflecting multiple rules, such as case IV and V (Figure 5.2), depending on the socio-spatial distribution of the city. Case IV would need fewer resources than case V, and would not have the clashes between social and economical sustainability. However, the distribution of the infrastructure can create other social clashes depending on which social groups are served more and which less. Finally, Case V would have similar opportunities, implications, and costs as the case of equality, because of the high infrastructure required.

Since fairness is a subjective assessment, one hypothetical case can be “fairer" to one person than other, depending on moral intuitions (Varian, 1975), culture, (Rochat et al., 2009; Stobart, 2005), individual preferences (Ambec et al., 2019) or situation (Schmitt et al., 1994). A possible “general fair" assessed allocation would exist “when all agents have the same tastes, even though they may have different abilities" or needs (Varian, 1975). Otherwise, conflicts can occur after deciding what is fair or not. However, by interviewing a segment of the population that is at a transport disadvantage, we have shown that equity-based distribution rules are the ones desired by this population.

If spatial equity rule is reflected, underprivileged people can have greater access to opportunities and improve their mobility for a more balanced society. This rule was the only one referred to by the unprompted participants in Strasbourg. This shows that the equity-based or any combination of rules including equity distribution are the desired form of distribution from the perspective of the mobility vulnerable group that are NMH. Spatial efficiency might be profitable, but can be perceived as being for elites, in which the neediest are not served and the system can be subject to vandalism. On the other hand, “national elites set the standard" and “people hope to move on in life by imitating prestigious styles and behavior" (Kuipers, 2013), consequently if the elites use the system, disadvantaged social classes might want to use the system as well. Spatial equality might be very expensive to fulfill the needs of the whole service area but everyone can have access to it. According to (Varian, 1975), equity + efficiency would be called “fair", in which the allocation would have the properties of efficiency and equity. Finally, equity+efficiency+equality would be costly but it would fulfill the three rules which would minimize conflicts or interests. In the end, even if BSS are considered “fair", resources could be allocated somewhere else e.g. to build a school in a needed neighborhood. Would this case be fair? Therefore, an absolute fair system might not be possible.

The qualitative assessment helps us to understand how people perceive the spatial fairness of the BSS and if it is a concern. For the qualitative assessment, we chose the city of Strasbourg, France as a case study because of the data available from interviews with non-motorized households. The quantitative analysis helps to numerically assess which distribution rule(s) the allocation of infrastructure follows. We studied Munich since the city has a hybrid bike-sharing system with available data. The qualitative assessment helped us to prepare, validate and interpret the numerical outcome from the quantitative assessment. One approached informed the other. Even though we used two different cities, they are somewhat comparable. Both cities used as case studies are located in central Europe, are not capitals but are representative cities of their countries, have a “relatively w>ell-developed bicycle infrastructure" (Martens, 2007), and are both located next to a river that greatly impacts the urban structure.

Furthermore, in the qualitative assessment, participants were not asked directly about their opinion on BSS but we extracted the content where BSS are referred to. The disadvantage is that we do not have extensive information because BSS perception was not asked directly, but the advantage is that we have their honest thoughts, feelings, and opinions because participants talked about these systems without being asked. Those who felt socially excluded were 2.4 times less likely to discuss BSS compared to those not feeling socially excluded. To the best of the authors' knowledge, this is the first time that feeling socially excluded is associated negatively with BSS. This demonstrates that some of the most vulnerable populations in terms of mobility is not inclined to think about BSS as a solution and could be interpreted to reflect a lack of equity in BSS.

Theoretical knowledge for cycling planning is poorly developed, in comparison with motorized traffic planning (Koglin and Rye, 2014; Aldred, 2015), especially because of the difficulty for data collection. However, for BSS the GPS-based data helped as to collect trip information to implement our theoretical spatial justice framework. Then, we apply it the distribution of the availability in the service area of the HBSS in Munich from the quantitative assessment, which mainly showed three classifications:

1. Efficiency + Equity (Case IV, see Figure 5.2). Underprivileged and privileged people live in areas with higher availability. Therefore, we assume that the allocation follows these two rules together.

2. Efficiency. Efficiency is present where the usage of the system is directly proportional to the availability, i.e. where usage is higher, there is a higher availability, and vice versa.

3. Distribution oriented to progressive values. Social status was not an indicator of the distribution of availability. However, the distribution was oriented to the basic values. Social groups with an orientation to progressive values (especially cosmopolitan avant-gardes) instead of traditional-oriented values (especially established) live in areas with higher availability.

By revealing the distribution rules that the BSS infrastructure follows, policy makers and stakeholders can assess if the accessibility to a bike-sharing system follows their ideologies. Urban and transport planners can assess the design or modification of a bike-sharing system based on distribution rules and stakeholders' preferences, or influence on policy makers (Koglin and Rye, 2014) to mitigate injustices. Finally, the general public can have information about the system in their cities to judge if it is spatially fair or not based on their ideologies, world views, and needs. They can protest if urban politics excludes certain groups (Koglin and Rye, 2014; Swyngedouw, 2008).

In terms of the efficiency rule, the system is partly economically viable because the demand is higher where the supply is more accessible. Also, under- and privileged people both have physical access to the system. If we would have stopped the analysis there, we would have assumed that the system is socially sustainable, since most disadvantaged people have high access to the system. However, the distribution of the availability of bikes seemed to be following basic values rather than social status. A social clash is present: traditionalists vs progressives. In this sense, traditionalists might perceive that the system is not oriented to them. Their main orientation is tradition, they might think that traditional transport modes as public transport or driving are more convenient, or because owning is also one of their main values, they prefer their own bike (Fishman, 2016). Similarly, in the qualitative assessment, BSS in Strasbourg were perceived to be for students, and we, therefore, assume that it is not perceived for elderly or traditionalist people.

As being the system tending to efficiency, we confirmed the argument of Aldred (2015): “current policy prioritises 'commuter' and 'utility' cycling ", marginalizing those with traditionalist orientation, which tend to be older people with lower IT and technology affinity (Sociovision, 2018) and cycling for leisure. It might be that the stratifying force on new mobility systems relays on adaptation to the new technologies, which the traditionalists might not follow.

The uneven distribution can lead to complaints about public resources being oriented to transportation systems that traditionalists do not use. Reciprocally, in Strasbourg, non-motorized interviewees feeling socially excluded perceived BSS being oriented to the rich and not for the poor, and not targeted at those in need. Potential political impacts could include a decrease in the political acceptance and trust in the government (Ariely and Uslaner, 2017) and the tendency for low acceptance of the system and resistance to approve it or to use it (Wüstenhagen et al., 2007), as well as a possibility of vandalism of the infrastructure. As an extreme analogy, in Chile, people caused damages to the metro in Santiago valued in 300 million dollars. Even though Chile has relatively good macroeconomic figures (efficiency), "if the image of Chile is scratched, an enormous social, cultural, economic and political injustice becomes evident" (inequity) (Zuñiga, 2019).

Moreover, high social status traditionalists in Type III areas (see Table 5.4) have good access to the system but they do not use it, leading to an oversupply. Oversupply can lead to the same rejection as a feeling of “unfair" use of the public space. A privately owned free-floating service in Munich closed in 2018 due to vandalism to their bicycles because of the uneven use of the public space: “Within a short time, the provider showered the city with bicycles in the summer of 2017, often placing up to 30 of them in one location" (Rau, 2018). Furthermore, as shown in the qualitative assessment, BSS were perceived to be increasing the number of bikes in Strasbourg which presented conflicts with pedestrians in the public space.

The critical situations are Type II areas (see Table 5.4), in which mainstreamers and precarious are significantly more prevalent than in Type IV areas. This population might be potential users of the system, and decision-makers might focus their attention on them due to the low availability. These areas can serve as potential places to implement new stations, and also to improve re-balancing strategies, such as operator-based relocation strategies, where trucks take bicycles from oversupplied areas e.g. Type III and take them to Type II areas, or user-based strategies by offering incentives to the users as discounts when driving from Type III to Type II areas or a mix of both (Reiss and Bogenberger, 2017).

Implementation of new stations and changing the re-balancing strategies can be performed where the allocation does not satisfy the fairness perception of the disadvantaged population in the distribution or does not fit the ideologies of transport planners and policy makers. If the distribution is to be tailored specifically to underprivileged populations, more stations have to implemented where these people live and also where they commute, and the re-balancing strategies user- or operator-based should be planned so that the residential blocks of the underprivileged population have at least one bicycle close to them the most of the time. Moreover, in terms of access to opportunities, we found that in Munich the deprivation index is negatively correlated to the distance from the city hall, which shows distance constrains underprivileged people's use of the bike-sharing system. Therefore, if the goal is to increase the usage and thus, the availability among this population, electric bicycles might be a suitable option. Another approach can be serving all social groups equally. In this approach, stations and re-balancing strategies have to focus on Type I and Type II areas, inserting more bicycles or taking them from Type III and Type IV areas until there is not a group living significantly more in Type I and II areas than in Type IV, and Spearman's coefficients are positive between in all the groups and availability.

A remaining question is whether cities should bother providing access to BSS when the motivation to use it is virtually nonexistent (e.g. Type III areas). This might happen according to the preferred distribution rule(s). For example, if we want to follow primarily an equity rule in the system, we might implement stations and focus on re-balancing strategies where underprivileged people live. If the infrastructure is not being used, user-based discounts can be applied not only in the drop-off but in the pick-up. If the main value of the targeted population is tradition, educational workshops can be useful to teach them how to access technology. Electric bicycles might also be a good option, so traditionalists see the system as convenient as driving. The qualitative investigation revealed that the population of NMH in Strasbourg had an abundantly positive impression of BSS mentioning several positive aspects and only a single negative aspect to BSS. Furthermore, several participants who had not used BSS mentioned their willingness to become users.

Regarding the access of opportunities, we found that in Munich the deprivation index is negatively correlated to the distance to the town hall, which shows distance constrains for underprivileged people using the bike-sharing system. Therefore, if the goal is to increase the usage and thus, the availability among this population, electric bicycles might be a suitable option.

Knowing that the demand is greater where progressive people live means that market orientation for the implementation or expansion of new systems can focus on this population. However, targeting milieus to make BSS more attractive could be argued as meeting a psycho-social need. This approach can be assessed as fair when efficiency is the targeted distribution rule. Media, political parties, ministries, unions, churches, and associations use similar approaches to identify potential followers, as well as for product development, and market positioning (Sociovision, 2018). For instance, two luxury automobile makers have used milieus to position and to segment their markets (Barth et al., 2017). Public transport and shared mobility could compete with private autos by doing the same, and carry out further research “beyond sociodemographics".

Moreover, this research presents similar results as a study carried out by Sinus-Milieus® from an online survey funded by the Federal Ministry of Transport and Digital infrastructure in Germany (Sinus Markt und Sozialforschung GmbH, 2019). They found that cosmopolitan avant-gardes and performers are associated with above-average usage of BSS, whereas, traditionalists and precarious people use BSS at a rate below average.

Another particular strength of this study is the selection of HBSS as a case study. Regarding the type of BSS, few studies have dealt with HBSS (Albiński et al., 2018). Chen et al. (2019) is one of the only studies which assessed the accessibility to the hybrid system in Tampa, United States. Moreover, Hirsch et al. (2019) suggested the neighborhood level as a spatial unit for further research on FFBSS, and we considered an even lower spatial level: residential blocks. Finally, Reynaud et al. (2018) stated that only a few studies focused on the availability of bicycles. We developed a new concept of bikes availability that includes different types of BSS, considers a typical desirable walking distance to access the system, and also, focuses on real access to the system by having at least one bicycle available. We could not include the temporal component due to the lack of long-period data availability of the observed demand.

According to the concept of accessibility (Geurs and Van Wee, 2004), four main components shape accessibility: 1) land-use, 2) transport, 3) temporal and 4) individual. Our paper is one of the few considering a spatial fairness assessment that includes the transport, land-use, and individual components. For the land-use component, we considered opportunities at the destination of a trip, such as residential locations and opportunities at the destination such as jobs, shops, healthcare, social and recreational facilities. The individual component is the needs and opportunities of travelers, which we included as social status and basic values. We did not include the temporal component due to the long-term data availability of the observed demand.

5.6 Conclusions

How fair is the allocation of the infrastructure of a bike-sharing system? Policy makers, stakeholders, transport planners, and the general public have now available 1) the perception of a group of the underprivileged population about BSS, and 2) a quantitative methodology to identify which distribution rule(s) the infrastructure of a bike-sharing system follows and which social groups are spatially advantaged or disadvantaged by it. If they consider the system unfair, the implementation of new stations, and user- and operator-based strategies can be used to refocus on the target population.

Non-motorized households feeling socially excluded rarely talked about cycling at all. They perceived that BSS present a spatial conflict with pedestrians and are oriented to students and the rich rather than those who need it the most.

The quantitative assessment was carried out in a HBSS in Munich. Results show that the system follows the spatial efficiency and equity rules because the higher availability is in areas where privileged and underprivileged people live. Moreover, it is also efficient in terms of the supply being more accessible where the observed demand is higher. Surprisingly, availability was not oriented to the social status but rather to basic values of progressive vs traditional. This result is complemented by a statement in the interviews that BSS serve mainly students.

Is this system fair? This depends on the subjective perspective. For some, it might be fair because where there is high demand, the system presents high availability. But for others, it might be unfair, because BSS do not fulfill the needs of the traditional population or it should be exclusively oriented to the underprivileged who do not have access to their own vehicle. It also might be unfair to some who believe the whole service area should cover all blocks equally. And maybe for others, the money invested in BSS should be used to improve conventional cycling infrastructure.

The two split perspectives proposed by Lucas (2019) appear to be mutually exclusive but after including marketing, education, proper infrastructure planning, design, and re-balancing strategies, BSS can be efficient and at the same time practical, simple to use, convenient (as stated in the qualitative approach), and accessible for those who might need them the most.

Further research can be oriented to carrying out a qualitative and quantitative approach in the same city or applying them to more case studies. Interviews can be carried out asking specifically about the perception of spatial fairness on BSS to privileged and underprivileged populations. The approach in Munich can be extended to compare the population inside and outside the service area and to more types of BSS in the city.

Chapter 6

Built environment factors associated to bike-sharing ridership

This chapter has been published in Duran-Rodas, D., Chaniotakis, E., & Antoniou, C. (2019). Built Environment Factors Affecting Bike Sharing Ridership: Data-Driven Approach for Multiple Cities. Transportation Research Record, 2673(12), 55–68. https://doi.org/10.1177/0361198119849908

Bike sharing has been found to present environmental, economic and social benefits. Identification of factors influencing ridership is necessary for policy–making, as well as when examining transferability and aspects of performance and reliability. In this work, a data–driven method is formulated to correlate arrivals and departures of station–based bike sharing systems with built environment factors in multiple cities. Ridership data from stations of multiple cities are pooled in one data-set regardless of their geographic boundaries. The method bundles the collection, analysis, and processing of data, as well as, the models' estimation using statistical and machine learning techniques. The method was applied on a national level in six cities in Germany, and also, on an international level in three cities in Europe and North America. The results suggest that the models' performance did not depend on clustering cities by size but by the relative daily distribution of the rentals. Selected statistically significant factors were identified to vary temporally (e.g. nightclubs were significant during the night). The most influencing variables were related to the city population, distance to city center, leisure-related establishments and transport related infrastructure. This data–driven method can help as a support decision-making tool to implement or expand bike sharing systems.

6.1 Introduction

Bike sharing is defined as the shared use of a bicycle, in which a user accesses a fleet of bicycles offered on public space (Büttner and Petersen, 2011). It is part of the shared economy social–economic phenomenon, in which individuals or organizations prioritize use over ownership of items (Böckmann, 2013). Bike sharing systems have a long history, with the very first system launched in 1965. Its deployment was in Amsterdam with fifty free and unlocked bicycles. Theft and vandalism led to a coin–deposit system, also not successful, mainly due to the user's anonymity. Today, information and communications technology (ICT) enables wireless pick–up, drop–off, and a real–time GPS tracking of bicycles (Shaheen et al., 2012), which lead to the widespread of bike sharing to more than 1,600 cities around the world (Meddin and DeMaio, 2020). Europe and Asia are the continents with the majority of bike sharing systems worldwide. In 2015, China presented the biggest fleet in the world with 753,508 bicycles, followed by France with 42,930, and Spain with

25,084 (Meddin and DeMaio, 2020). Categorization of bike sharing systems can be defined by the use of stations or not: (a) station–based (SBBS), b) free–floating (FFBS) and c) a mix of the two (Firnkorn and Shaheen, 2016).

The wide deployment and observed growing trends of bike sharing can be attributed, among others, to its associated social, economic and environmental benefits. These are related to creating a larger cycling population, increasing transit use, reducing greenhouse gases, decreasing congestion, creating environmental awareness, improving public health, among others. A comprehensive review of benefits attributed to bike sharing can be found in Shaheen et al. (2012), Shaheen et al. (2010) and DeMaio (2009). However, not all systems were deployed successfully. Some were perceived as a public nuisance or were misused and vandalized (Hamann and Güldenberg, 2017). Possible reasons for a system failure were bicycles' poor quality, lack of funding, oversaturated market, delayed expansion, inconvenient system design, and others (Hamann and Güldenberg, 2017; Nikitas, 2017).

The identified benefits strongly suggest the necessity to further increase the use of bike sharing systems and to enable their deployment in more cities. At the same time, the unsuccessful deployment of some projects makes the examination of the factors that affect ridership and system reliability rather imperative. These two needs have been the driving force for a high number of studies on the influencing factors that affect on bike sharing usage (e.g., built environment, socio-demographic characteristics, system settings). Most studies analyze the influencing factors in a) multiple cities, with each city considered as one observation (Chardon et al., 2017; Zhao et al., 2014) or b) a single city at a local (station) level, where one city is analyzed and observations are based on an area of influence, e.g. near stations (Faghih-Imani and Eluru, 2016; El-Assi et al., 2017; Tran et al., 2015; Faghih-Imani et al., 2017).

The multiple–cities approach suffers from an exclusion of varying characteristics within a city, which provides an indication of how the system should be structured to enable a successful deployment. Conversely, the station level approach is performed in a single city and is bounded by the urban settings examined. The main issue with this approach is that it does not examine the system's transferability but the ridership within a city.

Aiming at overcoming the above–discussed drawbacks of existing approaches, this paper contributes to the related literature by focusing on the investigation of bike sharing systems as one entity regardless of the city they belong to. We present a multiple–cities data–driven approach focusing on the comparison of general built environment characteristics on a station–level beyond geographic boundaries. As such, the data used for each city is pooled in one complete data-set, in which each observation refers to one station's area of influence (as defined in the Method Section). The influencing factors chosen to be investigated describe the characteristics of the built environment (guided by the high influence found in the majority of previous studies).

The second main contribution of this study lies upon the modeling techniques used for the most influencing factors selection. As discussed in the Related Work Section, in most cases a predetermined set of factors is used. This set is hypothesized to contribute to a successful deployment of bike sharing, and thus, could omit possible patterns revealed by an alternative selection approach. In this study, a data–driven approach is followed to allow the discovery of factors that might not be commonly addressed. This is done by using different linear and non–linear modeling techniques which are evaluated upon modeling performance criteria such as goodness–of–fit, information criteria, and (cross–)validation.

Two applications of the methods discussed are included: a) a national application in six cities in Germany, Europe and b) an international application in three cities in Europe and North America with comparable urban characteristics. The first application intends to illustrate the performance of different modeling techniques, while the second intends to illustrate the applicability of the methods in an international setting, while taking into account seasonality. In both cases, different validation techniques are exercised with very positive results. All the factors are defined using open–source data and by the derivation and deployment of an automated feature creation method.

6.2 Related Work

Spatial–temporal factors influencing historical rentals of SBBS systems have been studied in various sized cities all over the world. The resulting factors have been compared between cities with factors within a city scale (Chardon et al., 2017; Zhao et al., 2014) or in a single city on a station scale (Faghih-Imani and Eluru, 2016; Noland et al., 2016; Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani et al., 2014; Tran et al., 2015; Faghih-Imani et al., 2017; Mattson and Godavarthy, 2017). The modeling approach followed in most of the cases above can be summarized as a) the model estimation method used is mainly a linear regression using ordinary least squares (Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani et al., 2014, 2017; Mattson and Godavarthy, 2017); b) the dependent variable is the logarithm of the number or rates of arrivals and departures (Faghih-Imani and Eluru, 2016; Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani et al., 2017; Mattson and Godavarthy, 2017); c) the model assessment is usually performed using the indexes: log-likelihood (LL), R^2 and AIC–BIC.

Regarding the multiple–cities approach, Chardon et al. (2017) studied the trips per day per bicycle (TDB) in 75 SBBS systems in multiple cities worldwide. They used a robust regression to build the model with the logarithm of the TBD as the dependent variable. The resulting influencing variables were the operator's attributes, the compactness, the weather, the transportation infrastructure, as well as system–related characteristics, such as helmet requirement and the number of docks at stations. Faghih-Imani et al. (2017) aggregated arrivals and departures into an hourly interval in Barcelona and Seville into a Sub-City district level. They correlated the logarithm of the dependent variable linearly to sociodemographic variables and Points Of Interest (POIs) but considering both cities separately. Barcelona and Seville presented a similar pattern where the common influencing POIs were related to business, leisure, and restaurants.

On the other hand, considering a single–city approach, Tran et al. (2015) developed models for bike sharing in Lyon using weather stations, restaurants, cinemas and embankment roads, topography, among others. They also found that the population density showed a positive effect in the morning and the number of jobs had a positive impact in the afternoon. Faghih-Imani and Eluru (2016) correlated the hourly arrivals and departures for one month in the SBBS "CitiBike" in New York with temporal, spatial and weather variables. They concluded that the fit of the model improved significantly by adding temporally and spatially lagged dependent variables. The length of bicycle routes, the presence of subway stations, the area of parks on weekends, and the number of restaurants increased the usage of the system, while the length of railways decreased it.

Commonly, commuting and leisure activities are associated with bike sharing (Fishman et al., 2013). These activities are vastly related to the built environment. Thus, many studies (summarized in Table 6.1) have examined their relationship to bike sharing upon the transport infrastructure, POIs and the land use categories.

To the best of the authors' knowledge, there is no data–driven method to measure built environment variables by assigning them automatically different types of indicators as quantity in the area of influence of the stations or proximity to the stations. Contrary to Chardon et al. (2017), we analyzed multiple cities, but on a station scale. Also, instead of comparing the influencing factors of multiple cities (Faghih-Imani et al., 2017), we model the cities together. Finally, in the literature review, there was not a comparison of different linear and non–linear modeling techniques to define which technique fits better the bicycle usage and the influencing built environment.

6.3 Method

The proposed method aims at building models automatically in different temporal scales to identify the built environment variables that influence the historical rentals of SBBS systems in multiple cities. The method goes through three main components: 1) automated data collection, 2) automated data analysis and processing, and 3) automated model building and selection of the

Table 6.1: Most influencing built environment factors based on historical data

Category	Factor	Study A	B	C	D	E	F	G	H	I
Transport	Cycling infrastructure	✓	✓							
	Railways length		✓							
	Subway stations		✓	✓		✓		✓	✓	
	Rail stations							✓		
POIs	Universities					✓	✓			✓
	Student residence							✓		
	Restaurants		✓		✓		✓	✓		
	Cinema							✓		
	City center				✓		✓			
	Number of business				✓		✓		✓	
Land use	Parks		✓							
	Residential land use			✓						
	Parking land use			✓						
	Bodies of water				✓					

A: Chardon et al. (2017), B: Faghih-Imani and Eluru (2016), C: Noland et al. (2016), D: Wang et al. (2015), E: El-Assi et al. (2017), F: Faghih-Imani et al. (2014), G: Tran et al. (2015), H: Faghih-Imani et al. (2017), I: Mattson and Godavarthy (2017)

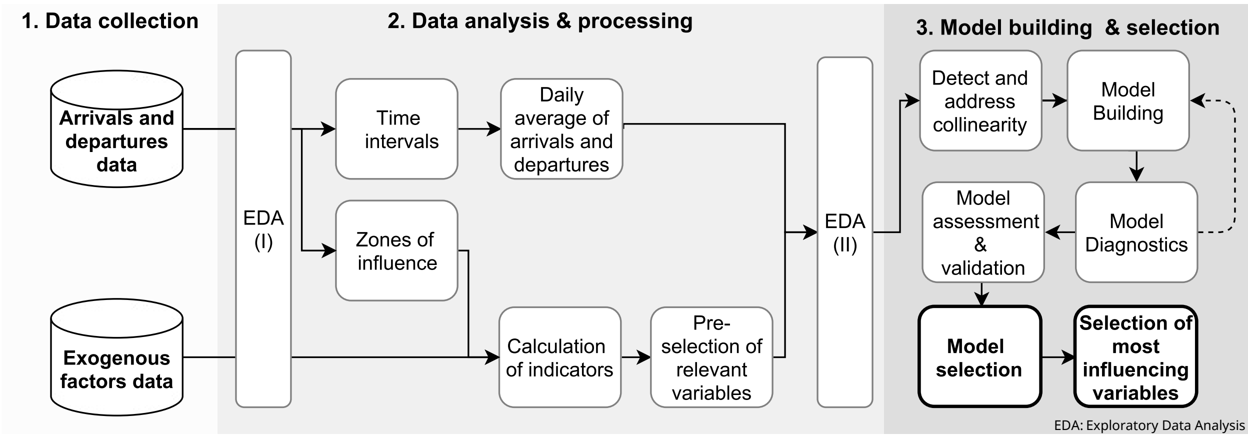


Figure 6.1: Methodological framework

modeling technique with the better fitting results, and automated selection of the most influencing variables (Figure 6.1).

6.3.1 Data collection, analysis, and processing

Data collection is performed on historical arrivals and departures from bike sharing systems (dependent variables) and the built environment (independent variables) in multiple cities. The independent variables are points, lines, and polygons of the built environment: e.g., POIs, public transport stations, railways, roadways, waterways, land use, and natural features.

– Ridership Data – An exploratory data analysis (EDA) of the historical ridership data (in terms of arrivals and departures to and from a station) is carried out to define time intervals to build models independent of time. This is performed to allow homogeneity in terms of dependent variables and to correct the effects of the time of the day. A clustering analysis is carried out to determine which days of the week illustrate significantly different ridership patterns. In each cluster, different periods are identified based on the hourly distribution of the rentals based on peak and off–peak times.

The cumulative ridership variable (dependent) and built environment variables (independent) are aggregated on a spatial scale, based on zones of influence. These zones are defined as the maximum area of influence that an individual is willing to walk to reach a bike-sharing station. Their boundaries are defined as the intersection of the Thiessen polygons of the stations, human-made and natural barriers and a buffer circumference from the stations representing the maximum walking distance [200 to 400 meters (Chardon et al., 2017; Noland et al., 2016; Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani et al., 2014; Tran et al., 2015; Schmöller and Bogenberger, 2014)] that a station can attract or produce.

– Built environment Data – Each built environment variable is assigned two indicators in each zone of influence: 1) proximity–based indicators (minimum distance from a station to the examined spatial feature inside the zone of influence), and 2) quantity or presence of the variable in a zone of influence. The selection of the appropriate type of indicator is decided based on some basic hypotheses. Let v be a random (independent) variable used to describe a particular built environment distribution across observations. Also, let σ_v represent its standard deviation (SD). A variable is defined as static if the SD is smaller than a threshold t ($\sigma_v < t$). Under the above hypotheses, indicators will be introduced in the model as dummy variables indicating "presence" rather than quantity. A sensitivity analysis is carried out to determine the value of the threshold of the SD. Only the variables that are present in all the cities of the study are considered. These variables are explored to exclude those presenting inconsistencies or irrelevant to the influence of bike sharing ridership.

Finally, Pearson and Spearman correlation tests are carried out to determine the variables that are collinear. If two variables are collinear, the variable that influences more the rentals is considered (multiple regression models are estimated).

6.3.2 Model building and selection

Model building and selection is based on a sequential model definition and model validation process. The aim pursued is to build linear and non–linear models to identify the models that better fit the dataset, while a) being parsimonious without a substantial loss of their fitting performance, b) avoiding over–fitting and c) including variable selection for computational efficiency, given a large number of independent variables. Mathematical transformations of the variables are considered to handle heteroscedasticity or non–linearity issues and to improve the models. Most common transformations are the square root, logarithmic, inverse (Bishara and Hittner, 2012), or Box-Cox transformation (Box and Cox, 1964).

– Model Structures – The model building techniques to be examined are stepwise Ordinary Least Square regression (stepwise OLS) (Chatterjee and Hadi, 2015), Generalized Linear Models (GLM) with a lasso selection technique (Tibshirani, 1996), and Gradient Boosting Machine (GBM) (Friedman, 2001).

Stepwise OLS is chosen based on its wide use in the pertinent literature for similar cases (Zhao et al., 2014; Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani et al., 2014, 2017; Mattson and Godavarthy, 2017). The core of stepwise OLS is the multiple linear regression, which is iteratively used to build a model using an observations vector Y that is linearly related to a matrix X (independent variables) and ϵ residuals [$Y = X \cdot \beta + \epsilon$] (Chatterjee and Hadi, 2015). Stepwise regression addresses the subset selection of a large number of k parameters. There are three types of stepwise selection procedures: 1) forward selection, 2) backward selection 3) both directions (Lin et al., 2011).

The forward selection initiates with only the constant term (i.e., no parameters) and adds variables based on a comparison criterion. The backward elimination process, in contrast, starts with a full equation and excludes the uncorrelated parameters. The stepwise method in both directions sequentially adds or deletes parameters. It starts with a forward selection, but at each step, it can remove a parameter. Its advantage is in the case that a non–significant parameter is included in the process, it might be eliminated later. The selection of the parameters is based on criteria to compare the regression in each step. Commonly used criteria are the Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC) (Chatterjee and Hadi, 2015). AIC (Akaike, 1973) is defined as:

$$AIC = n * ln(MSE) + 2 \cdot k \tag{6.1}$$

where n denotes the number of observations, MSE the mean squared error and k the number of parameters. A direct implication of using AIC is that for two models with the same error, AIC would penalize the one with more parameters. However, the use of AIC tends to improve with a larger number of k parameters, thus it is commonly accused of being prone to overfit models selection. BIC (Schwarz, 1978) tends to control the overfitting of AIC. It is proportional to AIC but it uses a logarithmic factor for the effect that the number of variables has:

$$BIC = n * ln(MSE) + ln(n) \cdot k \tag{6.2}$$

GLM are an extension of OLS based on the maximum likelihood estimation. GLM assume that the error ϵ presents a distribution from the exponential family, such as binomial, Poisson, Gaussian. Also, they consider the mean function μ_i as a function of the linear observations $[h(\mu_i) = \beta_0 + \beta_1 x_{i1} + \beta_1 x_{i1} + ... + \beta_1 x_{ik}$ where, $h(\mu_i)$ is a function that links μ_i with the observation $Y_i]$ (Chatterjee and Hadi, 2015). The least absolute shrinkage and selection operator (lasso) technique (Tibshirani, 1996) shrinks the coefficients β increasing stability while retaining the best variables. Lasso assumes that X_ij are standardized with a mean of zero and a $SD = 1$. Then, it minimizes the sum of the squared differences between the observation and the linear regression $[\hat{\beta}_{lasso} = argmin_{\beta}(\sum_{i=1}^{n}(Y_i - \beta_0 - \sum_{j=1}^{k} X_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{k} |\beta_j|)]$. The selection of λ is calculated after a cross-validation test to select the λ that presents the smallest error (Lin et al., 2011).

GBM is a machine learning algorithm that performs regression, classification, and ranking (Friedman, 2001). It is a mix of boosting and gradient steepest descent. Boosting is a procedure to reduce the variance of a model. It involves the creation of multiple B training sets. Then, it builds a prediction for each training set $\hat{f}^1(x), \hat{f}^2(x), ..., \hat{f}^B(x)$ and it fits different decision trees to each copy. Each tree is a modified version of the original data set, and they grow sequentially by using the information of the previously grown tree. The residuals are fit to the decision tree, rather than a single decision tree to the data. We choose the sample data that modeled poorly in the system before, i.e., in areas where the system is not performing well. Then, the residuals are updated after adding the new decision tree into the fit function. Finally, it combines all the trees to create a single model. A faster approximation to find the model is to consider a differentiable loss criterion that can be derived by numerical optimization. Regarding the loss function, a Gaussian function is used for numerical efficiency to minimize the squared error and the Laplace for minimizing the absolute error.

GBM is considered in the study because the dataset might fit better in a nonlinear model. It uses the input arguments: loss function, number of iterations, terminal nodes of each tree and shrinkage factor (Friedman et al., 2001). A sensitivity analysis has to be carried out to determine these values. In addition to the resulting model, GBM provides a ranking list of the variables with their relative influence normalized to sum one hundred. To carry out a variable selection from the ranking list, mean square errors (MSEs) are calculated starting from highest ranked variable and then adding a subsequent variable until a non–significant difference of the MSE is present. GLM and GBM have shown high fitting performance in similar applications in the literature, e.g., (Willing et al., 2017).

Model building is carried out with a training set and the model validation with a testing set for each time unit and for the linear and non–linear regression models. After the models are built, two types of criteria are used to assess them: a) Indirect methods: lowest number of predictors, lowest Mean Square Error (MSE), lowest BIC, and greatest goodness of fit measures (R^2 and adjusted R^2 - R^2_{adj}); and b) Best validation results: selection of the model that adequately predicts the arrivals and departures on a validation dataset.

6.4 Application

The data–driven method was applied in two cases: 1) national level in six German cities and 2) international level in Hamburg, Montreal and Chicago. The national level application provides evidence on the applicability and performance of the different model structures and estimation techniques, allowing for a more comprehensive evaluation of the impact that different techniques have to the identification of the factors affecting ridership. Germany has been used as the national case, due to the bike sharing fleet (fifth largest fleet in the world; approx. 12,000 shared bicycles) (Meddin and DeMaio, 2020) and data availability. The international level application builds on the first application and focuses on the extraction of conclusions for the application of the methods in an international comparison.

6.4.1 Multiple National Cities approach

This approach includes six German cities for the SBBS system "Call a bike" (Deutsche Bahn AG, 2017): Hamburg, Frankfurt am Main, Stuttgart, Kassel, Darmstadt, and Marburg. Arrivals and departures of the bicycles were downloaded from the Open–Data–Portal offered by the German train company (Deutsche Bahn) under the link: `data.deutschebahn.com/dataset/data-call-a-bike` in June 2017. The dataset included the rentals in fifty cities in Germany for approximately 3.5 years. The majority of the data, however, referred to the six selected cities, because of their high usage of bike sharing (>250,000 rentals in total, around 3.5 GB of raw data).

In total, 10.5 million rentals were included in the dataset referring to the period between 01.01.2014 and 15.05.2017 (1232 days). Around 73% of the rentals referred to the city of Hamburg, followed by Frankfurt with 12%. Peaks were identified in the summertime (May to July). It is worth mentioning that Wednesdays and Thursdays showed the highest ridership, which was found to decrease during the weekends. Regarding the hourly distribution, there was a different trend between workdays and weekends (Figure 6.2). In workdays, there were two peak periods at 8:00 and at 17:00 (based on the median values). Figure 6.3 shows the spatial distribution of the intensity of the rentals. Each area represents the frequency of a station with the help of Voronoi Diagrams for better visualization.

– Data analysis and processing – The rentals were clustered into days of the week using Pearson correlation analysis. The three resulting clusters were workdays, Saturdays, and Sundays. Arrivals and departures were aggregated into time intervals representing peak and off–peak periods in the morning, afternoon and night (Figure 6.2). The built environment variables were downloaded from the collaborative open–source dataset OpenStreetMaps (OpenStreetMap-contributors, 2017). Unclassified roads and a selection of variables, which were found to be inaccurately positioned or irrelevant, were excluded (e.g., vending machines, wastebaskets). The distance to the city center was also considered as a built environment variable since it was present in the literature review.

For the zones of influence, a 300m buffer ratio was used as it is the most common value used in the literature. Four indicators were assigned to around 200 types of spatial features (around **800** spatial variables). A threshold value selected of $SD = 5$ was selected after a sensitivity analysis to determine if the indicator of a variable is related to the quantity or presence. A total of

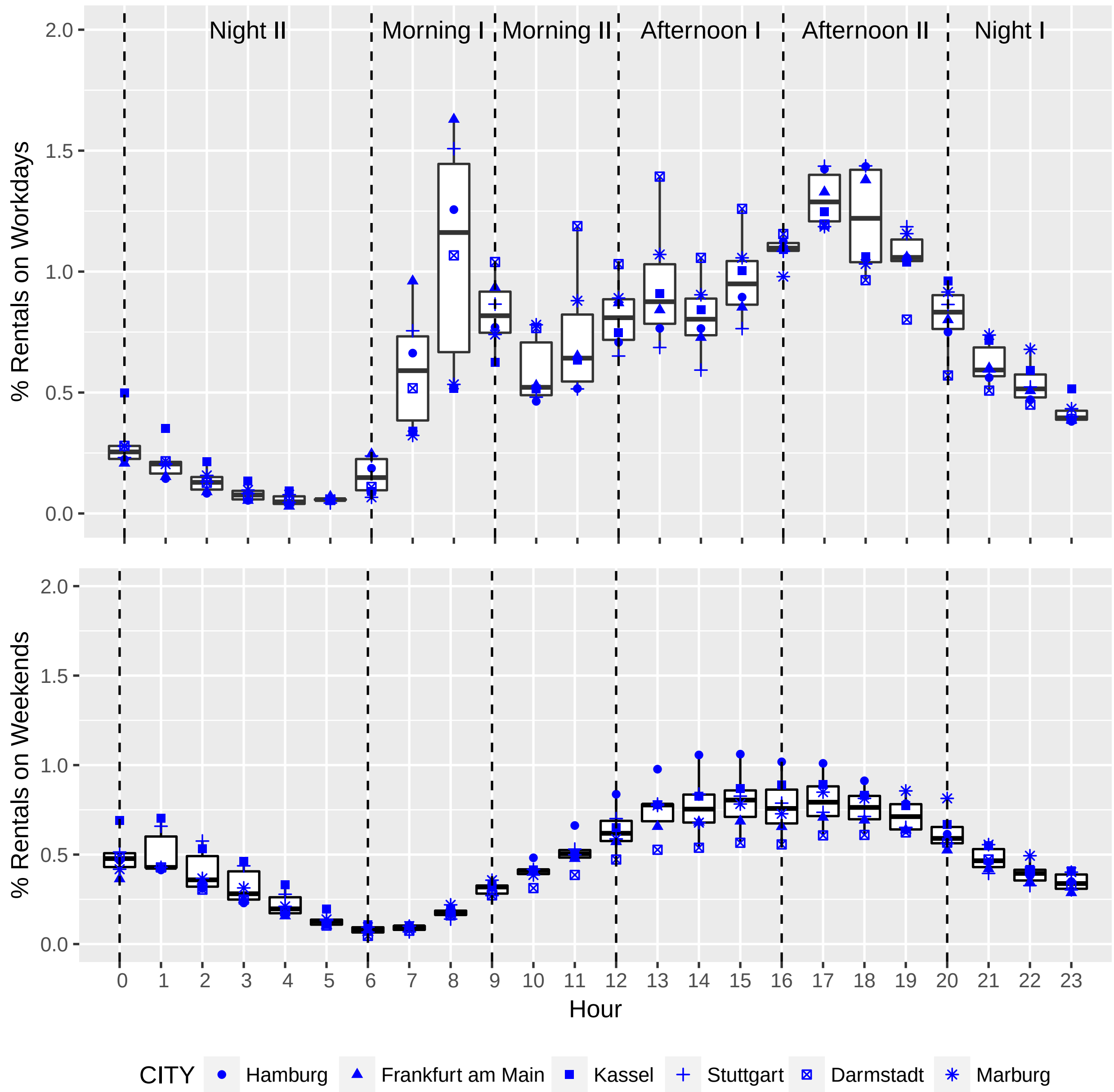


Figure 6.2: Hourly distribution and definition of times intervals

194 variables were examined with **144** non–collinear variables to be selected after Pearson and Spearman correlation tests. A correlation threshold value of 0.7 was considered as explained in Zhao et al. (2014).

– Model building, diagnosis and validation – Aiming at examining applicability and performance of the different model structures and estimation techniques, all methods discussed in the Methods section were used (OLS, GLM with lasso and GBM). In all cases, the relationship between arrivals and departures to 144 non–collinear built environment variables was examined. The city population was used to weight ridership (for different cities' sizes) (Statistisches Bundesamt, 2012). Apart from model fitting and model diagnostics, model validation was performed by dividing ridership data into a training set including the zone of influence of 5 cities and a testing set of one city's zone. Validation was performed on a city level (and not using a random sample of zones) to examine how well the models would perform in a German city without a bike-sharing sys-

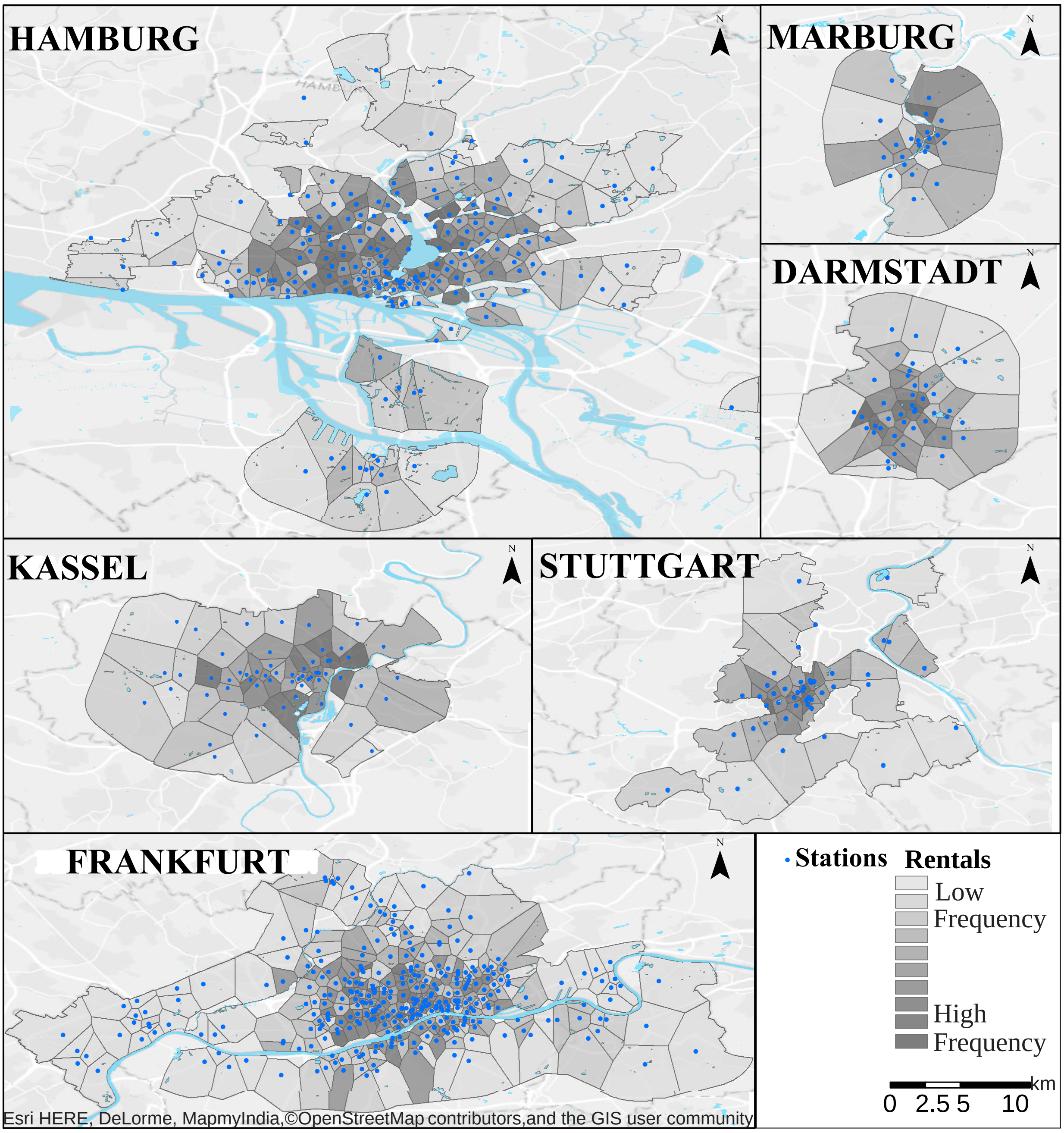


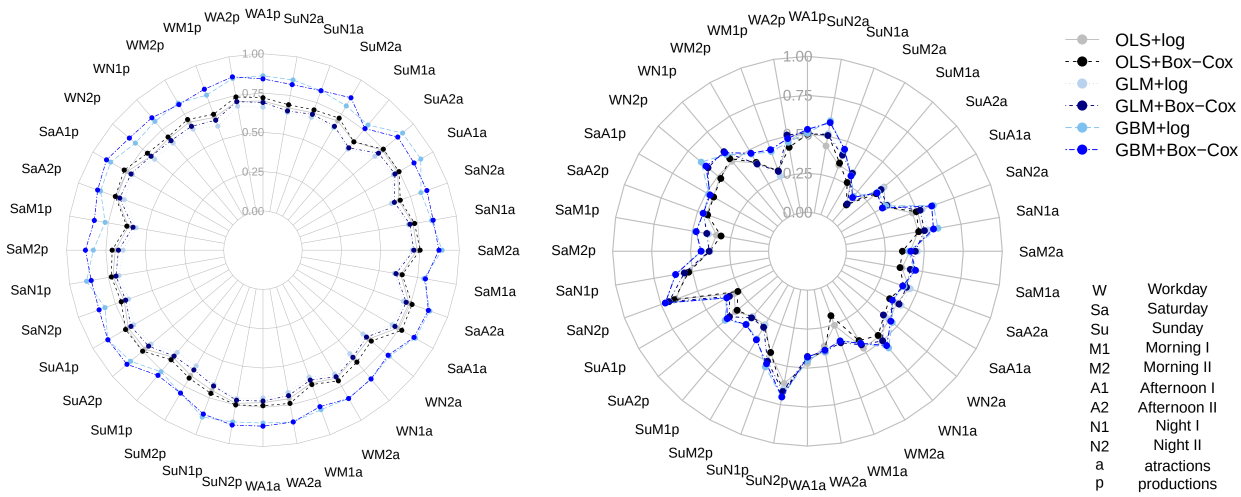
Figure 6.3: Spatial rentals distribution in cities of the study

tem. The city of Kassel was chosen for validation due to its high ridership. Hamburg and Frankfurt were not considered because they involved together around 76% of the zones of influence.

Stepwise OLS was considered in both directions, while BIC was chosen as a selection criterion. For GLM with lasso models, a Gaussian distribution was considered because it fit better the training data. A k–folds cross–validation (James et al., 2013) was implemented to calculate the shrinkage factor that helped the models to fit better the data. Concerning GBM, K–fold cross–validation was realized to find the better number of trees or iterations with an input of 5 folds, a shrinkage factor of 0.0001, and an interaction depth of 6. The presence of heteroscedasticity and nonnormality in stepwise OLS and GLM led to the selection of logarithmic and Box-Cox transformations. Although these properties were not identified using GBM, the transformations were also carried out for matters of completeness. Outliers analysis was performed that indicated that zones with zero arrivals and departures should be removed.

In total 324 models were built, considering arrivals and departures for three cases (workday, Saturday, Sunday), 6 time intervals (morning, afternoon and night at peak and off–peak periods), 3 regression modeling techniques (stepwise OLS, GLM, GBM) and 3 transformation techniques (no transformation, logarithmic and Box-Cox).

Regarding the parsimony the models, stepwise OLS selected the fewest number of variables with an average in all temporal scales of 15.55 variables, followed by GLM with 26.13 and finally, GBM with 39.90. According to the fitting results in the training cities (Figure 6.4a), R^2adj in the three regression methods trend together over different time periods. This indicates a rather indifference to time goodness-of-fit. Between the regression techniques, GBM usually presented higher R^2adj values. According to the validation performed with the city of Kassel, (Figure 6.4b) shows a slight difference between the R^2 values of different regression techniques, but there was a significant difference according to the time. Afternoons and nights showed the highest performances, especially during the weekends. Finally, in all cases, a logarithmic and a Box-Cox transformation illustrated a better goodness-of-fit with the logarithmic transformation to be slightly better.



(b) R^2 for validation case

(a) R^2 adjusted from fit models

Figure 6.4: Comparison of the R^2 adjusted from the fit values of different models

Based on the above results, we also performed cross-validation, by dividing ridership data in a training set of 5 cities' zones and a test set of one city's zone, for the case of GBM with a logarithmic transformation. Hamburg and Frankfurt were excluded from this analysis since they represent the majority of the zones of influence. The results presented in Figure 6.5 illustrate a rather high performance in most cases, with workdays to have less variation of the validation scores than on weekends. The city of Stuttgart, as a testing set, was the only case that showed a better performance than the city of Kassel.

– Factors Affecting Bike Sharing – Aiming at constructing an overview of the factors found to affect ridership, the occurrence of parameters in all model structures were used. Figure 6.6 presents the most often selected variables by the regression techniques per time interval. Darker color indicates higher selection frequency. The most repetitive variables are the city population, the distance to the city center, bakeries, bicycle parking, memorials, residential areas and car sharing stations.

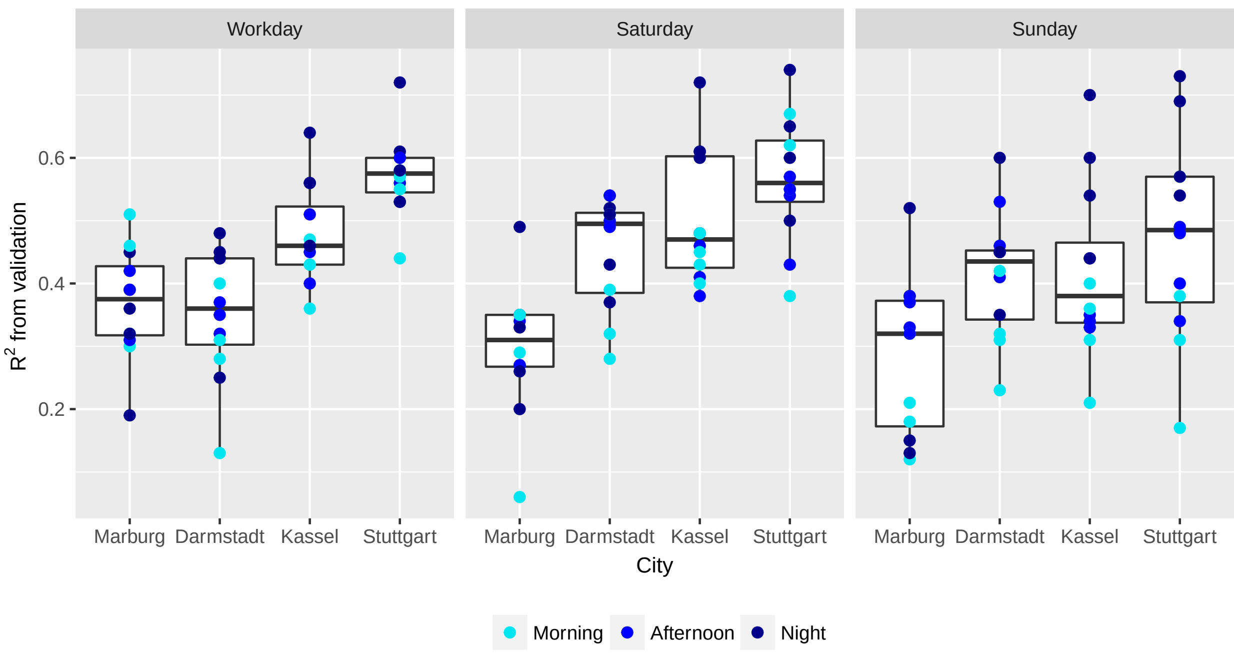


Figure 6.5: R^2 from validation by testing other cities (GBM with log transformation)

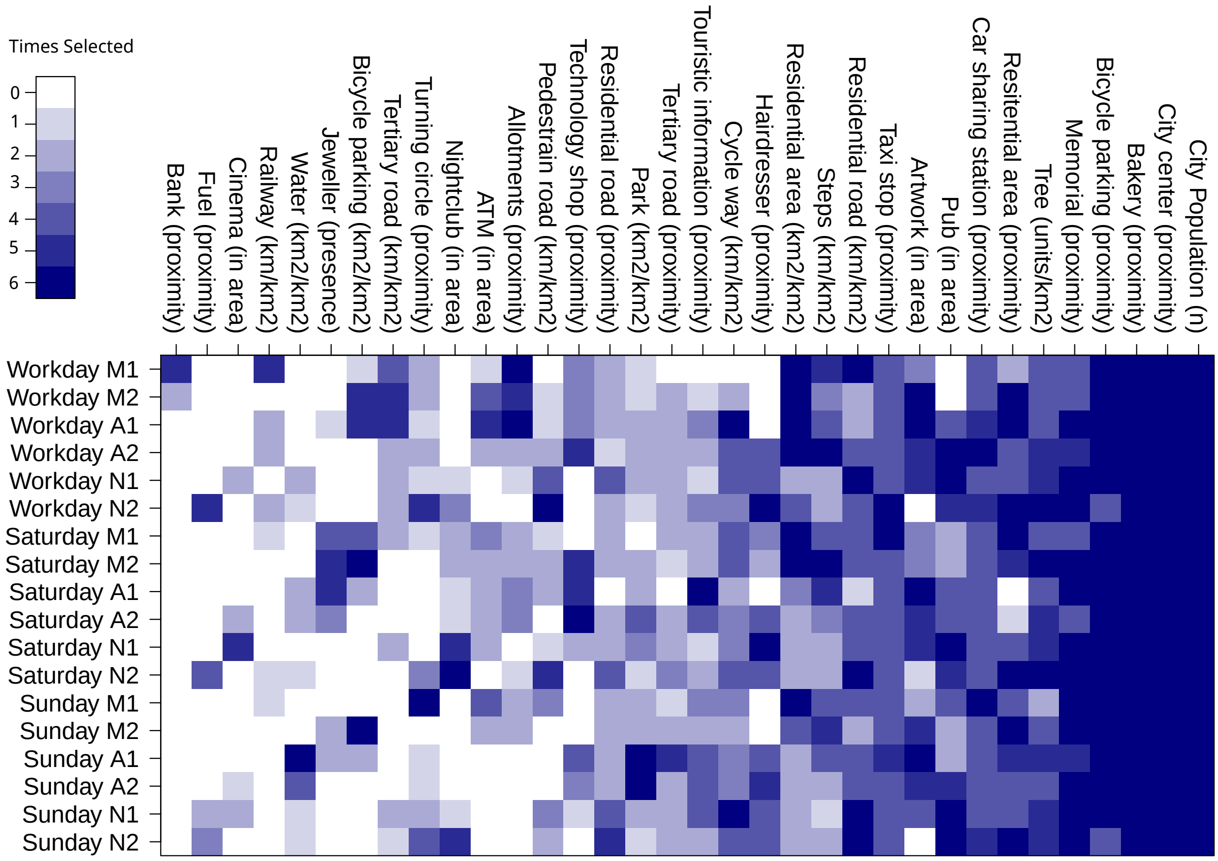


Figure 6.6: Repetitive outcome variables influencing the arrivals using the modeling techniques after logarithmic and Box-Cox transformations

6.4.2 Multiple international cities approach

The international application focused on the SBBS systems *"Call a Bike"* in Hamburg (www.callabike-interaktiv.de/de/staedte/hamburg), *"Divvy"* in Chicago (www.divvybikes.com) and *"Bixi"* in Montreal (montreal.bixi.com). The main objectives of this application were the exploration of model transferability and the extraction of conclusions for the application of the methods for different city structures on an international level.

These three cities where chosen since they share common characteristics as representative cities in their countries with a border limited by a body of water. However, in terms of population, Montreal and Hamburg have relatively same number of inhabitants, but Chicago has around one million more inhabitants. Thus, we are referring to mainly large cities, with a rather high population that could have different travel characteristics and ridership patterns. As a consequence, the analysis was performed from the beginning guiding a somewhat different modeling and validation approach.

Bixi-Montreal data (BIXI-MONTREAL, 2017) was collected from April 2014 until November 2017 with a data size of 734 MB in 545 stations. Divvy system works with 585 stations, where 1.75 GB data (Bikes, 2018) was collected from June 2013 until December 2017. Finally, 2.5 GB of Call a bike rentals were collected in Hamburg from April 2014 until May 2017 in 207 stations (Deutsche Bahn (DB), 2017).

– Data analysis, and processing – The approach followed for the data analysis and processing was the same as the one for the national case, with the exception that the rentals data were aggregated at an additional seasonal level. The seasonality was added to analyze its effect on the resulting models. Chicago presented 9.93 rentals per day interval per station, while Hamburg 24.59 and Montreal 16.47. Figure 6.7 shows the distribution of rentals per day interval in Chicago, Hamburg, and Montreal. These three cities present a relatively similar distribution with an exception on the day interval "Morning I" on weekends. Figure 6.8 illustrates some examples of the spatial distribution of the rentals per time interval. It shows higher ridership close to bodies of water. Concerning independent variables, **154** built environment variables were present in the three examined cities following the procedure as in the national approach, where finally **113** non-collinear variables were considered for the modeling procedure.

– Model building, validation and variables selection – Stepwise OLS with a logarithmic transformation was used for the model building. The choice of using only one method was based on the computational time required to estimate all models and because in the national application it was the most parsimonious method while preserving relatively good fitting results. 72 models were built (one for each of four seasons, six day intervals, and workdays, Saturdays, and Sundays). On validation, we considered an alternative approach of the national case study by training 70% of the stations, and 30% for validation, without taking into account the cities boundaries.

Model fitting and validation scores for Hamburg, Chicago an Montreal are shown in Figure 6.9. R^2adj resulted of 0.68 as an average in the 72 models, and 0.63 as a R^2 score in the testing process. We run five times the model building as a cross-validation process, where the R^2 from the validation varied on average around the third decimal. The lower validation results were during mornings on the weekends during all seasons, while higher values were associated with summer and winter.

As an example of the resulting influencing factors in summer and winter on workdays, Figure 6.10 presents the t-scores of the resulting models. On average 18.5 variables where selected per model. The most common selected variables were the population and the proximity to colleges and marina areas, bus stations, restaurants and cafes. Land use influencing ridership was mainly residential and parks.

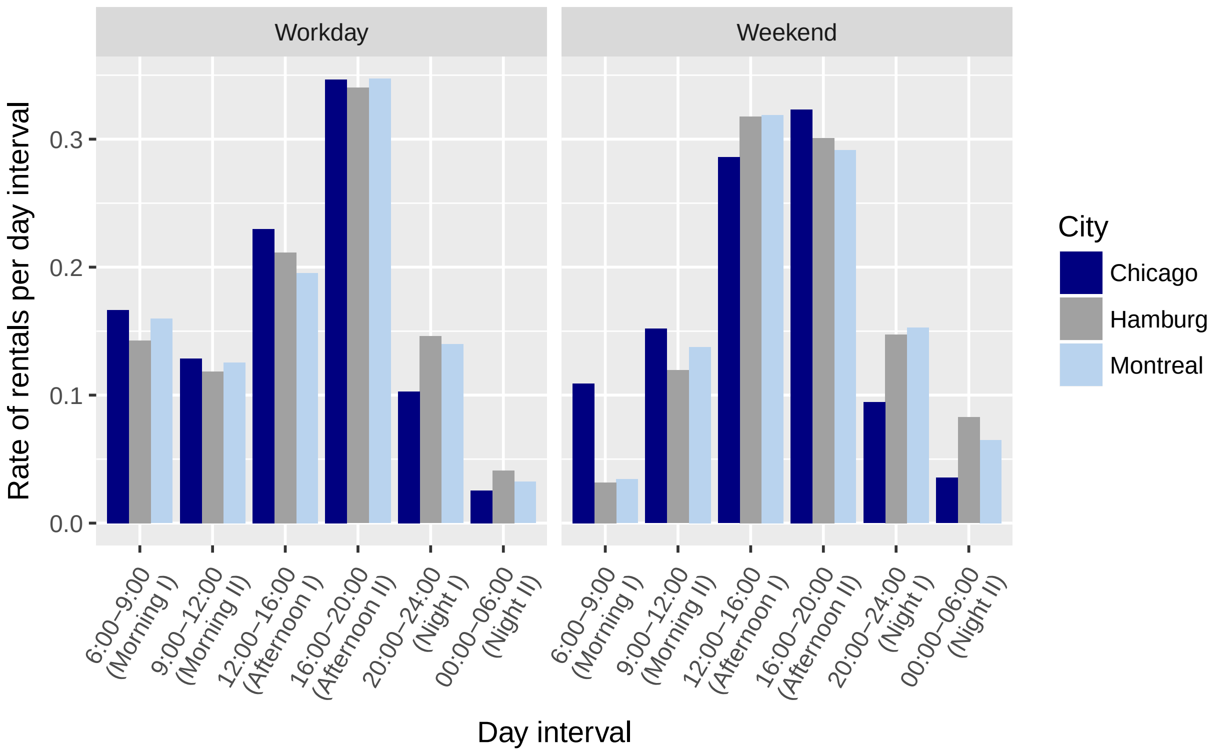


Figure 6.7: Distribution of rentals per day interval in Chicago, Hamburg and Montreal

6.5 Discussion

A data–driven method using exclusively open-source data was applied in two case studies considering multiple cities in a national and an international level. From around 800 possible built environment variables, the 144 most relevant and non-collinear variables were selected for the model building for the national approach, while 113 were selected for the international approach.

Concerning model applicability, linear and non-linear modeling techniques were tested in the national approach. GBM was the regression method that best fit the data, followed by GLM. GLM and GBM required cross–validation tests to select the input arguments that helped to build models. However, stepwise OLS was parsimonious with fewer input arguments, and its results were easier to interpret. The three modeling techniques presented similar validation results. Logarithmic and Box-Cox transformations helped the models to predict better the arrivals and departures and to select logical variables that would influence the shared bicycles ridership. Generally, for the three regression methods, the logarithmic transformation performed a higher R^2 in the validation phase.

The advantage of stepwise OLS and GLM was that a variable selection process was implicit in the methods, but for GBM a variable selection process had to be developed to select those with more influence from the ranking list. The most influencing variables in all of the built models and through all time intervals were the population of the city and the distance from the city center (old town) to the stations. The population of the city helped to weight the models to have a common scale that was not biased if the city was large like Hamburg or small like Marburg. The distance to the city center played a significant role for ridership as seen in Figure 6.3. The third most influencing variable is the distance to bakeries. If a station is close to a bakery, this increases the probability of higher ridership at that station.

In all developed models, several selected variables were logically correlated to bike sharing ridership, were similar to literature review findings (Table 6.1), and they were coherent on the authors' expectations in influencing the arrivals and departures of bike sharing. For instance, the most influencing variables are related to leisure activities, parks, green areas, and bodies of

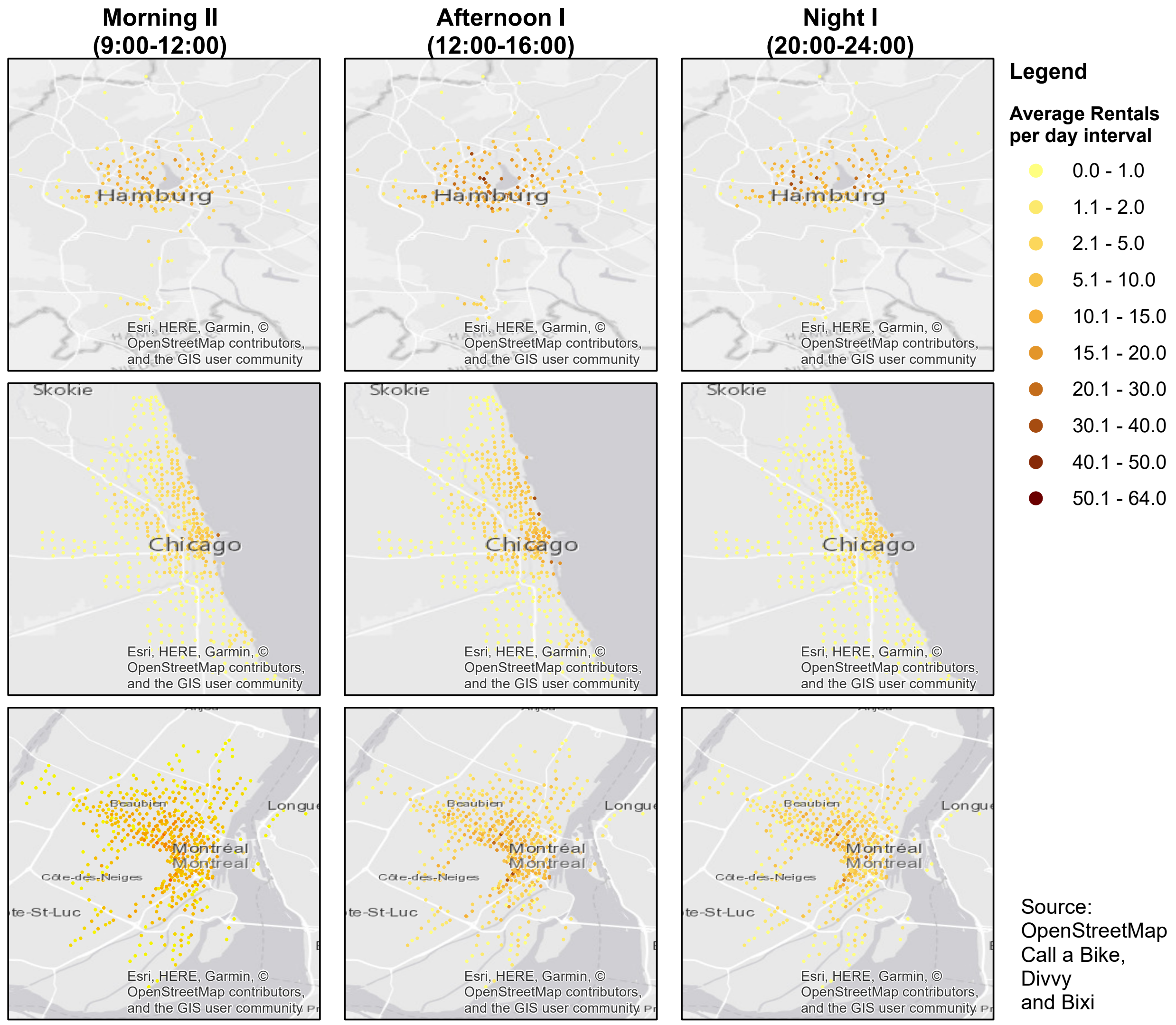


Figure 6.8: Spatial distribution of rentals per day interval in Chicago, Hamburg and Montreal

water on the weekends, banks in the morning, gas stations, pubs, cinemas, clubs at night, shops on Saturdays, and memorials outside of working hours. Just a few transport–related variables significantly influenced the models. Distance to a car sharing station was significant for all time intervals as well as bicycle parking. With regards to public transport, railway stations were found significant for the German case for workday mornings, while for the international case, distance to bus stations was identified as an highly influencing factor. This discrepancy might be related to the fact that tram and metro variables were not considered, because they were not present in most of the studied cities (at least for the German case). However, there is a strong indication that public transport plays an important role, which should be further investigated in the future.

According to the international approach, stepwise OLS with a logarithmic transformation was chosen after the benefits identified in the national approach. On average, 18.5 variables were selected per model. Urban structure was found to play an important role based on the distance from all stations to the marina and colleges and also land use represented by residential area and parks. Summer and winter presented different factors, for example, bakeries, bus stations, and restaurants were more significant in summer than in winter. Logical variables were present as the influence of bar and railway station in summer night or colleges influencing negatively at night. An important observation is a correlation with car sharing stations during the night representing a possible correlation between car and bike sharing.

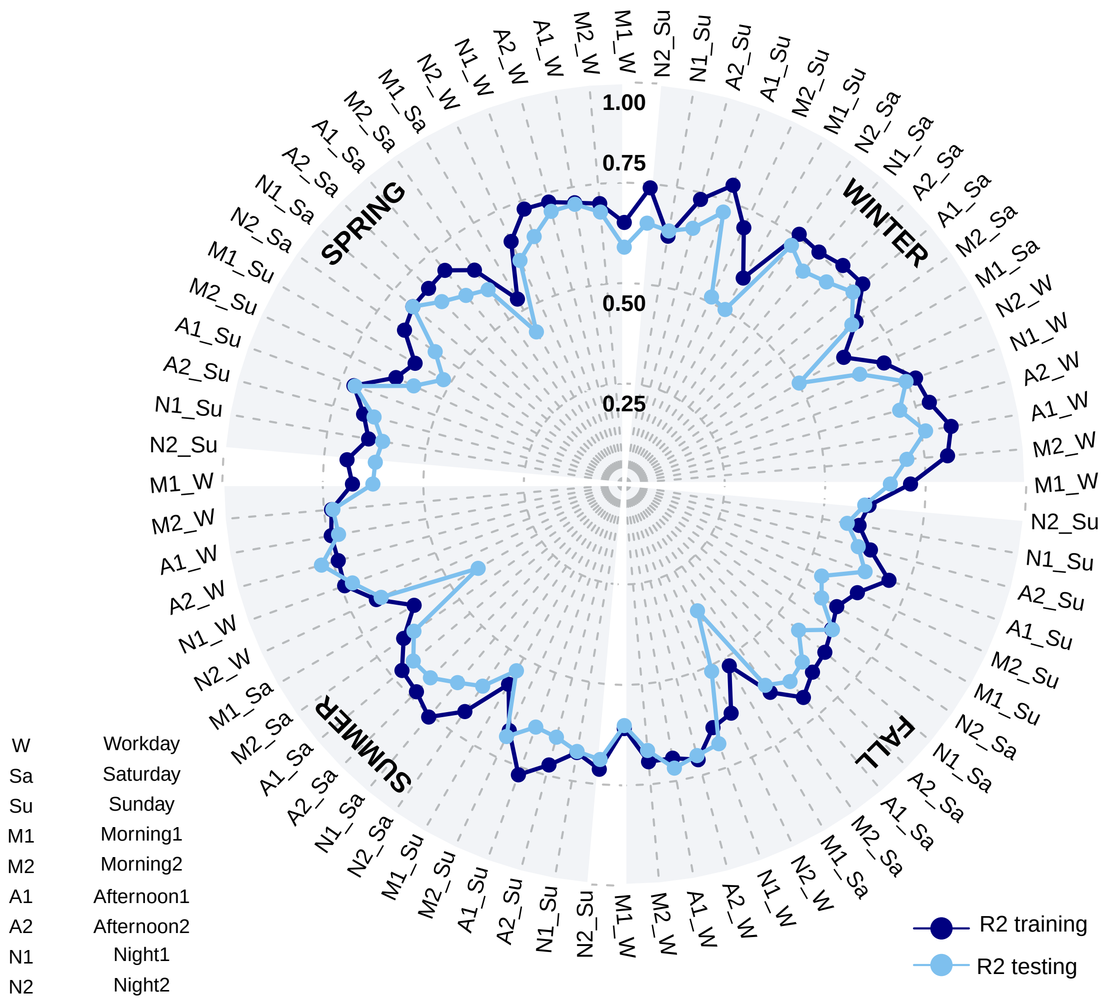


Figure 6.9: Model fitting and validation scores for Hamburg, Chicago and Montreal (70% of the total stations for training)

Both approaches showed that the modeling validation results were correlated to the hourly ridership distribution. Similar relative ridership hourly distribution was associated with higher scores. For example, in the international approach in morning on weekends showed the most different distribution between the cities (Figure 6.7), presenting the worst modeling performance. On the other hand, in the national approach, the models that fit better the data were in the afternoon and at night where the different cities showed smaller variance in the bike sharing usage (Figure 6.2). Also, in these time periods, models presented better results from the validation and illustrated a more logical selection of variables that influenced ridership. Also, on weekends the rate of ridership distribution was more similar between the cities than on the workdays (Figure 6.2) showing higher validation results. Finally, it was found that the modeling results did not depend on the size of the cities but on the similarity of the distribution of the rate of rentals.

6.6 Conclusions

To the best of the authors' knowledge, this is the first study that analyzes factors affecting bike sharing systems ridership on a local level in multiple cities. The resulting influencing factors are not only based on one city but beyond the geographic boundaries, which will help to use the resulting models to forecast the bike sharing usage in a different city. A data–driven method was

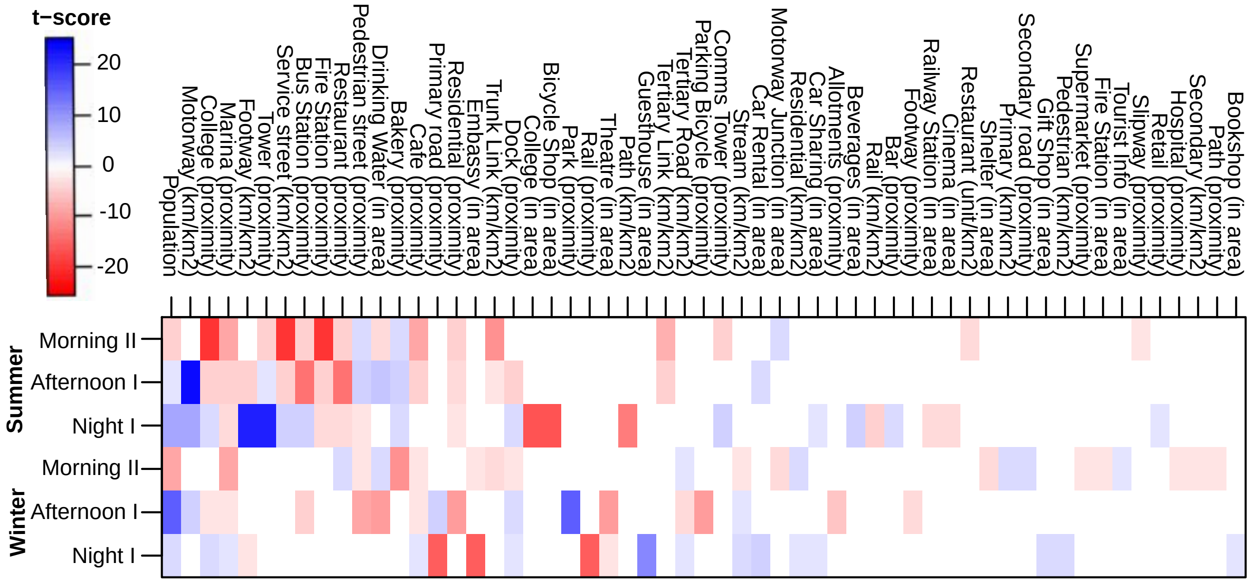


Figure 6.10: Example of t-scores for the international approach (Workdays)

developed to analyze the influence of the built environment in the rentals of station–based bike sharing systems in multiple cities. An original approach was considered by modeling different cities with different sizes in two case studies 1) on a national level and 2) on an international level.

GBM with a logarithmic transformation of the dependent variables were found to validate slightly better the dataset. Stepwise OLS and a logarithmic transformation of the dependent variables was found to select fewer variables than other models without decreasing the validation results significantly. In Germany, the most influencing variables selected were the city population, the distance from the stations to the city center, bakeries, memorials, car sharing stations, among others. Logical relationships between the variables with the historical bike sharing rentals over time intervals were displayed, such as higher arrivals on nights close to pubs, cinemas, and nightclubs; or the presence of bodies of water, parks or green areas on Sundays. On an international level, the distance to the marina and colleges played an important role. Different influencing factors were present between different seasons.

With a wider implementation of such an analysis, transport planners will have available a method that would help them to understand the factors that affect ridership of bike sharing systems, and thus, ease and optimize the setting of coverage areas and placing stations where they may be most successful. This method can also show the validity and increase the reliability of measures, policies, and shared mobility projects. Although the focus of this work was to investigate built environment variables, improvements and expansion of the case of study are envisioned to include other possible influencing spatial variables found in the literature (e.g., topography, population density, parking regulations, traffic congestion, etc.) to enhance the model performance.

Chapter 7

Demand And/oR Equity (DARE) Method to Plan Bike-sharing Systems

This chapter has been published in Duran-Rodas, D., Wright, B., Pereira, F. C., & Wulfhorst, G. (2021). Demand And/oR Equity (DARE) method for planning bike-sharing. Transportation Research Part D: Transport and Environment, 97, 102914. https://doi.org/10.1016/j.trd.2021.102914

Most bike-sharing systems in cities aim to maximize demand, an approach that tends to inadvertently favor wealthier neighborhoods. Therefore, we developed a heuristic and data-mining-based method to weigh both Demand And/oR Equity (DARE) in the station distribution and allocation process of planning bike-sharing. Equity is measured using a deprivation index and the potential demand is estimated using structural equation models via the built and social environment. The DARE method was applied first to the BSS service area in Munich, Germany, and then, to the area surrounding Munich, demonstrating the method's transferability. Incorporating equity resulted in disadvantaged areas being better served by bike-sharing stations while favoring ridership (demand) tended to cluster stations in the wealthier city center. This method allows decision-makers to build scenarios for allocating infrastructure based on their desired fairness criterion, and can also be applied to other shared modes or public transport.

7.1 Introduction

Bike-sharing systems (BSS) can provide an opportunity to access cycling regardless of a person's purchasing power (Lucas, 2019). However, "most bike share schemes were never designed with equity or social justice in mind . . . [but] designed around environmental and economic goals intended to stimulate urban renewal" (de Chardon, 2019; Hoffmann, 2016)[p.410]. BSS studies have shown inequality in the implementation, usage, and benefits across demographics. The common profile of a BSS user in the Global North tends to be a young white male, who is highly educated, higher income, already engaged with cycling, and has access to bank accounts and credit cards (Fishman et al., 2015; Ogilvie and Goodman, 2012; McNeil et al., 2017; Stöckle et al., 2020; Mooney et al., 2019). Historically, the distribution of stations and the service areas have been focused on central and densely populated regions, (Fishman et al., 2015; Duran-Rodas et al., 2019b; Chen et al., 2019) where residents tend to reflect BSS user profile (Chen et al., 2019; Ursaki and Aultman-Hall, 2015; Mooney et al., 2019). Deprived and low-income areas are reported to have less access to BSS infrastructure (Ursaki and Aultman-Hall, 2015; Mooney et al., 2019; Ogilvie and Goodman, 2012; Smith et al., 2015), even though many BSS promote themselves as being equitable (Duran-Rodas et al., 2020b).

Are BSS planned fairly? Justice involves rules that are based on a shared understanding of morality among individuals in a global, cultural, or circumstantial context (Goldman and Cropanzano, 2015; Leventhal, 1980). *"Fairness"* is a subjective judgment that varies depending on whether justice rules are applied or not (Goldman and Cropanzano, 2015). What is fair for one person may not be fair for other people (Goldman and Cropanzano, 2015; Duran-Rodas et al., 2020a). Distribution of a particular resource is considered as fair when the distribution meets criteria that certain individuals believe is fair (Leventhal, 1980). The most common criteria for the spatial distribution of resources are: a) spatial equality or horizontal equity (equal distribution of resources), b) spatial equity or vertical equity (distribution according to people's needs in terms of social status, opportunities, and abilities), c) spatial efficiency (distribution according to the people's ability to contribute or access resources) (Leventhal, 1980; Talen, 1998; Duran-Rodas et al., 2020a). These distribution criteria are *"fair"* depending on the point of view of each individual (Duran-Rodas et al., 2020a).

We identified three gaps in the existing research on the fair allocation of stations and service area boundaries. First, only a few studies have considered equity as an input for planning BSS, such as Caggiani et al. (2020). Previous systematic planning methods for BSS have not prioritized infrastructure distribution according to the neediest populations in terms of social status and opportunities. The second research gap is that in systematic methods, the opportunity to balance efficiency and equity has not been deeply explored. Finally, the third research gap is the failure to account for confounding variables when estimating BSS ridership (spatial efficiency) and its associated spatial factors. Exploring causality can increase the generalization and transferability of the model (Thakkar, 2020). Usually, linear regressions are performed by learning from historical trips using spatial factors from the built and social environment. However, with linear regressions, we cannot detect confounding variables. For instance, an increase in population density has a high probability of generating an increase in the number of trips. However, the relationship between population density and ridership is not causal: trips are not caused because of the number of people but rather their need for mobility to perform activities (Wegener and Fürst, 1999).

To address the lack of spatial equity criteria in planning the distribution of BSS infrastructure, we aim to develop a heuristic and fairness-based method in which the fairness criteria for the distribution of stations and service areas can be chosen depending on the desired focus: spatial equity as represented by deprivation, spatial efficiency represented by the potential ridership, or a balance of both. Based on these criteria, and accounting for limited resources, the method ranks zones of analysis based on four heuristic algorithms to prioritize the allocation of infrastructure. The resulting allocation is then assessed based on the resulting coverage area and density.

We applied this method to the hybrid bike-sharing system (HBSS) in Munich, Germany. Testing a hybrid system was advantageous because HBSS are rarely studied in the literature. Additionally, since HBSS have characteristics of both docked and dockless systems, our method can be implemented with those types of BSS as well.

The second contribution of this study is the estimation of potential ridership as an indicator of spatial efficiency using Structural Equation Models (SEMs) To train SEMs, the paper will also build a theoretical structure of links between BSS ridership and its previously associated spatial factors from the built and social environment. This structure will be shaped by merging two theoretical models: a) "land-use and transport interactions" that includes the factors from the built environment (Wegener and Fürst, 2004; Wulfhorst, 2003), and b) "urban mobility cultures" that includes factors from the social environment (Kuhnimhof and Wulfhorst, 2013; Deffner et al., 2006; Klinger et al., 2013).

This paper continues with a literature review of BSS concepts and previously used methods to plan BSS and estimate potential ridership demand. Hence, it presents the DARE (Demand And/oR Equity) method followed by the results of its application. Finally, it discusses the strengths, limitations, and possible future applications for this method.

7.2 Literature review

7.2.1 Bike-sharing: overview

BSS are programs in which people can pick up a bike and drop it off in the public space within a service area (Büttner and Petersen, 2011; Toole Design Group, 2012). BSS have the potential to improve access to cycling and its benefits as a healthy and convenient transport mode, enhance last-mile connections to transit, increase transport resilience, help build support for future cycling initiatives, and change attitudes towards cyclists (Cohen and Shaheen, 2018; Shaheen et al., 2014; Teixeira and Lopes, 2020; Manca et al., 2019; de Chardon, 2019; Bauman et al., 2017). BSS can also reduce CO2 emissions in a city, depending on the balancing system of bicycles and their ability to replace trips that would otherwise be made by private motorized vehicles (Ricci, 2015). However, BSS have also faced some challenges. For example, improper sizing and distribution of stations can lead to areas that are over- or under-supplied with bicycles (McNeil et al., 2017; Li et al., 2019; Sun, 2018; Ma et al., 2018). The sustainability of BSS can also be compromised by the massive amounts of waste that are generated when bicycles are no longer used (de Chardon, 2019), or by the emissions of the rebalancing and maintenance operations (Ricci, 2015). Projected health benefits can also be overstated when bike-sharing trips replace walking or private cycling trips that provide comparable health benefits (Ricci, 2015; de Chardon, 2019; Bauman et al., 2017).

BSS include conventional bicycles, cargo, tandem, or e-bikes in three types of systems: a) docked or station-based, b) dockless or free-floating, and c) hybrid, a mix of docked and dockless (HBSS) (Shaheen et al., 2020). Docked systems have the advantage of designated parking and easy-to-locate bikes. On the other hand, dockless systems have lower capital costs, a more flexible service area, and provide greater convenience to users since the trip can end anywhere in the service area. However, dockless systems can also be more difficult for users to locate a bike nearby and require more effort for operators to rebalance the fleet (Shaheen et al., 2020). If not carefully monitored, bikes can accumulate in one area and improperly parked bikes may conflict with pedestrians, especially those with limited mobility. Analysis of social media sites such as Twitter reveal that people often complain about piles of dockless bikes encountered in certain areas (Duran-Rodas et al., 2020b). However, Brown et al. (2020) performed a systematic observation of parking behavior of different transport means including bike-sharing, and concluded that only 0.3% of the bikes presented conflicts with pedestrians. Hybrid systems share advantages of dockless and docked systems (Yanocha et al., 2018) but have not been studied in great depth. Therefore, we aimed to develop a method that would help to plan these systems.

7.2.2 Bike-sharing: planning process

According to guidelines in North America and Europe, four "macro" steps are commonly used for planning BSS (Yanocha et al., 2018; Gauthier et al., 2014; Anaya Boig and para la Diversificación y Ahorro de la Energía, 2007; Büttner and Petersen, 2011; Toole Design Group, 2012): I) set goals, II) estimate the potential demand and potential bike-sharing users, III) define the potential location of stations and service area, and IV) fix the locations (Figure 7.1).

The planning process of BSS (Figure 7.1) often starts with the definition of the system's goals (e.g. mobility, sustainability, equity). Next, historical data from systems in comparable cities are used to build potential demand models. The potential station locations and service area boundaries are defined using design inputs such as budget, rebalancing method and strategies, and key performance metrics (e.g. stations density, number of bicycles). BSS guidelines recommend preparing a "first draft" of the design and then adjusting it based on-site visits and stakeholder involvement (Gauthier et al., 2014). If potential sites are not accepted or cannot support BSS stations, new sites should be identified until suitable locations are found. Should a system change its goals, expand, or relocate to a new area, the process begins anew. The goals of BSS could be potentially modified when systems do not fulfill the requirement of, for example, expected ridership,

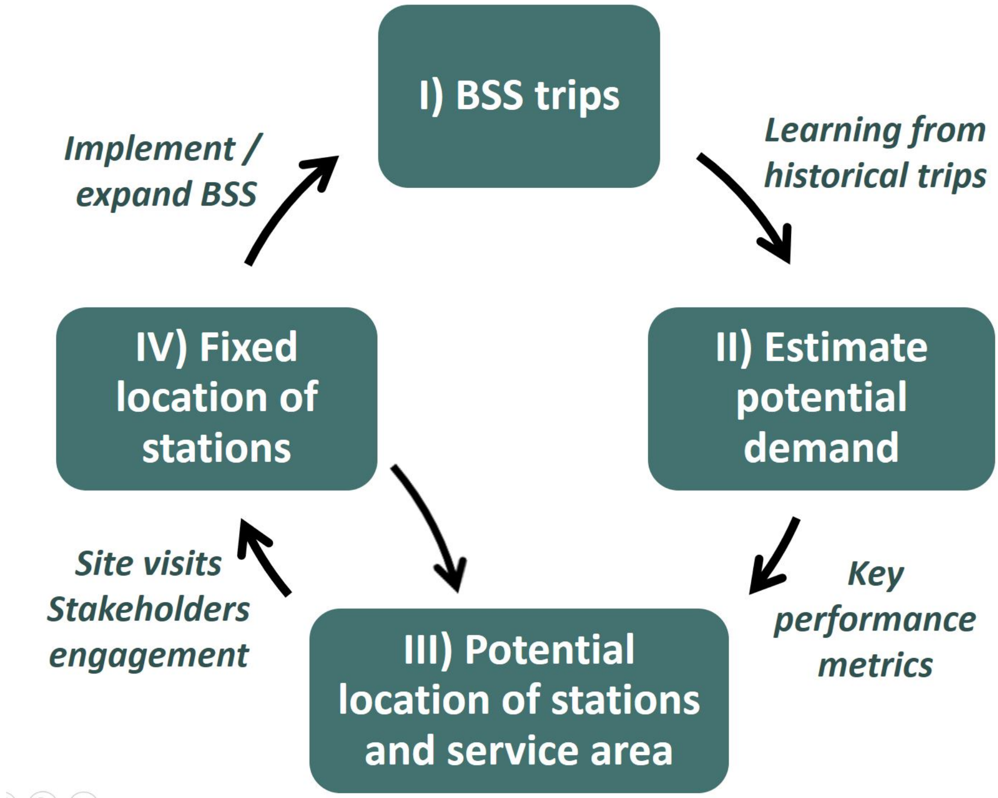


Figure 7.1: Typical planning cycle for BSS

service, or equity. Therefore, assessing inequity in a system, as in previous studies (Ogilvie and Goodman, 2012; McNeil et al., 2017; Fishman et al., 2015), can justify changing a system's goals and looking for new locations of stations or service areas in a more equitable way.

7.2.3 Bike-sharing: estimation of potential demand

Past research has studied how the spatial factors are associated with the historical trips of BSS to estimate the potential demand. Some common spatial factors that have been studied are shown in Table 7.1. These factors can be classified into three main components: 1) social environment, 2) mobility behavior, and 3) built environment. In this table, "Guidelines" refer to the spatial factors for which design guidance suggests that BSS stations should be allocated according to. "User-based" are studies which have identified factors associated with usage without a spatial level (e.g. surveys), while "spatial studies" have preformed a spatial analysis. Guidelines are commonly in line with spatial studies. Socio-demographics have rarely been included in spatial studies, in contrast with built environment factors. The social environment factors most associated with ridership are population and employment density, while the most common built environment factors are transit stations and cycling infrastructure, leisure, and student-oriented activities.

Ordinary least squares models have been one of the most frequently implemented techniques to build potential demand models and identify the most influential factors on BSS ridership (Duran-Rodas et al., 2019a; Faghih-Imani et al., 2014; El-Assi et al., 2017; Wang et al., 2015; Faghih-Imani et al., 2017; Mattson and Godavarthy, 2017; Zhao et al., 2014). Other approaches have performed robust linear regression (Chardon et al., 2017; Tran et al., 2015) and negative binomial regression (Noland et al., 2016), among others. The dependent variable in these studies is typically the logarithm of the number of bicycles' rentals or returns in an area or station (Wang et al., 2015; El-Assi et al., 2017; Faghih-Imani and Eluru, 2016). Although Ranaiefar and Rixey (2016) built SEMs for predicting potential ridership for BSS, a limitation of all these studies is that causal relationships

Table 7.1: Influential factors on bike-sharing ridership: literature review

Factors			Guideline				User-based studies		Spatial studies			
			A	B	C	D	E	F	G	H	I	J
Social environment	**Population**	City population	✓	✓	✓				✓			
		Population density	✓	✓		✓				✓	✓	
	Socio-Demography	Employment density				✓			✓		✓	
		Age					✓	✓				
		Gender						✓		✓		
		Household income					✓	✓				
		Household size					✓			✓		
		Education level					✓					
Mobility Behaivor	Mode to commute (work/school)		✓		✓		✓					
	Time / distance to commute						✓					
	Bicycle ownership							✓				
	Cycling propose							✓				
	Driver license ownership							✓				
	Already combine cycling and PT							✓				
Built environment	**Topography**	Slope (max 4%)	✓			✓						
		Altitude							✓	✓		
	Urban Structure	Distance to city center	✓	✓				✓			✓	
		Accessibility		✓	✓			✓				
		Mixed use land use	✓	✓								✓
		Industrial land use		✓								
		Single land use		✓								
		Residential land use										✓
		Commercial activity				✓						
	Transport infrastructure	PT stops	✓	✓	✓	✓						
		Metro									✓	✓
		Railway station							✓			
		Major roads									✓	
		Streets									✓	
		Embankment road							✓			
		Transport POIs								✓		
		Cycling infrastructure	✓	✓	✓	✓					✓	
	POIs	Student residence							✓			
		Cinema							✓			
		Worship POIs								✓		
		Hotel								✓		
		Restaurant							✓	✓	✓	
		Universities	✓			✓					✓	
		Parks		✓								
		Sports Centers	✓									
		Recreation POIs								✓		
		Tourist attractions				✓						

A: Anaya Boig and para la Diversificación y Ahorro de la Energía (2007), B: Gauthier et al. (2014), C: Büttner and Petersen (2011), D: Toole Design Group (2012) , E: Efthymiou et al. (2013), F: Bachand-Marleau et al. (2012), G: Tran et al. (2015), H: Faghih-Imani et al. (2017), I: Faghih-Imani et al. (2014), J:Noland et al. (2016)

between factors were not examined.

– Milieus as a spatial indicator of the social environment – In the application of the study's method, milieus were considered the spatial factors representing the social environment for estimating the potential demand. Milieus are groups of like-minded people concerning the social status and core values (INTEGRAL, 2018). Milieu clusters categorize socio-spatial characteristics including people's attitudes, values, lifestyles, etc. (Markt, 2017). They represent an approximation of perceptions and lifestyle orientations in this study. This categorization, therefore, expands on traditional social demographics by considering core values. Milieus have been tested for market segmentation in "leading manufacturers of branded goods and well-known service providers from politics, media, and associations as well as advertising and media agencies" (Markt, 2017).

This additional inclusion of core values of the inhabitants (e.g., tradition, adventure, modernization) is the main advantage for using milieus for the sociodemographic analysis. Milieus also help overcome the limitation of the so-called "sociodemographic twins" (Sociovision, 2018) where areas with the same sociodemographic parameters are expected to behave similarly. The prominent orientation or values helped to further categorize and further divide the social environment and better understand the social environment of an area. In a previous study, values were even found to have a higher correlation with BSS use than traditional sociodemographics (Duran-Rodas et al., 2020a)).

As an example of the application of using milieus in the transport sector, potential buyers for two luxurious automobile brands were identified: BMW vs Rolls-Royce. BMW autos were preferred by adaptive navigators, whose goal was to show their financial situation and improve their social position. On the other hand, Rolls-Royce targeted exclusivity rather than mass production, which was attractive to more traditional and rich people, or the established milieu (König, 2017). Furthermore, milieus have been used in transport research e.g. for agent-based modeling (Schwarz and Ernst, 2009; Jensen et al., 2016), multi-agent simulation (Soboll et al., 2011), marketing research (Diaz-Bone, 2004), as well as for understanding social changes (Manderscheid and Tröndle, 2008) and mobility preferences (Von Jens, 2018; Sinus Markt und Sozialforschung GmbH, 2019).

7.2.4 Bike-sharing: methods for searching the potential location of stations

Gavalas et al. (2016) summarized four types of algorithm approaches for determining optimal station locations:

1. *Integer programming-based approaches* take into account BSS' historical trips to optimize the level of service and costs (travel, operation, infrastructure) to identify the optimal location of stations (Lin and Yang, 2011; Sun et al., 2019; Caggiani et al., 2018; Reiss and Bogenberger, 2015).

2. *Heuristic approaches* use (meta)heuristic techniques that search for the near-optimal solution. Cintrano et al. (2020) use five meta-heuristic techniques to solve the p-median problem (minimize the distance to stations to all points). Also, Lin et al. (2013) developed a heuristic method for station location based on costs for both users and operators.

3. *GIS-based approaches* are developed using geographic information systems tools. For instance, Banerjee et al. (2020) calculated a bike station suitability score using GIS tools. Another example is García-Palomares et al. (2012), who used a GIS-based methodology to develop a heuristic approach, locating stations by minimizing impedance (p-median), and maximizing coverage based on the density of spatial features associated with BSS ridership.

4. *Data mining-based approaches* use data to discover knowledge to plan BSS. Gehrke and Welch (2019) clustered existing stations based on built environment factors. Every candidate station was classified into five different groups on a suitability spectrum. In a similar approach, Vogel et al. (2011) proposed to plan BSS by clustering stations based on the bicycles' pick-ups and drop-offs and then correlated them to their most common geographical information.

Most of these techniques share a common approach of learning from historical trips to estimate potential demand, locate stations, and define the service area. However, techniques that learn from unfair systems are likely to perpetuate the same systematic inequities. Our proposed approach provides an opportunity to target equity and thereby break an unfair planning cycle.

7.2.5 Bike-sharing: Overcoming inequalities

Including spatial equity when planning BSS can lead to a reduction in social disparities and social exclusion (Fainstein, 2009), resulting in less social conflict and more social peace (Tomlinson, 2016). Providing access to those who have the greatest needs can allow them to participate in new transport trends. Even though lower-income neighborhoods with BSS supply have shown low usage Caspi and Noland (2019), a high level of fairness perceived by the population can reduce resistance towards implementation, increase project consent, or generate greater political acceptance (Ariely and Uslaner, 2017; Wüstenhagen et al., 2007). Moreover, prioritizing the neediest does not mean that a project is not serving those that contribute the most. Those most in need have the potential to be customers when provided with information and incentives (Hoe, 2015).

Commonly, when BSS include a goal of equity, access is improved in these two ways: a) reducing barriers to entry into the system, and b) improving physical access to the infrastructure in underprivileged areas. Yanocha et al. (2018) recommended reducing barriers to entry into the system for ensuring equity in BSS, such as higher accessibility for people with different abilities, affordable pricing, or renting mechanisms that do not require smartphones or credit cards. For example, in Philadelphia, fees can be paid with cash at local convenience stores, or in Boston, residents classified as "low-income" only pay an annual fee of 5 U.S. dollars Yanocha et al. (2018). Moreover, system fleets have included adaptive bicycles such as electric bikes and standard trikes for people with less physical abilities (MacArthur et al., 2020). Regarding the access to infrastructure, in Philadelphia, extra stations were placed after considering the income levels and public participation in the planning (Hoe, 2015).In New York, one system has concentrated shared bicycles in low-income communities that have low access to transit (Kodransky and Lewenstein, 2014).

Only a few studies have incorporated equity-based concepts in the planning cycle (Figure 7.1) of BSS. Conrow et al. (2018) optimized the distribution of stations by minimizing the average distance to stations in the service area and maximizing the potential demand. While this approach is referred to as equitable, it does not prioritize the neediest population. Therefore, according to our definitions, this study targeted spatial equality. In a similar approach, Caggiani et al. (2020) optimized the location of stations by minimizing walking distances to access the system and distributing a similar number of bicycles in all the districts of the city. To the best of the authors' knowledge, Caggiani et al. (2017) is the only study that systematically considers the concept of spatial equity by including the neediest population when planning BSS. They develop an allocation method that prioritizes areas with greater underprivileged populations using a bike equity index. The system cost was also made more equitable by funding the implementation of dockless BSS in deprived areas using toll payments collected in other areas.

After reviewing the literature, we aim to develop a heuristic fairness-based method for planning BSS that would incorporate spatial fairness criteria according to its targeted goals. Thus, our method employs a mixed approach of heuristics, data-mining, and equity criteria to develop the "first draft" of station locations and service area boundaries. As described above, previous studies and applications have considered equity in the sitting of stations by prioritizing lower-income neighborhoods or increasing coverage areas. In this study, we expanded the spatial equity concept of underprivileged by including areas with poor access to basic opportunities (e.g. health, food, education). Since resources are limited and stations or service areas cannot be placed everywhere, we developed a method called Demand And/oR Equity (DARE) to build scenarios for station locations and coverage areas. This method provides an opportunity to balance the priorities of serving underprivileged areas and serving areas with high potential ridership with an alternative to balance the priority in underprivileged areas and also areas where it is expected to be high ridership.

7.3 Demand And/oR Equity (DARE) method for planning bike-sharing systems

Demand And/oR Equity (DARE) is a heuristic-based method for planning the allocation of BSS stations and their service area based on spatial fairness. Spatial fairness summarizes three criteria for transport supply allocation: spatial equity, efficiency, and equality (Leventhal, 1980; Talen, 1998; Duran-Rodas et al., 2020a). Spatial equity has a broad justice focus and it refers to a spatial distribution of resources that prioritizes areas where people have the greatest need in terms of social status, opportunities or abilities. For example, if spatial equity alone were to be considered in the distribution of BSS's infrastructure, the allocation would be exclusively in underprivileged areas. Hence, people in these areas could not cycle to privileged areas as the city center. Spatial efficiency has a narrow concept of justice, focusing on the allocation of resources to maximize ridership. If spatial efficiency is considered, underprivileged areas might be excluded from access to the system. It should be emphasized that this study incorporates distribution according to (estimated) effective demand or ridership into spatial efficiency. It is inferred that effective demand occurs when people can "contribute", or have an ability to access or pay a mobility system. Another way of defining spatial efficiency is a distribution of public resources favoring those who pay more taxes, in other words, those who "contribute" the most. Spatial equality is related to the equal distribution of resources regardless of need or potential ridership. It is achieved when spatial resources are evenly distributed across an area, i.e., resources are not specifically prioritized in any area and all areas receive the same amount of resources. Spatial equality was not considered in this approach because resources are limited and the difficulty of evaluating and compensating equally each individual's access to resources.

The primary goal of DARE is to create scenarios in which stations are located and service areas are bounded based on the preferred fairness criteria for design: spatial equity, spatial efficiency, or a balance of both. In general, DARE divides a study area into analysis zones (ZAs). In each of these zones, indicators of spatial equity and spatial efficiency are calculated. Then, the zones are ranked by their weighted combination of spatial equity and spatial efficiency. Finally, these scenarios are evaluated based on the resulting coverage and density of infrastructure. Specifically, DARE includes the following seven main steps (Figure 7.2).

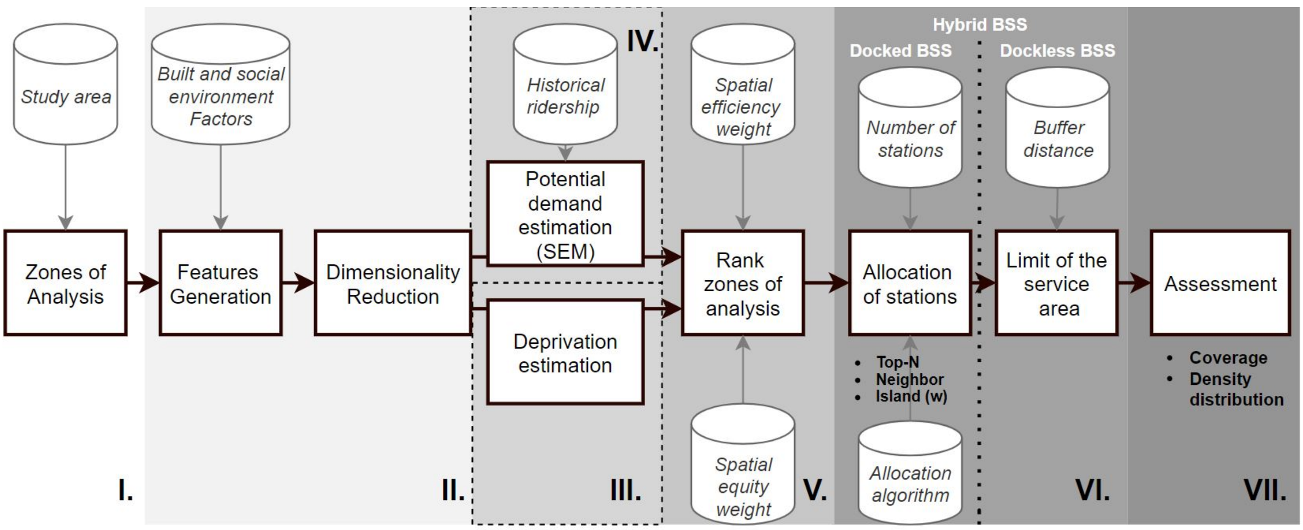


Figure 7.2: DARE method procedure

7.3.1 Choosing a study area and defining zones of analysis.

The first step in the DARE method is to select a study area which is further divided into a training area with an existing BSS and an implementation area with similar characteristics where bike share will be added or modified. Historical data from the training area is then used to build a ridership model with which to estimate behavior in the implementation area. The learning area and the implementation area are each subdivided into zones of analysis (ZAs), which define the spatial resolution of the results.

The shape of the ZAs is typically determined by administrative boundaries, such as neighborhoods (Cintrano et al., 2020; Mooney et al., 2019), districts (Caggiani et al., 2020), traffic zones (Caggiani et al., 2017) census blocks (Frade and Ribeiro, 2015), buffer radius from candidate stations (Chen et al., 2015; García-Palomares et al., 2012), demand-based delimitation (Reiss and Bogenberger, 2015), grid-based hexagons (Albiński et al., 2018), squares (Lin et al., 2020) or road network-based (Noland et al., 2016). Of these, road network-based delimitation is recommended because it best aligns with natural cycling barriers such as buildings, highways, railways, and water bodies.

The distance for delimiting the areas ($Dmin$) determines the size of the ZAs and it should be based on desired station density or the maximum distance that a user is willing to walk to access the system. Distances ranging from 200 to 400 meters are commonly used in previous research (Tran et al., 2015; Chardon et al., 2017; Duran-Rodas et al., 2019b; Wang et al., 2015; Noland et al., 2016; Faghih-Imani et al., 2014; El-Assi et al., 2017; Chen et al., 2015; García-Palomares et al., 2012; Caggiani et al., 2020). According to Kabra et al. (2019), most BSS ridership originates within 300 meters of stations, and it is the recommended value in guidelines (Yanocha et al., 2018) and in Banerjee et al. (2020).

7.3.2 Spatial data collection, feature generation & dimensionality reduction

Three main types of spatial data must be collected: 1) historical BSS trips, including the time and location of rentals' origins and destinations, station locations, and service area boundaries, 2) built environment data (e.g. transport infrastructure, POIs), and 3) social environment (e.g. transport's mode choice, milieu, sociodemographics).

The spatial data for each ZA may be represented in different types of units. In this approach, spatial data types can be represented in terms of 1) feature density for each spatial unit, 2) feature percentage by category within each ZA, or 3) walking accessibility from the centroid of the ZA, which is measured with the exponential cost function (Geurs and Van Wee, 2004):

$$A_{ij} = min(e^{-\beta c_{ij}}), \ \ j = 1, 2, 3, ...n_{op} \tag{7.1}$$

where A_{ij} is the walking accessibility, defined as the lowest cost to access n_{op} opportunities of category j in ZA_i, c_{ij} is the travel cost from the centroid of ZA_i to the opportunities, and β is a cost sensitivity parameter. Equation 7.1 assumes that the effect of an opportunity on the zone's accessibility to the centroid diminishes as the distance from the zone centroid increases (Geurs and Van Wee, 2004).

Multicollinearity might be present between variables of the same category. For instance, the density of cafes in a ZA may be highly correlated with the density of restaurants. Therefore, we used a hierarchical agglomerative clustering method (HC) for dimensionality reduction to group highly associated variables belonging to the same category. HC represents the dissimilarities between the different types of variables using a distance matrix (Everitt et al., 2011). Initially, each variable is distinct. Then, each variable is clustered to its closest neighbor, with the distance being estimated using linkage methods (Everitt et al., 2011). This procedure continues iteratively until there is only one cluster. We used HC because the results are plotted as dendrograms, which helped visualize which variables clusters should be included in the model.

7.3.3 Estimating the neediest population in terms of opportunities and social status

After creating ZAs and collecting the spatial data, the next step is estimating the neediest population in terms of opportunities and social status. This need is based on access to opportunities and social status demographics and is calculated using a deprivation index for each zone of analysis. The Deprivation Index (DI) is an indicator of how deprived and unprivileged a ZA is (Duran-Rodas et al., 2020a) and is adapted from the concept of deprivation defined by Townsend (1987)): "a state of observable and demonstrable disadvantage". Based on this concept, we calculated this index using the percentage of the underprivileged population (e.g. migration background, low-level education, low income, and manual occupations), such as in Messer et al. (2006); Eibner and Sturm (2006); Pampalon et al. (2012), as well as the level of access to basic opportunities (e.g. groceries, healthcare, public transportation). An example of how access to basic opportunities influences deprivation is provided by Pearce et al. (2007) who correlated deprived areas to those with less access to healthy food. Therefore, our formulation of the deprivation index includes the average walking accessibility to basic opportunities (Geurs and Van Wee, 2004; Büttner et al., 2018) (Equation 7.2).

$$DI_i = \frac{UP_i}{1/n_B \sum_{k=1}^{n_B} A_{ik}} \tag{7.2}$$

where DI_i is the deprivation index of ZA_i, UP_i is the percentage of the underprivileged population, A_{ik} is the walking accessibility to the k basic opportunity, and n_B is the number total types of basic opportunities considered in the study. Thus, a high deprivation index represents an area of a greater underprivileged population and/or limited access to basic opportunities.

7.3.4 Estimating the potential demand

As described in the literature review, different regression methods can be used to estimate potential demand in each zone of analysis. The recommended variable for potential demand is the density of arrivals in a zone of analysis. Arrivals are often more closely correlated with spatial factors than departures are. Table 7.1 showed examples of the various factors in the built and social environment that are associated with the potential demand for BSS.

We chose Structural Equation Models (SEMs) as the regression method to estimate the density of bike arrivals for each zone. SEMs help to predict behavior using multiple types of variables and searches for causal relationships, which improves the generalization and transferability of the model (Thakkar, 2020). SEMs are multi-equation frameworks applied to a multivariate problem to understand the interactions between dependent and independent variables in a system using one causal network (Lefcheck, 2016; Grace and Keeley, 2006). The result accounts for "the roles of the multiple factors in a single analysis" and separates the direct effects from the indirect effects (Grace and Keeley, 2006). Every hypothesis of a causal relationship is represented by a linear model in which every path is the coefficient of the regression. Therefore, SEMs help to mitigate the impact of potential multicollinearity between the built and social environment.

When using SEMs, it is important to consider that they are linear models having a constant distribution of the error term for all observations. To normalize the distribution and increase the data fit of the model, non-linear transformation techniques can be used, such as square root, logarithmic (Bishara and Hittner, 2012), or box-cox (Box and Cox, 1964). The first variable to be included in the model is the one having the highest correlation with BSS ridership, followed by the one with the second-highest correlation, and so on. Variables that neither improve the goodness of fit (CFI>0.9) nor help reduce the poorness of fit (RMSEA<0.1) (Hooper et al., 2008) of the model are omitted. Randomness in the fitting process of both techniques is mitigated by modeling with a training data-set and validating with a testing set (Natekin and Knoll, 2013). Moreover, we performed cross-validation with k-folds as a re-sampling procedure of the training and test sets in order to control biased results.

7.3.5 Ranking the zones of analysis

The most important design input for DARE is the weights (from 0 to 1) that are applied to efficiency and/or equity. These weights are the heart of the fairness-based method. They are set based on the preferred fairness allocation criteria of the decision makers, planners, stakeholders, or politicians developing the system and steer the allocation of infrastructure for the BSS being implemented, expanded, or restructured.

Efficiency is related to the estimated demand and equity is based on the deprivation index. A weight of 0 for efficiency means an allocation that prioritizes deprived areas, whereas a weight of 0 for equity prioritizes areas with higher estimated BSS usage. Both weights range from 0 to 1, subject to $Eq_w + Ef_w = 1$. $Eq_w = 1$ signifies consideration of equity alone, whereas $Ef_w = 1$ means only efficiency is considered.

After estimating the potential demand and DI for each ZA and assigning the respective weights for spatial efficiency and equity, we calculated the rank index (RI). RI is an indicator for each ZA that orders and prioritizes the allocation of stations in each ZA. RI is defined in Equation 7.3:

$$RI_i = scale(DI_i) * Eq_w + scale(PD_i) * Ef_w \tag{7.3}$$

where RI is the rank index in ZA_i, Eq_w and Ef_w are the equity and efficiency weights respectively, DI_i is the scaled value of the deprivation index in each ZA_i, and PD_i of the estimated potential ridership. DI_i and PD_i are scaled based on their distributions. If the distribution of DI_i and PD_i are not similar, mathematical transformations should be performed to obtain comparable distributions. Another alternative for different distributions of DI_i and PD_i is to consider the rank position of DI_i and PD_i respectively instead of scaling (Equation 7.4).

$$RI_i = rank(DI_i) * Eq_w + rank(PD_i) * Ef_w \tag{7.4}$$

7.3.6 Setting different scenarios for the potential location of stations and boundaries of the service area

At this point, all zones of analysis in the implementation area should be ranked. After setting policies, regulations, system operation strategies, financial models (Yanocha et al., 2018), design inputs should be established (such as budget, rebalancing method and strategies, and key performance metrics) (Gauthier et al., 2014; Büttner and Petersen, 2011; Toole Design Group, 2012). The number of stations (n_S) is dependent on the available budget. We propose four different algorithms yielding different results in coverage and station density. The algorithms' inputs are the potential number of zones in the implementation area, the number of stations (n_S), and RI for each ZA. All algorithms start by ordering the ZAs in descending fashion based on the RI_i. The output of each algorithm is the zones named ZSt in which stations are allocated.

1. **Top-N.** ZSt's are the top-n_S zones based on their RI_i, a similar approach as in (Chen et al., 2015). This algorithm tends to result in high coverage but a low density of stations.

2. **Neighbor**. This algorithm starts by creating a matrix of the ZAs, in which the cells take a value of 1 if two ZAs are contiguous and 0 otherwise. We order the ZAs based on RI_i, and start by allocating a station in the highest raked zone ZSt_1 (the ZA with the highest RI). The procedure continues by allocating a station in zone ZSt_2, which is the zone contiguous to ZSt_1 with the highest RI. This step is repeated until the desired number of stations n_S are allocated. If a neighbor of a ZSt has already been chosen, the next ranked neighbor is selected. However, if all the possible neighbors have already been selected, the next ranked ZA_i, which is not a neighbor of ZSt_k, is chosen (Algorithm 1). This algorithm tends to have a high density of stations but low coverage.

7.4 Neighbor algorithm

Data: n_S, $ZA_1...ZA_n$, $Neighbor_{matrix}$
Result: $ZSt_k;\ k = 1, 2, 3...n_S$
ZSt_1 = ZA_1;
i = 2 ;
while *i <=* n_S **do**
    ZSt_i = Neighbor of ZSt_{i-1} with the highest RI from $Neighbor_{matrix}$;
    if ZSt_i *has been already selected* **then**
        chose the next ranked neighbor;
        if *all neighbors of* ZSt_{i-1} *have been selected* **then**
            chose the next ranked ZA which has not been chosen yet;
        end
    end
    i = i+1
end

Algorithm 1: Neighbor algorithm

3. **Island.** This algorithm is a mix of the Top-N and Neighbor algorithms. It starts like the Top-N algorithm by setting n_{isl} number of zones ("islands") with fixed stations $ZSt's$. Then, the remaining stations are split equally among the fixed stations $ZSt's$ and allocated using the Neighbor algorithm for each "island".

4. **Island weighted.** This algorithm is the same as the basic island algorithm, except that the remaining stations are not equally split between islands, but instead follow a weighted distribution. The allocation algorithm with the weighted distribution is shown in Equation 7.5

$$n_{neighbor}(x_i) = n_{isl} * \frac{n_{isl} - x_i}{n_{isl}^2 - \sum_{i=1}^{n_{isl}} x_i},\ for\ x_i = 1, 2, 3, ...n_{isl} \tag{7.5}$$

The Island and Island weighted algorithms represent a middle ground between the first two algorithms. They tend to have higher coverage than the Neighbor algorithm and higher density values than the Top-N algorithm. As a hypothetical example of the application of the four algorithms, Figure 7.3 shows the allocation of six stations in 30 ZAs.

Figure 7.3: Hypothetical example of application of the four algorithms. ($n_S = 6, n_{isl} = 3$)

In dockless systems, the stations are virtual and a service area boundary must be defined as an additional step. The service area is defined as a buffer area of a distance B_{min} around the shortest path tree connecting the selected stations. The distance B_{min} defines the buffer distance an average person is willing to walk in order to access the supply of BSS. This distance B_{min} is often similar to D_{min}.

7.4.1 Assessment of scenarios

The most commonly used approach for assessing or optimizing the allocation of infrastructure for docked systems is to minimize the impedance (p-median) and maximize the coverage area (García-Palomares et al., 2012). However, these approaches do not consider the balancing costs of the system. The allocation goal in this study is to minimize the balancing costs while maximizing the coverage area. This requires a dense station network. Therefore, we considered the bi-problem which minimizes the percentage of ZAs without access to the system ("non-coverage" area) and maximizes the distribution of the Gaussian kernel density estimate (KDE) of stations (density distribution). This approach considers the impedance.

We aim to maximize the distribution of the KDE, which maximizes the number of areas that have a high density of stations and therefore minimizes the balancing costs. KDE for $ZSt_1, ..., ZSt_{n_S}$ zones of analysis which have a station is defined by Equation 7.6.

$$\hat{f}_h(x) = (n_S h)^{-1} \sum_{i=1}^{n_S} K((x - ZSt_i)/h) \tag{7.6}$$

where K is the normal kernel function, and h is the buffer distance of the area to account for stations' density. The outcome is a raster with values $\hat{f}_h(x)$, in which the average is calculated for each ZA. The distribution of the average KDE is assessed using a Gini coefficient, for which the Lorenz curve is a cumulative line of the percentage of ZAs which have a station and the cumulative percentage of the KDE. Gini coefficients range from 0 (signifying an equal distribution in all ZA), to 1 (meaning only one zone gets all the resources).

In summary, the three inputs in DARE that can be modified to build different scenarios are the equity weighting, the number of stations, and the number of islands. Coverage and density of stations are indicators suggested for comparing the different scenarios. Top-n presented higher coverage, neighbor presented higher density and the island algorithms fall in between both. The equity weighting can be adjusted depending on the desired spatial fairness criteria, the number of stations depending on the budget, and the number of islands depending on the desired balance between coverage and density. A coverage goal can improve equality (equal distribution of resources) in the allocation because it serves more people and thus more parts of the community (Walker, 2012). In addition, users have more destination choices and may perceive high service quality. However, high coverage but low density can lead to inefficient service. In this situation, stations may be located far apart, which may be especially inconvenient for users of docked systems if a station does not have empty racks and a bike cannot be returned. Moreover, balancing bikes between stations involves higher costs for the operator due to the greater distances involved.

7.5 Application

7.5.1 Choosing an area of study and setting zones of analysis.

We applied the fairness-based DARE method to a hybrid BSS in Munich, Germany. In 2018, the system reached around 90,000 users with its 1200 bicycles and 118 stations (Rube, 2018). Users can pick-up and drop-off bicycles at stations or at a free-floating location in the public realm. To incentive station use, users get a 10 minute discount on the trip if a bicycle is returned to a station. The rental of a bike costs 0.08 euros per min (or 0.05 euros per min for students). Users can also pay 12 euros to use a bike for the whole day. There is also a 48 euro subscription package in which users can rent a bike for 30 minutes every day for six months (12 euros for students) (MVG Rad, 2019).

Munich's hybrid BSS provides data on the bicycles' locations every five minutes when they are not being rented (Transit.robbi5, 2019). It is assumed that a trip ends when a bike “appears" in a new area since there is no location available during the trip. We call this a bike movement, which approximates a drop-off or end of a bicycle rental. Bike movements longer than 150 minutes or with a displacement of fewer than 100 meters are not considered in the study. Rebalancing of bikes might be counted as movements within the dataset. In total 93,615 bike movements were collected from March 15, 2017 to October 10, 2017. However, within this time period, only 138 days with complete information were considered in this study. The month with the greatest number of bike movements was in July and movements tended to decrease in winter.

To delimit the ZAs based on the road network, we first created a point grid (virtual stations) separated a distance $Dmin$ in the study area based on the values previously described. We then removed virtual stations in areas where it was not possible to locate stations, such as water bodies or railways. Then, a service area for each virtual point was generated by assigning the road network that can be reached within a distance $Dmin$ from each virtual station. Finally, to split overlapping service areas, they were intersected with Voronoi diagrams (Voronoï, 1908) created from vertices and intersection points of the road network.

Next, we generated the service area for each virtual point by calculating the road network that can be reached within a distance $Dmin$ from each virtual station. Finally, we split overlapping ZAs using Voronoi diagrams created from vertices and intersection points of the road network.

For the study area, the service area from the current hybrid BSS system was used as the training area. Two implementation areas were considered: 1) the same service area but a reallocation of stations and 2) the outskirts of Munich County as an implementation approach with new infrastructure. The minimum distance between stations (D_{min}) was 300 meters, which is the most common distance used in previous studies and is also recommended in guidelines (Yanocha et al., 2018). The ZAs were thus created based on a grid of virtual stations separated $D_{min} = 300$ meters apart within Munich's service area and excluding areas within railways and water bodies.

7.5.2 Spatial data collection

As a dependent variable, we considered the density of bicycle drop-offs observed in each ZA instead of the count due to the heterogeneity of the ZAs' shape. To pick-up a bicycle, the user must walk to the place where it is located, which may be in a different ZA from where the activity was performed. Since we wanted to develop demand models based on the built environment, considering bicycle drop-offs rather than pick-ups offered a greater accuracy in studying the ZA of the trip purpose.

Built environment information was downloaded from OpenStreetMap (OSM). OSM is an online platform, in which volunteers geolocalize built environment features and make them publicly available (OpenStreetMap-contributors, 2017). Information collected from OSM includes transit stations, POIs, land-use, roadways, cycleways, railways, and waterways.

Milieus data, representing the social environment in this approach, was collected from the Sinus-Geo-Milieus data-set from 2014. In this data-set, every address in Munich was probabilistically assigned one out of ten Sinus-Milieus categories (Figure 7.4) based on ground values (tradition, modernization, individualization, re-orientation) and social status (low, middle, high) (Markt, 2017). Sinus-Milieus® on a spatial scale are called Sinus-Geo-Milieus and are defined as the probability of every address in Germany to belong to a certain milieu group (Küppers, 2018). Sinus-Geo-Milieus use data from Sinus-Milieus® interviews, official national survey data, and data collected from the marketing company Microm (`https://www.microm.de/`). Then, a multinomial regression model was run on all the addresses in Germany to calculate the probability of each house in Germany belonging to one of the ten milieus (Küppers, 2018). Population density was also extracted from the Sinus-Geo-Milieus dataset.

Mode split data was collected from the national mobility survey "Mobilität in Deutschland 2017" (Nobis and Kuhnimhof, 2018) with a spatial accuracy of 500x500m. Mode split was extracted from questions related to the mode ridership frequency (daily, 1-3 times a week, 1-3 times a month, less than monthly, never) of the following modes: bicycle, car, transit (local and regional), and car-sharing.

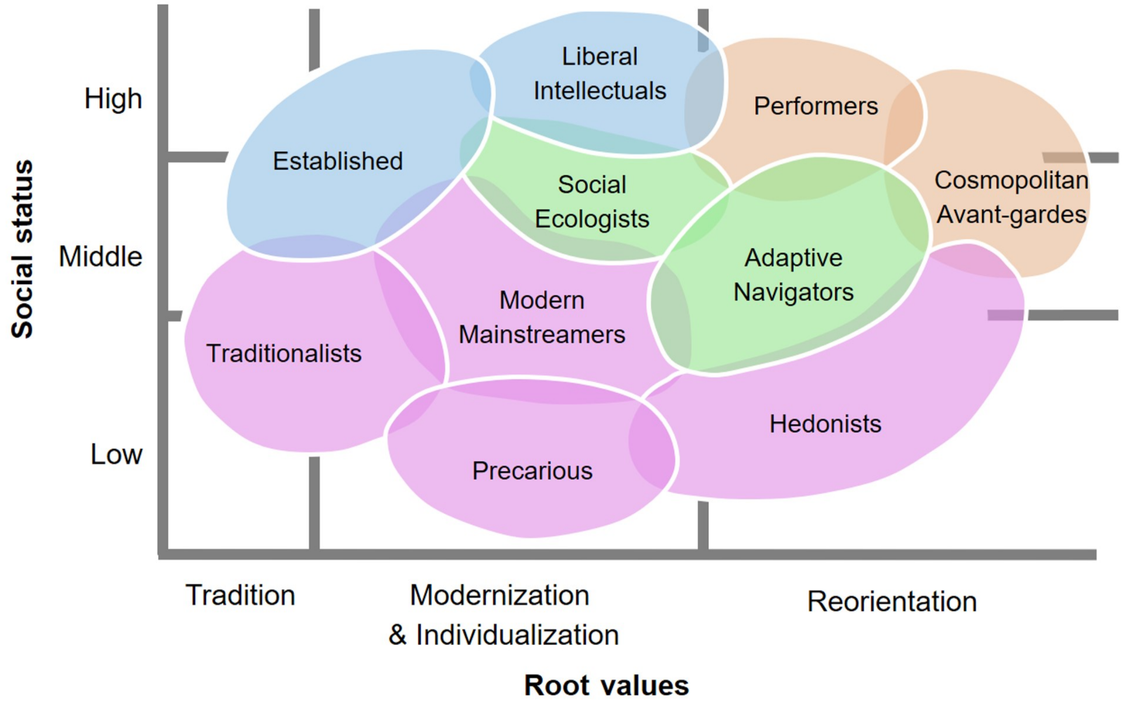


Figure 7.4: Sinus-milieus definition of categories. (Markt, 2017)

7.5.3 Feature generation & dimensionality reduction

In order to calculate walking accessibility to POIs and transport infrastructure, we used the values of $\beta = log(1.0126) + 0.013$ for distances to the centroid of the ZA in Equation 7.1. These values were estimated in feet and were taken from Zhao et al. (2003) who studied the walking accessibility to public transport. The spatial units used for land-use, milieus, and mode choice were the percentage of each category in each ZA. Furthermore, we included an index of walkability as an additional spatial factor, defined as the density of street crossings (crosswalks) (Moudon et al., 1997). Walkability is an indicator that an area may also be more attractive for cycling since walkable areas make it easier for BSS users to walk to rent a bike.

Once the units of measure of the built and social environment were estimated, we clustered milieus and POIs using hierarchical clustering. Milieus were clustered into four categories: a) Cosmopolitans-Performers, b) Traditionalists - Precarious - Hedonists - Modern Mainstreamers, c) Socioecologists - Adaptive navigators, and d) Established Liberal - Intellectuals. POIs were clustered using hierarchical clustering into 15 categories: essential needs POIs, essential services POIs, luxury shops, non-luxury shops, public building, doctors, education, food service, children-friendly, do-it-yourself shops, tourist attractions, open-air activities, convenience stores, department stores, and cinemas & theaters.

7.5.4 Estimating people's need with regard to opportunities and social status

The deprivation index for each ZA was calculated based on the number of households with low social-status milieus: Traditionalists-Precarious-Hedonists with reduced access to basic opportunities: pharmacies, supermarkets, organic food stores, bakeries, butchers, transit stations, cycleways. Figure 7.5 shows the spatial distribution of the deprivation index and the density of bike drop-offs.

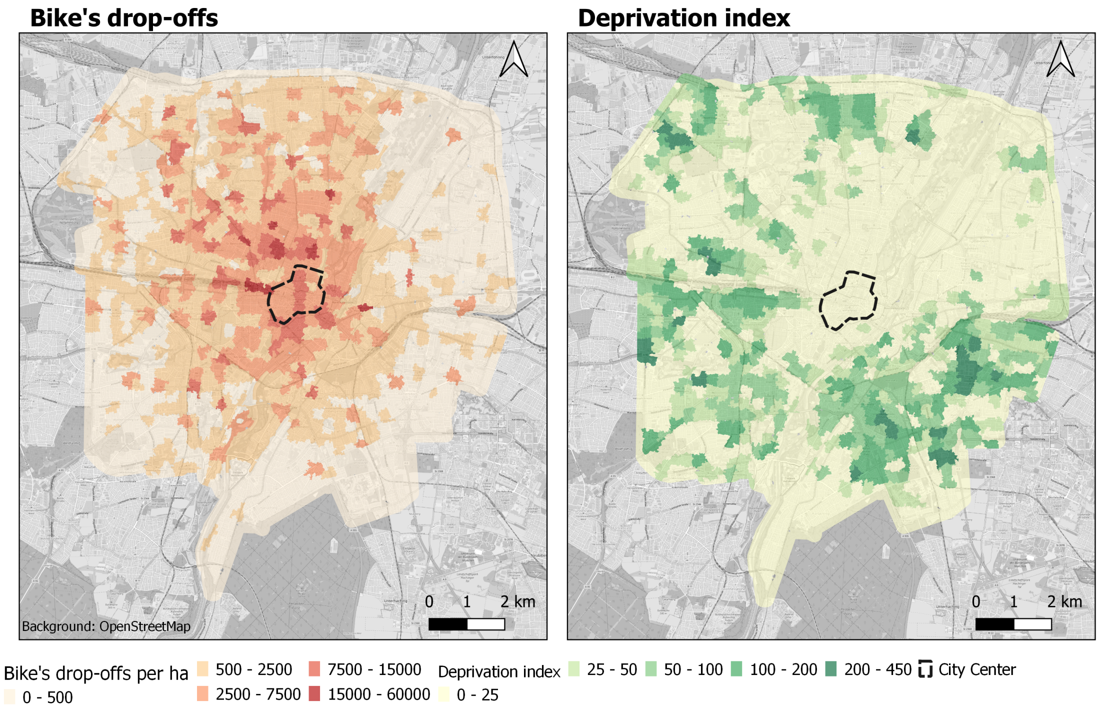


Figure 7.5: Map of the density of bike drop-offs vs the deprivation index

7.5.5 Estimating the potential demand

Prior to the station assignment, potential demand was estimated using SEM for each ZA as an indicator of spatial efficiency. In order to build SEMs, the first step was to set up a structure with the linkages between the independent variables (built and social environment) among them and also with the dependent variables (BSS ridership). Linkages between the built environment and ridership were taken from the theoretical model "land-use and transport interactions " (Wegener and Fürst, 2004; Wulfhorst, 2003), while the linkages between the social environment were taken from "urban mobility cultures" (Kuhnimhof and Wulfhorst, 2013; Deffner et al., 2006; Klinger et al., 2013).

The land-use and transport interactions model is based on the "land-use and transport feedback cycle" (Wegener and Fürst, 2004). Different land-uses (e.g. residential, industrial) determine the location of activities (e.g. shopping, living, working, leisure), and their distribution in space requires a transport system (transport demand) to overcome the distance between these activities. Accessibility serves as a measure of the distribution of transportation systems (transport supply), and its spatial distribution guides decisions to change land-use (Wegener and Fürst, 2004; Wulfhorst, 2003). The three chosen spatial factors from this theoretical model are:

- *Urban structure.* Built environment 3D's (Cervero and Kockelman, 1997): density (population density), diversity (land-use), and design (walkability)
- *Attractiveness.* Walking easiness (cost) to reach activities (e.g. points of interest). This actor can be also called accessibility to activities. The attractiveness of a zone is higher when different activities are easier to reach.
- *Accessibility to transport supply.* Walking easiness (cost) to reach transport infrastructure (e.g. cycleways, public transport).

The urban mobility culture model involves socio-material interactions between material characteristics (e.g. transport supply), and subjective components (e.g. attitudes, preferences, lifestyles, milieus) (Deffner et al., 2006; Klinger et al., 2013). Kuhnimhof and Wulfhorst (2013) summarized this theoretical model in four key dimensions: spatial structure and transport supply, policy-making and governance, perceptions and lifestyle orientations, and mobility behavior. The three chosen spatial factors links from the urban mobility culture definition are the spatial structure and transport supply, perceptions and lifestyle orientations, and mobility behavior. Perceptions and lifestyle orientations include milieus and mobility preferences. The policy-making and governance dimension was not included in our approach because it is more likely to be quantified at the city level rather than at the local level.

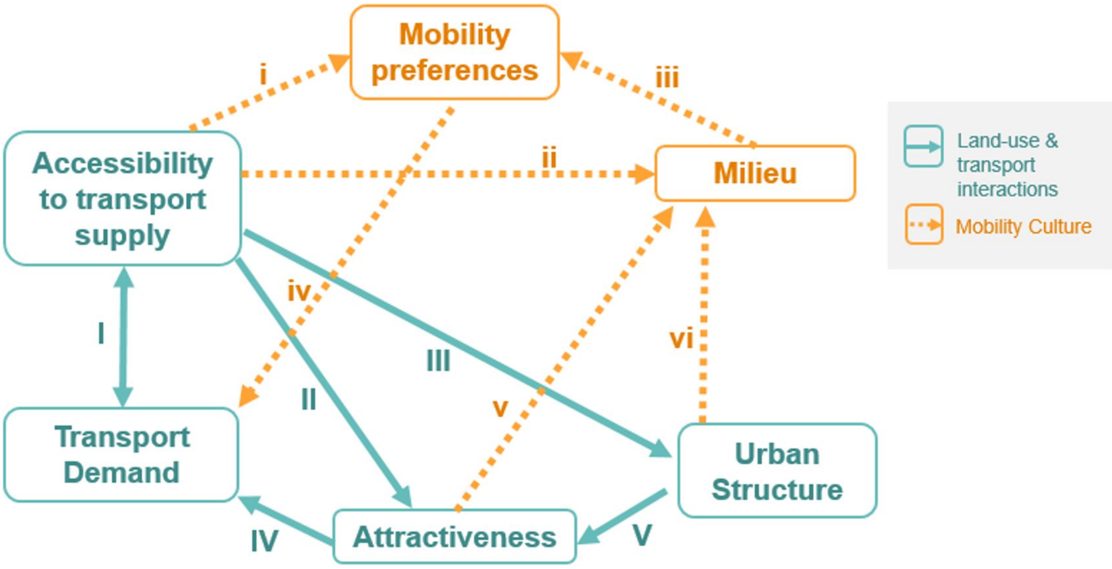


Figure 7.6: Theoretical links of the spatial factors associated to BSS ridership

The land-use and transport interactions model and the urban mobility culture model are linked together by the common factor of transport demand (or mobility behavior). This factor refers to the effective (observed) demand for a mode of transportation (e.g. bike-sharing). The unit of measurement for this study is the density of aggregated origins and destinations for BSS trips in the study area.

Figure 7.6 shows the spatial factors and their interactions. Green links are taken from the land use and transport interactions model, while the orange links are from the urban mobility cultures model. Table 7.2 lists the supporting concepts for the theoretical linkages between the spatial factors. We selected the spatial factors and their interaction links from these two theoretical models.

For better model fit and to meet the requirement of homoscedasticity in linear regressions i.e. uniform variance of the error, the data set was mathematically transformed. Various transformations were established (e.g. log, squared root), however, the power of $2/7$ presented the lowest heteroscedasticity. Appendix B shows the variables selected to build the model and Spearman's correlation coefficient. Also, we adapted the theoretical structure, in which we combined “Urban structure" and “accessibility to transport supply" into one latent variable. There was not a significant direct relationship between transport supply and bike drop-offs. SEM was estimated with the package “lavaan" (Rosseel, 2012) developed for the R programming language (www.r-project.org). The results (Table 7.4) revealed a good fit model with RMSEA=0.065 (90% CI:0.056-0.075, p=0.03), and CFI=0.955. After 100 runs of splitting the data into training data (70%) and testing data (30%) and performing cross-validation, the median of the R^2 from the training set was 0.587, and the median from the test set was 0.582.

Table 7.2: Theoretical links between spatial factors associated to BSS ridership

LINK	TO	FROM	DESCRIPTION
v, ii, vi	Milieus	Attractiveness, Transport supply, Urban Structure	Lifestyle, as part of the milieus, are decisive at the moment of choosing a residence location (Aeroe, 2001; Handy et al., 2005), based on different preferences towards access to opportunities and transport supply (Klinger et al., 2013).
i	Mobility preferences	Transport supply.	Different mobility preferences depend on the transport infrastructure available. "Locations with good accessibility by car will produce more car trips, locations with good accessibility by public transport will produce more public transport trips" (Wegener and Fürst, 2004). Preference for a transport mode is not possible if this mode is not accessible. For example, train orientation is not possible in areas without a train connection. Klinger et al. (2013) stated that a possible reason why US cities are car-dependent is because of the lack of public transport systems.
iii		Milieu	"Mobility is not limited to purely rational decisions, but is influenced by a cluster of feelings, norms, value orientations, desires, and fears" (Deffner et al., 2006), i.e. milieus.
III	Urban structure	Transport supply	"The distribution of accessibility in space co-determines location decisions and so results in changes of the land use system." (Wegener and Fürst, 2004). For example, industrial areas are more attracted to be located close to motorways or railways, or office areas are attracted to areas close to airports, railway stations, or motorways (Wegener and Fürst, 1999).
IV	Transport demand	Attractiveness	Locations with high accessibility to multiple activities will generate more travel demand (Wegener and Fürst, 2004).
iv		Mobility preferences	Mobility orientations and attitudes have shown to be particularly relevant to behavior (Hunecke, 2002). When there is a choice or preference towards a mode of transport, its ridership will increase.
I		Transport supply	Access to transport supply enables intermodal transportation (e.g. bike and ride, park and ride), which can raise trips to a certain location to change from one transport mode to another.
I		Transport Demand	This linkage happens when demand is considered as allocation criteria for transport infrastructure (spatial efficiency) (Duran-Rodas et al., 2020a), and therefore, supply is higher accessible in areas where there is higher demand.
V	Attractiveness	Urban Structure	"The distribution of land uses, such as residential, industrial or commercial, over the urban area determines the locations of human activities such as living, working, shopping, education or leisure." (Wegener and Fürst, 2004).

Table 7.3: Descriptive statistics from the selected spatial factors

Statistic	Unit	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Bikes' drop-offs density***	[# / ha]	1,620.52	3,162.81	0.00	160.48	1,715.03	57,383.25
Department stores*	[acc.]	2.04	1.16	0.09	1.13	2.84	6.12
Food services*	[acc.]	0.28	0.25	0.003	0.11	0.36	1.88
Tourist attraction*	[acc.]	0.27	0.21	0.002	0.12	0.37	1.52
Cinema and theater*	[acc.]	1.38	0.93	0.02	0.64	1.99	4.55
Transit stations*	[acc.]	0.21	0.14	0.002	0.11	0.28	0.93
Cycle ways*	[acc.]	0.11	0.10	0.00	0.03	0.15	0.64
Population density****	[# / ha]	4,439.24	4,413.58	0	870.1	6,792.2	21,385
Road intersections (Walkability)*	[# / ha]	4,230.01	3,996.90	0.00	1,965.07	5,283.01	51,690.53
Cosmopolitan-Performers****	[%]	0.23	0.25	0	0.02	0.4	1
Car ridership: 1-3 a month***	[%]	0.09	0.09	0	0.002	0.1	1
Car-sharing ridership: <monthly***	[%]	0.17	0.11	0	0.1	0.2	0

Data

Source: * OpenStreetMap-contributors (2017), ** www.bmvi.de/, *** Transit.robbi5 (2019), **** www.microm.de

7.5.6 Setting different scenarios for the potential location of stations and boundaries of the service area

We chose 100 stations to be allocated among 1234 zones of analysis. and the buffer distance (B_{min}) for the service area was assumed to be 300 meters. Then, we applied each of the four algo-

Table 7.4: SEM results

LATENT VARIABLES:		**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**
Attractiveness=˜					
	Department stores	1			
	Food service	1.22	0.077	15.746	0
	Tourist attraction	1.066	0.077	13.889	0
	Cinema & theater	0.946	0.069	13.622	0
Urban structure =˜					
	Transit station	1			
	Cycle ways	0.511	0.087	5.876	0
	Population density	-2.373	0.155	-15.353	0
	Walkability	-1.051	0.067	-15.672	0
Mobility preference =˜					
	Car ridership: 1-3 a month	1			
	Car-sharing ridership: < monthly	1.246	0.115	10.831	0
Milieu =˜					
	Cosmopolitan-Performers	1			

REGRESSIONS:		**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**
Attractiveness˜					
	Urban structure	0.871	0.072	12.108	0
Mobility preference ˜					
	Milieu	0.025	0.025	1.034	0.301
	Urban structure	-1.291	0.148	-8.715	0
Milieu ˜					
	Urban structure	-2.549	0.407	-6.266	0
	Attractiveness	0.045	0.356	0.128	0.899
Bikes' drop-offs density ˜					
	Attractiveness	-1.511	0.113	-13.415	0
	Mobility preference	0.151	0.05	2.989	0.003

INTERCEPTS:	**Estimate**	**Std.Err**	**z-value**	**P(>|z|)**
.Department stores	0.725	0.004	161.615	0
.Food service	0.579	0.005	126.148	0
.Tourist attraction	0.663	0.005	138.235	0
.Cinema & theater	0.699	0.005	140.48	0
.Transit station	0.66	0.004	155.02	0
.Cycle ways	0.578	0.006	95.587	0
.Population density	0.569	0.009	66.91	0
.Walkability	0.506	0.004	138.777	0
.Car ridership: 1-3 a month	0.692	0.008	88.702	0
.Car-sharing ridership: < monthly	0.47	0.01	47.486	0
.Cosmopolitan-Performers	0.546	0.011	50.871	0
.Bikes' drop-offs density	0.327	0.005	64.495	0

Note: RMSEA = 0.089, CFI = 0.917

rithms previously presented, and determined which zones of analysis would be allocated a station in each algorithm. We studied the two extreme cases, allocating infrastructure entirely based on spatial equity ($Eq_w = 1$), and entirely based on spatial efficiency ($Eff_w = 1$) (Figure 7.7a). In the estimation of RI (Equation 7.3), deprivation index and estimated ridership presented similar non-normal distributions. Therefore, min-max normalization was performed, assigning 0 to the minimum value and 1 to the maximum value, and the range of RI_i thus being from 0 to 1.

Finally, we applied DARE in the surrounding county of Munich, which is the peripheral region of the city (Figure 7.7b). We excluded this region when building the demand model in order to use it as a validation set, demonstrating the method's transferability. There are 107 stations in this peripheral region. We applied the island-weighted algorithm to assign the same number of stations. In addition, we used different equity weights (Eq_w) and the number of islands (n_{isl}) to test the different scenarios when these variables change. In the estimation of RI (Equation 7.3), deprivation index and estimated ridership presented similar non-normal distributions. Therefore, min-max normalization was performed, assigning 0 to the minimum value and 1 to the maximum value, and the range of RI_i thus being from 0 to 1.

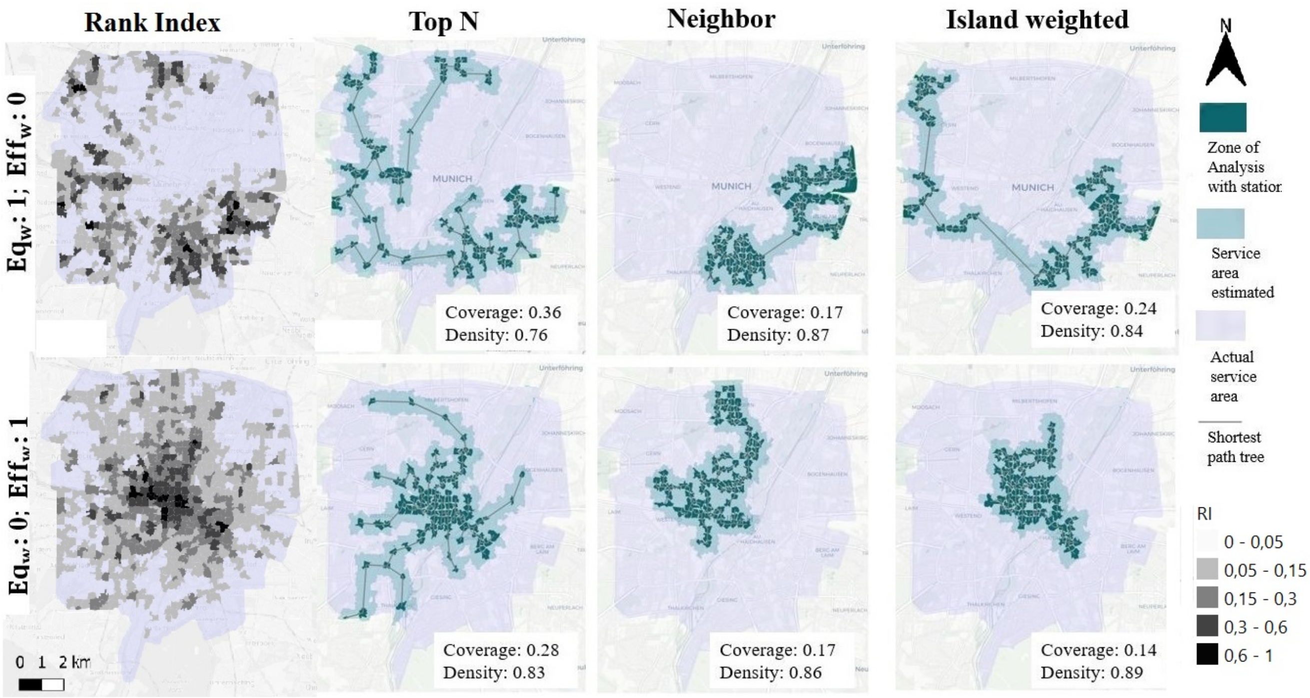
7.6 Discussion

The presented method can be used as a "first draft" 1) to relocate stations based on shifting priorities or goals (e.g. Figure 7.7a), 2) to expand BSS after learning from an existing system (e.g. Figure 7.7b), or 3) to implement new systems, after applying the method to a city with similar characteristics. This method can help planners prioritize the distribution of infrastructure according to their BSS goals by adjusting the spatial equity and efficiency weights, and to communicate these design priorities transparently.

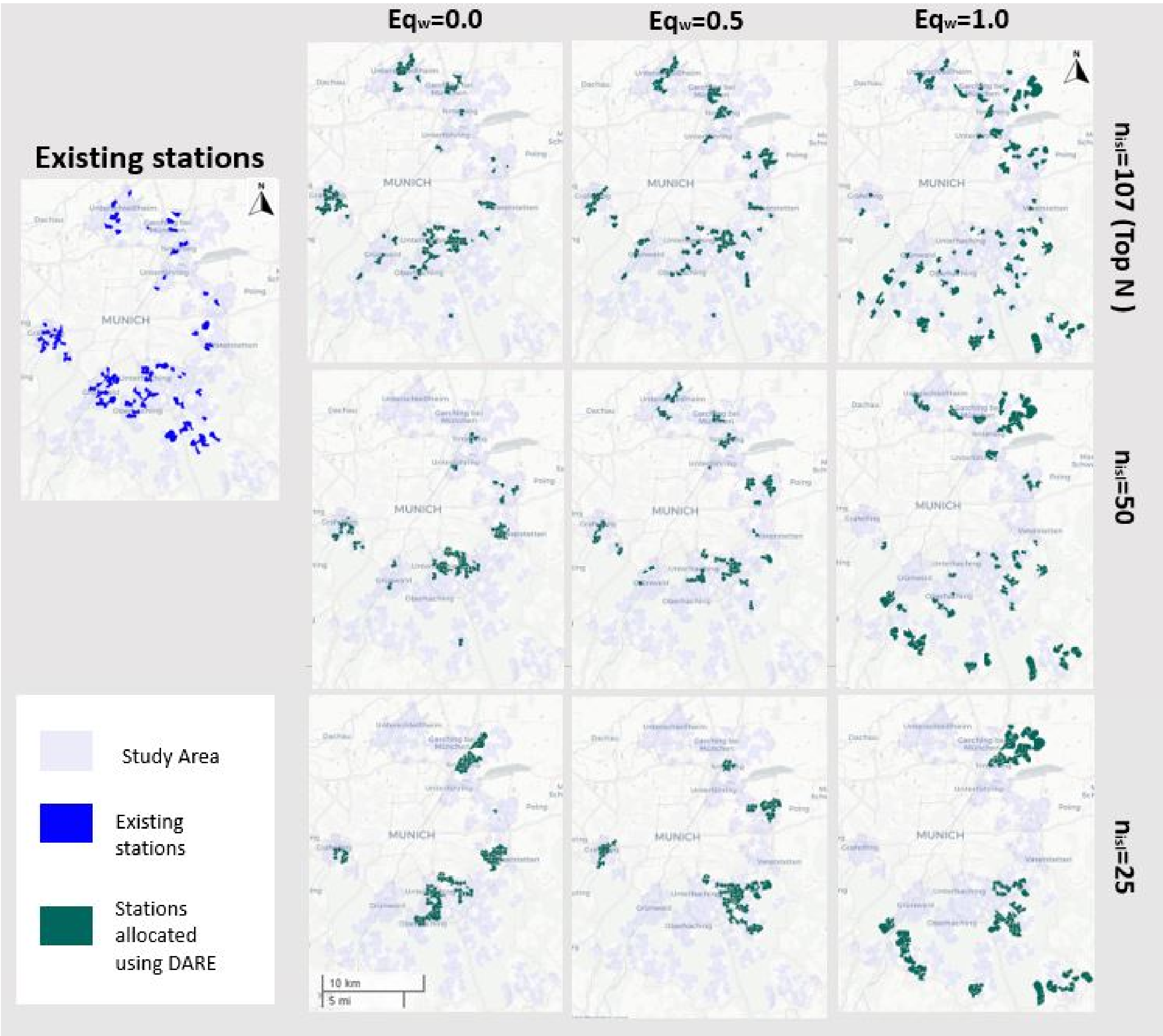
DARE method can be summarized by the following steps which can be further applied in other systems:

1. selecting a study area, and dividing it into zones of analysis,
2. collecting data from the built and social environment, generating features and aggregating them into categories,
3. estimating deprivation in each analysis zone or an index showing where underprivileged people live,
4. estimating potential ridership in each analysis zone or other variables related to "productivity" (e.g. systems' earnings),
5. ranking zones of analysis in terms of equity (step IV) and efficiency (step V),
6. creating scenarios based on the number of (virtual) stations according to the available budget and the four algorithms previously presented (e.g. Top-n) for infrastructure allocation. For dockless systems, a service area is set using the collective buffer distance from the virtual stations.
7. comparing scenarios in terms of density and coverage.

Depending on the desired fairness criteria of decision-makers, the allocation of stations can be oriented toward equity, efficiency, or a combination of the two. An equilibrium between efficiency and equity can potentially be found, in which deprived areas are not abandoned but the system can still be efficient (e.g. Figure 7.7b). Previous methods have considered minimizing impedance (García-Palomares et al., 2012; Conrow et al., 2018) such that all areas of a city or region would have access to the system. However, when the cost for this approach is considered too high, identifying priority areas could be useful for planners to distribute infrastructure according to their budget, while taking into account the weights of the preferred fairness criteria. Furthermore, DARE has the strength to automate the development of multiple scenarios, which can assist decision-making. Moreover, having different scenarios available can help decision-makers justify and be transparent about the planned BSS service area and station distribution.



(a) Allocation of stations and service area in Munich ($n_S = 100,\ n_{isl} = 10$)



(b) Island weighted algorithm results for the allocation of stations in the county of Munich

Figure 7.7: Application of DARE in Munich, Germany

Furthermore, DARE provides transparency in terms of the efficiency and equity weights selected, and the varying actors involved in BSS planning can aim to reach a consensus on a preferred scenario. Methods for public participation can include online map-based commenting, smartphone app crowdsourcing platform, public hearings, public opinion survey, consensus conference, citizens' panels, focus groups, and others (Rowe and Frewer, 2000; Griffin and Jiao, 2019). Further recommendations are to integrate the physical design, technology, and payment methods for the system with those of other public transportation and shared means of transport. Finally, the process of determining station locations should include site visits and the involvement of the general public and other stakeholders.

A limitation of DARE is the lack of stakeholder inputs in the decision-making method. This method could be improved by adding an extra parameter to the rank index based on crowdsourcing or community input and also an extra weight considering the environmental impact. Another improvement might include the modeling of ridership and spatial factors in terms of trips between zones, rather than exclusively origins or destinations.

7.6.1 Application of DARE in Munich, Germany

For our application of DARE to the HBSS service area in Munich, we compared both extreme cases of maximum spatial equity vs maximum spatial efficiency with a low budget of 100 stations (Figure 7.7a). When spatial equity was desired, deprived areas were served. However, there were a very limited number of stations in the city center, making it difficult for people living in deprived areas to cycle to and from the city center. In contrast, spatial efficiency focused on the city center and deprived areas were poorly served. It is worth mentioning that some areas were well served under both criteria, mainly those deprived areas that had significant potential demand for bike-sharing.

Regarding the algorithms for building different scenarios. The Top-n algorithm prioritized the highest ranked areas, and based on the spatial parameters, it provided a higher coverage and lower density of stations than the other algorithms. More people could access such a system but it might be expensive for balancing the bicycles during the operation. The neighbor algorithm provided a dense allocation of stations but only located them in a few neighborhoods. The island algorithm combined the advantages of the two previous methods. It resulted in adequate density with reasonable coverage. However, the method that we recommend is the island weighted algorithm, in which zones with the highest-ranking are provided with a denser network of stations, thus prioritizing the whole neighborhood. Though having multiple allocation algorithms might increase the method's complexity, developers can then build different scenarios with varying balances of coverage and density.

DARE was also applied in the peripheral region of Munich by using the SEM built in the central part. With a lower equity weight, the stations were located closer to the city of Munich. The Top-n algorithm with a higher efficiency weighting presented similarities (40%) with the existing allocation of stations, as opposed to 8% when equity weighting was considered. This analysis suggests efficiency was the fairness criterion chosen to allocate the stations. In addition, when the number of stations is small, the neighbor algorithm tended to be similar to the island algorithm because of the lower population density in the peripheral region.

In this study, we applied DARE specifically to a hybrid BSS. However, the method could also be used for docked or dockless BSS because hybrid BSS share characteristics of both systems. A key difference when studying station-based systems is that the service area is not required in the design. Completely dockless systems, in contrast, use virtual to help design the service area that defines the system.

7.6.2 SEMs for estimating potential ridership and understanding causal relationships between the social and built environment

This study uses SEMs to estimate the potential ridership of bike-sharing by associating historical trips with spatial factors from the built and social environment using their linkages from a hypothesized theoretical structure (Figure 7.6). Every spatial factor included in the theoretical structure represents one latent variable, which is a set of observed variables associated with BSS ridership (Table 7.1). If spatial efficiency is desired over spatial equity, areas with higher estimated ridership would be prioritized with an allocation of stations.

SEMs presented a good fit of the data and theoretical interactions. Areas with a high historical ridership were estimated with the model to have potential demand and vice-versa when considering spatial efficiency. These areas were densely populated, highly walkable, had a low preference for cars, many leisure and touristic activities, a predominance of cosmopolitan and performers residents, and good accessibility to transit stations. If we consider only spatial efficiency, the population with a low social-status population would be poorly served by the system. The variables identified were in line with guidelines (Büttner and Petersen, 2011; Gauthier et al., 2014) and studies (García-Palomares et al., 2012) that recommended locating stations in densely populated areas close to transit stations, cultural and tourists attractions, and major public spaces and parks (high walkable areas).

SEMs are a common tool for causal inference. Our use of SEMs to distinguish features that have causal effects from those that are purely correlative gives us a better understanding to predict behavior in a new domain. Other advantages of using SEMs are the incorporation of multicollinearity, which in linear regression would not have been possible. Moreover, we were able to test the hypothesized theoretical structure (Figure 7.6). A good model fit was shown after merging urban structure and accessibility to transport supply as one latent variable, which validated the concept of urban design including transport infrastructure (Cervero and Kockelman, 1997). Even though SEMs served to avoid multicollinearity between the factors, spatial factors might still have a spatial autocorrelation between zones. This issue should be considered in further research or applications.

Using SEMs, we also validated the theory that different milieus choose their residence based on the urban structure and the theory that urban structure determines mobility preferences. Therefore, we can infer that attractiveness, milieus, and mobility preferences are dependent on the urban structure. The two directly-linked factors determining bike drop-offs were attractiveness and mobility preferences. However, attractiveness had ten times the correlation with the drop-offs compared to mobility preferences. These results of the cosmopolitan population associated with BSS ridership were complementary with the survey by Stöckle et al. (2020), where the main value of BSS users in Munich was adventure (progressive values) but not tradition and security (traditionalist values). The drawback of using milieus is the complexity of their estimation and the lack of availability in other countries. Hence, in the absence of milieus for further research, sociodemographic characteristics, perceptions, or attitudes can be included as social environments.

SEMs have learned from the past by using spatial factors. When implementing BSS in a new area, the estimated ridership based on spatial factors is assumed to be the induced demand for BSS because there is no existing system in the area. To improve current practice, which mostly provides infrastructure to areas with higher estimated demand, we propose to include underprivileged areas in the ranking with a weighting in terms of spatial equity. Duran-Rodas et al. (2020a) showed that areas with underprivileged residents and traditional values had low BSS use. Possible reasons for this may include cultural barriers and attitudes toward bicycling (Stöckle et al., 2020; Pochet and Cusset, 1999; Van der Kloof, 2015).

7.7 Conclusions

Demand And/or Equity (DARE) is a method that can be used for building scenarios to allocate stations and limit the service area of BSS where fairness is considered as an input in the planning process. The distribution of stations and the service area boundaries are determined by the weights planners assign to spatial equity versus efficiency. This method was explored through a case study based on ridership as well as people's needs with regard to social status and opportunities. DARE provides transparent decision-making support for supply distribution and presents an alternative where the benefits of BSS are extended beyond privileged populations.

We validated a theoretical structure with SEM for estimating potential ridership. The social environment previously associated with BSS ridership (Faghih-Imani et al., 2017) was an approximation of the urban structure but not directly connected to the ridership. The variables associated directly with high BSS ridership were low car ridership and especially the attractiveness of a zone (defined mostly by leisure activities). Both of these variables depended on the urban structure.

Further research includes the adaptation of the method for decision-making with feedback from stakeholders. Also, possible weights for the ranking index can be suggested by stakeholders from different cities to obtain an average score. Additionally, further applications of DARE can include sensitivity analyses for using different design inputs, such as the minimum distance between stations, sizes, and shapes of the zones of analysis, beta values to estimate walking accessibility or a varying shape and size of zones depending on the location. To improve the usability of the method, DARE should be further developed as a practice-relevant user tool. This method can also be applied further to study the implementation of new bike-sharing systems and even to assist in planning for other transport modes such as car-sharing, scooter-sharing, or public transport. Moreover, the method can extend beyond transport to be other logistical and operational services that aim for spatial fairness.

7.8 Author Contribution Statement

The authors confirm the contribution to the paper as follows: David Duran-Rodas: conceptualization, methodology, software, verification, writing, visualization; Benjamin Wright: verification, writing; Francisco Camara Pereira: supervision, conceptualization, methodology, writing - review ; Gebhard Wulfhorst: supervision, writing - review & editing, visualization.

Part III

Discussion and Conclusions

Chapter 8

Key findings and discussion across the papers

This chapter summarizes the main findings of the four papers in the dissertation, including their significance and limitations. It has a top-down narrative, beginning with a discussion across the papers and ending with a discussion of each research question.

8.1 Connection of results and discussion across the papers

This study aimed to answer four main research questions to develop a method to build scenarios to allocate stations and limit the service area for BSS based on spatial efficiency, equity, or a balance of them.

8.1.1 Tweets as part of the literature review about BSS

The first step of this research was to get a broad understanding of the general opinion about BSS before developing a method for planning them. It was not enough to review the literature to know if it is worth developing additional BSS but also including the thought of people on a large and international scale. Previous researchers have conducted interviews with stakeholders and users (Shi et al., 2018; Hannig, 2015). In China, for example, governments stress the importance of further promoting BSS as part of national transport planning strategies for improving sustainability. Interviews allow a deeper understanding of people's perceptions, as the quote in Hannig (2015) shows: *"The providers don't always see themselves as users. It's in their mind that it is about recreation when we talk about bike sharing".* The problems and advantages of BSS could be summarized by a small part of the population. However, interviews have the limitation of the sample size.

A wider audience could be reached via social media. Posts on social media made it possible to analyze the relationships between the various stakeholders involved in BSS (Shi et al., 2018). The analysis of a public discussion in social media could, as part of the literature review, contribute to the understanding of the BSS dilemma between their advantages and disadvantages. Results helped to include perceived positive features in the design of BSS and exclude or mitigate their drawbacks. Furthermore, the public debate about the BSS dilemma showed people's, media's, and stakeholders' perceptions about BSS and their trends in the future.

This exploration was conducted as a mixed-methods approach to understand the public discussion about BSS through qualitative and qualitative analysis of English posts on Twitter and interviews with underprivileged populations, people feeling socially excluded in Strasbourg. The difference between the method of Andreotta et al. (2019) and this approach was that data was not randomly selected for qualitative analysis, but through sentiment analysis and the integration of data from interviews. The outcome was a list of the most frequently discussed topics related to the advantages, disadvantages, and future of BSS. As an additional contribution, the most common English terms related to BSS were collected to fill the research gap, and in the future, the most used terms to people related to BSS were used.

The social media analysis included the main benefits and drawbacks found in the literature. Different perceptions of people, media, and companies were identified, which were not in the literature and can be complementary to understand BSS further. For instance, people complained that BSS were not for all. It was reported that people perceived BSS as difficult to operate and tourist-oriented because locals 'should' prefer to own a bike. One of the main findings was the positive sentiments towards BSS when they are public, inclusive, affordable (or even free), keep communication with clients, and their design and allocation are based on public participation and people's needs (equity). Nevertheless, BSS were less accepted when people thought they were a company occupying their public space rather than a quick and pleasant way to move around.

The BSS dilemma was deeply explored and understood after reading the comments of many people. When people praised or complained about BSS, higher empathy was generated. A clearer understanding was achieved of why people like BSS and why not. Moreover, social media analysis helped to realize that BSS is worth developing further in the future because of its advantages. It was motivating to read that BSS has helped many people as a mobility solution when there was no transit or last-mile connection, also in getting to know the cities and motivating people to cycle. However, this approach helped to empathize why it is frustrating to have bikes spread in my public space and the feeling they are not "for me". Finally, it was concluded that BSS are neither good nor bad, but that there are some good and bad practices and experiences of people. Hence, similar approaches are considered to be crucial to get a broad understanding of the general opinion about mobility systems before planning them.

Based on the public discussion on BSS, the main outcome for this study is that people prefer hybrid BSS with electric and cargo options, and integrated with other shared modes and public transport. Furthermore, according to the topics identified, planning and implementing affordable and inclusive BSS is recommended.

The unequal usage and distribution of infrastructure of BSS contrast with the optimistic view of the supporters of shared mobility. They claim that shared modes of transport help to reduce the social gap in consumption of goods and services, depending on the purchasing power of a person (Lucas, 2019). As an example of lack of acceptance due to lack of equity, @MLH_ARCC published a post on Twitter on October 13, 2018:

> *"Bike share is NOTORIOUS for having no equity in its planning. BikeTown bikes were vandalized in Portland for its connection to gentrification culture."*

8.1.2 Spatial fairness assessment in BSS

Thanks to the results of the public opinion and the empathy generated, the motivation raised to assess how fair BSS are before they are expanded or implemented in a new area and what distribution rules follow their supply allocation. Since hybrid BSS were favored in the public debate on Twitter, this was an incentive to apply the spatial fairness assessment to a hybrid system.

In the literature, the analysis of spatial fairness usually focuses on comparing access to resources between different social groups. If the distribution is unequal among the population, systems would be classified as unfairly distributed, such as in Ogilvie and Goodman (2012). However, this study went beyond the identification of social groups with more or less access. The aim was to identify which distributive rule based on fairness a system follows. A combination of different techniques aimed to build a single framework for assessing spatial equity, equality, and even efficiency in order to have clearer knowledge of who is preferred in the distribution of resources: money, people, or both. Identifying this categorization can help stakeholders and the public know to whom public resources, including public space, are oriented to, and if desired, to modify the desired goals for BSS to the aimed population.

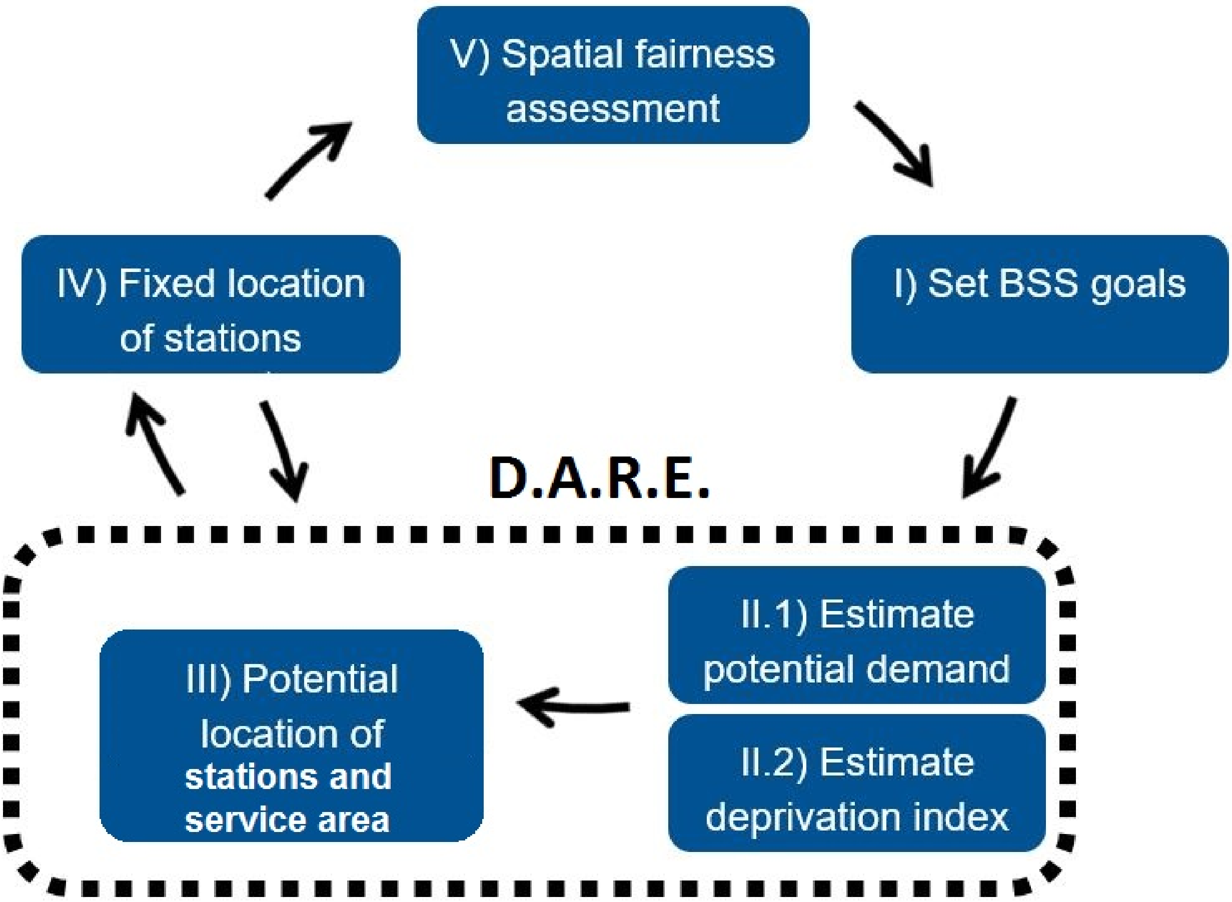


Figure 8.1: Planning cycle for BSS including spatial fairness assessment and Demand and or equity (DARE) method

The classification of BSS based on spatial fairness may help to set goals so that the systems are in line with the fairness criteria desired. The assessment based on fairness is recommended after the new infrastructure is implemented to explore who has access to the system in practice (Figure 8.1). New targets of the system could be set based on who is privileged in the distribution of the infrastructure or who is not. Moreover, a spatial fairness assessment might serve as a breaker of the "unfair" loop of planning BSS. If historical trips are learned from unfair systems, the corollary is that unfairness is being further enhanced. If a system is perceived to be unfair, the design inputs can then be changed.

8.1.3 Spatial Equity for planning BSS

The next question to be asked is whether the limited resources should primarily be equitable and benefit mostly the neediest population. For example, the following tweet states the need for equity in the design:

> *"... if we're serious about equity we have to look beyond where bike sharing is most profitable to where it's most needed."* @dave_bikes, 6 Sept. 2018.

Equality of opportunities can lead to a reduction in social disparities and social exclusion (Fainstein, 2009), resulting in less social conflict and social peace (Tomlinson, 2016). Also, when residents feel that a system is for them, the sense of belonging increases, which can lead to higher consent (Wüstenhagen et al., 2007), conservation and proper use of the system. Inclusive transportation systems would prevent vandalism and missuses. As an analogy, in Chile, some low-income families spend almost 30% of their salary on transportation, while within the richest socio-economic level, the percentage of spending may be less than 2% (Zuñiga, 2019). Protesters caused damages to the metro in Santiago valued at 300 million dollars claiming that a rise in the subway ticket was inconceivable. Even though Chile has relatively good macroeconomic figures (efficiency), "if the image of Chile is scratched, an enormous social, cultural, economic and political injustice becomes evident" (inequity) (Zuñiga, 2019). Therefore, it was deduced that people are less likely to destroy and misuse BSS infrastructure if the systems provide good bicycle quality, are accessible to everyone, and give residents the impression that BSS are a service for them.

In the case that areas with higher predicted usage are served and if the typical user profile belongs to the most privileged population, the underprivileged population would be left out of the system. If underprivileged people feel they are continuously not prioritized because of their physical, social, and economical limitations, this can lead to social exclusion (Jones and Lucas, 2012). In addition, they may feel that these systems, which take up their public space and public funds, do not benefit them, but only the already privileged population. Thus, this feeling may lead to a lack of acceptance of the infrastructure and possibly to vandalism and theft.

However, if only equity is considered, this can be economically inefficient. For example, if an isolated population were to be cared for, the cost of compensation and balancing within the system would be too high, and the system may fail, as the following tweet shows:

> *"Dockless bike share companies even came into low-income, struggling cities like Camden, with big promises, only to dump them completely about a month later."*, @schmangee 15 Oct. 2018

8.1.4 Spatial Efficiency for planning BSS

If an efficient system is desired to be developed, stations should be allocated based on the spatial factors associated with higher observed demand. In the literature, these factors were mainly part of the built environment and social environment.

In looking at several cities on a German and international level, factors of the built environment associated with historical ridership were similar to those in the literature review (Table 6.1). The variables with higher association were related to public transport, car-sharing stations, and leisure activities such as cafés, cinemas, bars, shops, green areas. These results were identified in previous studies (see Table 2.3)and show that these factors are associated with BSS across geographic boundaries. Moreover, stepwise Ordinary Least Squares was the regression technique that showed to be parsimonious with fewer input arguments, and its results were easier to interpret.

However, the built environment might not be the only spatial factor related to the usage of BSS. For example, how can we explain the paradox situation in which some areas have the associated built environment factors (activities and infrastructure) but still there is no demand for BSS. The following tweet discusses this issue:

> *City transportation officials abandoned efforts to make the bike share system more accessible to low-income residents, and an official with the vendor suggested low-income residents simply didn't want the bikes.* @ellenfishel, 19 Nov. 2018.

Perhaps they had the bicycles in the low-income neighborhood, they have the density, and probably the need to travel at a lower cost. However, people "just didn't want to have the bicycles". Beyond the built environment, it should not be forgotten that those who are willing to use a transportation system are human beings and not machines programmed to use what is on the streets.

Therefore, we used data from milieus, which includes the social status and prominent values of residents. In Munich, while performing the spatial fairness assessment, higher demand was identified using stepwise OLS in areas closer to the city center and in residential areas where most people with progressive values live such as cosmopolitan avant-gardes (Figure 5.9, pg. 73). The values of adventure and equity characteristic of the cosmopolitan population were also shown in the following post of asmall_word on 11 Oct. 2018:

> *"I tried Indego on my first **adventure** back to Philly since college this summer and it made me think about an underrated way bikeshare works as a community builder: It would have given me much **stronger ties to the city** and I might have even stuck around."*

– Structural equation models: merging built and social environment to estimate BSS ridership – Built and social environment factors were used to estimate the potential ridership, which is the indicator of efficiency in this study. However, these spatial factors presented high collinearity between them. To merge and use both social and built environment variables, using regression might not be appropriate. To estimate potential usage of BSS, SEM was selected as a modeling technique because of the advantages of 1) having a causal interpretation of the variables associated with the usage, 2) determining which variables can be included in models in other regions than those trained, and 3) to combine evidence from previous studies (Cox and Wermuth, 2004). As Handy et al. (2005)[286] suggested, "structural equations modeling, will help to establish the strength and direction of the relationships between attitudes, changes in the built environment, changes in travel behavior, and other factors".

SEM required previously established potential links between the variables that will be studied. These links of SEM were taken from 2 theoretical models which included the previously variables associated with BSS usage: a) interactions of land-use and transport (Wegener and Fürst, 1999)] and b) urban mobility cultures (Deffner et al., 2006). These two structures were combined into one theoretical framework which was validated using SEM to model together built and social environment. SEM contrasted the disadvantage of linear regression of not working with multicollinear variables, since the social and built environment presented a high correlation, these variables were modeled as structural equations. Moreover, SEM allows having a deeper understanding of how the variables relate and affect directly or indirectly to each other. The model's correspondence with reality could increase when the total amount of influence is taken into account when including the indirect effect that the independent variables have on the dependent variable (Youngblut, 1994).

8.1.5 Demand And/oR Equity (DARE) method for planning BSS

Demand And/oR Equity (DARE) was developed to allocate the supply of BSS prioritizing areas based on the preferred fairness criteria: spatial equity, spatial efficiency, or a balance of them. DARE was formulated to give the option to decision-makers to balance between serving both the most needed population in terms of social status and opportunities and neighborhoods with higher estimated potential demand.

To perform DARE, efficiency and equity indicators were estimated for deciding which areas should be privileged with BSS supply. A deprivation index was developed as an indicator of underprivileged areas in terms of low social status residents with low access to basic opportunities such as food, education, and health. Estimation of the potential demand, which represented efficiency was based on regression of spatial factors and historical trips (see Figure 8.1). Regarding the spatial factors that can serve as predictors of potential demand, this study learned from factors from the built environment in multiple cities and the social environment. Additionally, Structural Equations Models (SEMs) were built to explore which factors have a direct influence on historical usage.

Now that the indicator for efficiency can be estimated by SEM and equity by the deprivation index, different weights were set to define how much preference is desired in the design concerning efficiency and/or equity. Zones of analysis were ranked and then prioritized for having a station based on four criteria, which can help to set different scenarios. These scenarios can be compared in terms of density and spread. A higher supply density increases access to the system and makes it easier to balance bikes. Higher coverage is linked to higher global accessibility in the area of study. Moreover, the different scenarios can help decision-makers to have different options to choose the alternative that they consider better for the city and people's needs.

DARE was applied in Munich and its peripheral region. It showed the potential of the method for expanding existing BSS because models were built in the city of Munich and applied in the peripheral area. The results showed the potential to include equity in the design of BSS while considering efficiency as well. Based on DARE, efficient systems can be designed with inclusion of the neediest population.

Finally, Figure 8.1 shows the proposed and updated BSS planning cycle based on the results of the study. DARE can be applied after setting the goals of the system. DARE can be applied after the system's goals have been established. Finally, after a system is expanded or implemented, a spatial fairness assessment can help change the goals and the planning cycle would start all over again.

The following sections describe in detail the key findings based on the four research questions in this study.

8.2 RQ1. What is the public discussion on BSS concerning their benefits, drawbacks, and future?

The key finding concerning this research question is a list of the most frequently discussed topics related to the advantages, disadvantages, and future of BSS. A mixed-methods methodology was developed to analyze English-language posts related to BSS on Twitter. As an additional contribution, the most common English terms related to BSS were collected to identify the term that most people on Twitter relate to BSS.

8.2.1 Mixed methods approach: Social media analysis is only complete when considering both quantitative and qualitative perspectives

A mixed-methods approach was carried out to understand the public discussion about BSS through qualitative and qualitative social media analysis and complemented with interviews. The difference between Andreotta et al. (2019)'s method and this study is that data is not randomly selected for qualitative analysis, but through sentiment analysis and the integration of data from interviews. The analysis of social media helped to generalize what was identified in the interviews, and the interviews helped to include the opinion of the less privileged population. Moreover, the analysis of social media had the advantage to be written at people's initiative, so that people's opinions about BSS could be gathered on intercity and international level and from a larger number of participants Hannig (2015). However, social media analysis could be biased towards privileged groups of the population that use it. Perrin (2015) identified that 78% of high-income American households use social media, compared to the 56% of low-income households. Therefore, the social media quantitative analysis could be complemented with qualitative information from interviews of underprivileged populations.

The quantitative clustering approach helped to automatically analyze numerous tweets, find the most common terms used with BSS, and to link posts with sentiments. This approach served as a starting point for understanding the debate of FFBSS and also private versus public systems. The categories from the quantitative approach were a subset of the clusters of the qualitative approach. The qualitative approach served to understand the problem deeper, have fine-tuned categories, and diagnose sarcasm and misclassified tweets.

The quantitative approach helped as a starting point for the qualitative analysis. The quantitative methods are less labor-intensive, but their results are on a macro level and dependent on the implemented dictionary and contain sarcasm that could not be recognized. Limitations in the analysis include the exclusion of photos, videos, and URLs. They can serve to provide further evidence of the discussion. For instance, Kumar and Garg (2019) proposed a method to include images and videos in the sentiment analysis. They stated that including images and videos and their expressiveness could expand the sentiments from the text. Moreover, commercial names of BSS were not searched where it might have been missed during the collection of potential tweets related to BSS. The general public discussion on BSS was explored and by searching for specific names, the information could have been biased to a specific system. Another limitation in the quantitative social media analysis could have been "trolling", i.e. posts in which their "real intention(s) is/are to cause disruption and/or to trigger or exacerbate conflict" to have fun (Hardaker, 2010).

The qualitative approach helped to understand the quantitative results more deeply, understand the feelings, and have detailed categories. However, qualitative approaches are labor-intensive and blamed to be subjective, and cannot be generalizable. Subjectivity was reduced in this research thanks to the quantitative approach. Thanks to the quantitative approach and the frequency of the terms, the subjectivity in this research is reduced. In summary, one approach fed the other. The quantitative approach helped to generalize the categories identified in the qualitative approach, and the qualitative one helped to understand the categories of the quantitative more deeply.

The public discussion on Twitter with regard to BSS does not reflect the ideas, comments, or complaints of people who do not use Twitter, nor of Twitter users who have not posted in English. However, Twitter allowed us to collect opinions, thoughts, or ideas from a broad audience such as the news, activists, pessimists, people from different cities and nationalities, etc. Social media analysis does not replace approaches that involve interviewing, observing, or surveying. However, a higher understanding of people's thoughts was achieved on an international and intercity level in a relatively short time and with few resources.

8.2.2 Public discussion on Twitter regarding BSS dilemma and their future

The public debate on BSS was mainly part of two discussions: a) BSS are sustainable, fair and good for mobility vs BSS are not sustainable, unfair, and not good for mobility (Table 8.1), and b) Insufficient supply of public SBBSS versus oversupply of private FFBSS.

Bike-sharing was attributed to environmental benefits because they reduce congestion and thus emissions, but people complained when they became part of the urban litter when they were stacked, vandalized, or broken due to poor quality. In social terms, BSS were promoted as being equitable, but people complained that they were not in low-income neighborhoods and that they were not for the undocumented and elderly. Furthermore, BSS were perceived as helpful for sightseeing and as targeting mainly tourists. In the economic component, BSS have been recognized as affordable and supporting the local economy. People claimed that with a BSS they did not have to worry about maintenance, storage, purchase, or theft costs. However, some systems were considered too expensive. The last debate component was mobility. BSS were reported to be fast and fun, but also to collide with other modes of transport, such as walking or even cycling. BSS were considered a good alternative when there was no public transport or transit connection on the last/first mile. However, some people complained that there was not enough cycling infrastructure. Finally, people thanked BSS for its accessibility. They could rely on BSS if they did not have their own bicycle.

The second dilemma was related to the fact that people complained about the lack of stations or free parking possibilities in SBBSS. They would rather prefer a dockless option in their station-based system, which is usually publicly regulated. In other cities, however, FFBSS were perceived as garbage in the public space. Negative sentiments were expressed when postings were published about the FFBSS using bicycles of low quality and usually from Asian start-ups.

Moreover, in this study, data from interviews of the underprivileged population was included in the analysis of the public discussion. In the context of the doctoral thesis in Villeneuve (2017),

Table 8.1: Bike sharing dilemma: good vs bad for environment, society, economy and mobility (including interviews data)

Topic	BSS are Good	BSS can improve
Environment	–Less congestion & emissions	–Public rubbish dump
Society	–Equitable –Help to explore cities –Healthy	–Lack in low income neighborhoods and –Not for undocumented and old people **–Not for poor people and those in need but for rich, and students** **–Only for tourists** –Not safe
Economy	–Affordable –Supports local economy **–No maintenance**, storage, purchasing or **theft** costs	–Too expensive
Mobility	–Fast + fun + **practical** –Good for transport resilience and last-mile connection **–Easy to use** –Cycle when own bike is not available + **Better than owning a bike**	**–Conflict with other modes** –Not enough or bad quality infrastructure –Difficult to use –Better to own a bike

Note: Bold means that the information was included in the interviews

interviews were conducted with 27 non-motorized households feeling socially excluded in Strasbourg (France) on everyday mobility behavior, accessibility, and perceptions of social exclusion due to mobility. The data from interviews complemented the social media analysis, as thoughts and comments of underprivileged people were included in the analysis (Table 8.1). The main result was the perception that BSS were not intended for poor and needy people but for rich and students. Interviews complemented the analysis of social media and could provide a broader focus that includes perceptions of underprivileged people. They had the feeling that the system was not for them, and therefore this could increase their sense of social exclusion.

Regarding the future, people perceived that the future of BSS is electric, dockless, and integrated with other transport modes. Around 50% of the tweets about the future of BSS stated that hybrid, electric, and integrated with public transport and other shared modes will be part of the future of mobility. The hesitant statements that bike-sharing will be part of the future mainly referred to the systems with poor bicycle quality. Around 12% of the futuristic tweets stated that BSS is likely to collapse, especially concerning Asian FFBSS start-ups.

Politicians and stakeholders can use this information before implementing BSS to regulate the quality, maintenance, and number of bikes. Based on the tweets, people prefer hybrid systems with electric and cargo options and integrated with other shared modes and public transport. It was found that electric bikes have a strong positive feeling at the posts and can serve as a convenient alternative to long trips or steep topography. Moreover, when planning BSS, it is suggested that the perceptions of this population should be taken into account so that they are also part of the decision-making process, and they feel more involved in society. The posted benefits of BSS can be used by practitioners as their goals for the systems and also for marketing purposes to promote their systems. Nevertheless, practitioners should understand the disadvantages of BSS to mitigate or avoid them in their cities. Finally, the results had the advantage of including a wider picture of BSS beyond geographical boundaries.

8.2.3 English terms referring to BSS. Use the term: "Public bike share service" to post about BSS

To the best the author's knowledge, this was the first attempt to study the most common English terms that people relate to BSS. The most common term in English on Twitter for referring to BSS is "bike share", followed by "bike sharing" and finally "bike-sharing". It was more common to write "bike" than "bicycle" or "cycle". Errors in the search for related tweets were identified with the term "shared bike". It was associated with the sharing of bicycle infrastructure, such as "shared bike paths" or "shared bicycle lanes" with other means of transport like walking or cars. Tweets that referred to BSS as being public services were correlated with positive sentiments, and terms that referred to private companies and focused on the market had a more negative connotation.

The collection of the different terms related to BSS will help to find information about BSS, and to conduct more effective promotion campaigns. Using the terms "bike share", "bike sharing" or "bike-sharing" is recommended for marketing purposes or communication with riders. Since these terms were frequently used for referring to BSS, it is inferred that people would associate them better with BSS. Furthermore, BSS-related terms accompanied by the words "public", "system" "service", and "program" presented higher positive sentiments, while "firm", "company", "scheme" or "start-up" showed negative sentiments. It is therefore inferred that in English-speaking countries, possibilities are higher that people will accept BSS if they are public rather than private.

8.3 RQ2. How the allocation of BSS infrastructure can be assessed based on spatial fairness?

8.3.1 Conceptual framework and BSS classification according to spatial fairness criteria.

A conceptual framework was developed on "spatial fairness assessment" based on the most common distributive rules of resources: equity, equality, and efficiency (Figure 5.1, pg. 57). Fairness is a subjective assessment, in which what is fair for one person might not be for others (Goldman and Cropanzano, 2015). For instance, efficiency can be fair for some points of view because it might be considered that the people who contributed or can contribute the most should be prioritized in the distribution of resources. However, prioritizing exclusively efficiency, the justice focus of the distribution would be narrow. On the contrary, when the neediest population with regard to social status, opportunities, or abilities are prioritized in the distribution of resources, the justice focus would be broad, and this criterion might be fair for some people but unfair for others.

Furthermore, the assessment of whether a distribution of resources is efficient, equal, or equitable can be carried out on a social or socio-spatial level. The difference between the two is whether the social indicators (e.g. sociodemographic characteristics) have a spatial dimension or not. Finally, spatial fairness assessment was defined as the identification of the rules that follow the distribution of resources (spatial equity, equality, efficiency, or a mix of them) considering socio-spatial factors.

This developed framework helps to distinguish visually the connection between justice, fairness, and distributive rules with the concept of spatial fairness assessment. It synthesizes different justice concepts and their relationships. Spatial fairness assessment helps to know which criteria were chosen while distributing resources and the people affected in the distribution can judge how fair was the distribution in a spatial way, who was prioritized, and who not. This concept plays an important role in the distribution of public resources on different spatial scales. Assessment and communication of spatial fairness might lead to higher acceptance of infrastructure, higher political trust due to the transparency, and the potential inclusion of the less privileged population. Nevertheless, how spatially unfair a system is perceived, could lead to misuses and vandalism and could generate protests and demands for fairness.

The literature review distinguished different ways of classifying BSS e.g. according to the business model, presence of stations, etc. (Section 2.1). A new classification based on spatial fairness was proposed. In other words, a classification based on who lives in areas prioritized with BSS services and who does not. Five categories were distinguished (see Figure 5.2, pg. 58):

1. *Spatial equity.* Most of the infrastructure would be allocated in deprived areas.
2. *Spatial efficiency.* Most of the infrastructure would be allocated where those that contribute the most live and work.
3. *Spatial equality.* Equal allocation of infrastructure throughout social groups.
4. *Spatial efficiency + spatial equity*. The infrastructure is not evenly distributed and there is no clear distinction between privileged and underprivileged areas being served or not. Also, this classification can be present in service areas where the people who contribute the most are the neediest.
5. *Spatial equity + efficiency+ equality.* Spatial equity, efficiency, and equality would be present in the hypothetical case where there is no clear distinction between privileged and underprivileged areas and the infrastructure would be equally spread throughout social groups.

One limitation of this assessment and classification is that it is a human-based approach. Environmental rights were not considered in the spatial fairness assessment. Human-based equity, equality, or efficiency in the distribution of resources could be harmful or unfair to the environment. For example, providing for those most in need may require greater balancing efforts and emissions from balancing trucks may be unfair to the environment.

8.3.2 Quantitative and quantitative spatial fairness assessment framework: equity, equality or efficiency?

The conceptual framework served to generalize the spatial fairness assessment and classify BSS. The framework summarizes the methods found in the literature and combined them into one approach. Commonly, equity assessments have been carried out by different methods, however, the assessment combines spatial equality, equity, and efficiency to identify if more than one criterion was considered.

This combination of approaches was merged into one quantitative assessment. The criterion which is the most probable that a system follows could be numerically estimated. Moreover, different shallow and deep analyses (e.g. GINI coefficient, statistical test, regressions) previously identified in the literature were condensed in a single methodological framework to estimate who is prioritized in the distribution of the BSS supply.

The use of a single numerical approach may lead to a bias in the evaluation if another focus is not considered. This numerical assessment can help compare between systems and to validate that a system follows a certain criterion. Numbers also support the communication of the evaluation to stakeholders and the public and make the final results more transparent. Finally, the quantitative fairness assessment was complemented with people's perceptions in a qualitative approach. The qualitative analysis helped to validate the quantitative, and the quantitative helped to generalize the qualitative.

8.3.3 Availability of bicycles and Deprivation index: indicators for the quantitative assessment

The availability of bicycles was chosen as an indicator of accessibility to the supply of BSS. Availability as accessibility indicator has been used as the inverse of the idle time (number of bikes per day in an area) (Mooney et al., 2019) for FFBSS, or the "ratio of [the] number of bicycles available to [the] station capacity (ranging from 0 to 1 - empty through full)" for SBSS (Reynaud et al., 2018). It should be emphasized that access to a bike-sharing system does not depend on the availability of stations, but on the availability of bicycles. Therefore, an innovative concept was developed to define the availability of bicycles in an area. This new concept included both free-floating and station-based systems without a specific timescale. The percentage of time a person in an area can access a bicycle was suggested to be included in this concept. Thus, availability in this study was defined as the time rate in which there is at least one bike available in a buffer of distance “d" from a point where a user is willing to walk to access a bike-sharing system.

The algorithm for the estimation of the availability starts with assigning every bike drop-off to a spatial unit. Then, the time intervals are intersected between the bikes' drop-offs and the next pick-up per spatial unit. Finally, the availability indicator per spatial unit is the rate between the intersection of the time intervals and the complete period evaluated in the study.

Reynaud et al. (2018) stated that only a few studies focused on the availability of bicycles. Previous study consider only proximity to stations (Fuller et al., 2011) or idle time of bicycles in an area (Mooney et al., 2019). This concept of availability considers a desirable walking distance to access the system, and also, focuses on "real" access to the system by having at least one bicycle available. A person can be in the service area or close to stations, but if at least one bike is not available in a ratio that the person is willing to walk, the system is not "really" accessible.

Concerning the assessment of spatial fairness, if the availability is equal in all the areas, a system would follow spatial equality; if availability is higher in areas where people can contribute more to the system, a system would follow spatial efficiency; and if availability is higher in deprived areas, the system would follow spatial equity. In order to perform a deeper quantitative assessment, areas of analysis were classified into four types based on high or low availability, and high or low usage (observed demand) of bicycles (Table 8.2). *Type LH* areas (see Table 8.2) are critical for fairness assessment because there is a potential demand, but there is low supply. Decision-makers might focus their attention on them due to the low availability. If people need BSS and do not have access, it might be felt that the system is unfair. On the other hand, the oversupply of *type HL* areas can lead to the same rejection as a feeling of "unfair" use of the public space. Operator-based relocation strategies can take bicycles from oversupplied areas, e.g. *type HL* and take them to *type LH* areas. Furthermore, user-based strategies can be promoted by offering incentives to users when cycling from *type HL* to *type LH* (Reiss and Bogenberger, 2017) areas.

Table 8.2: Areas classification: observed demand vs availability.

Type	Availability	Usage	Efficiency	Strategies
LL	Low	Low	Efficient.	–Survey: is the availability low because of the low supply?
LH	Low	High	Inefficient (Undersupply)	–Improve balancing strategies orienting it to these areas – Potential location of new stations. –Critical areas for fairness assessment
HL	High	Low	Inefficient (Oversupply)	– Potential location of unused bikes. –Improve balancing strategies and system attractiveness (e.g. incentives, include electric bikes) –Improve the visual elements of the system –Enhance marketing and information. –Survey and focus groups to understand why people not use BSS.
HH	High	High	Efficient	

A remaining question is whether cities should bother providing access to BSS when the motivation to use it is virtually nonexistent, e.g. *type HL* areas. This might happen according to the preferred distribution rule(s). For example, if following primarily spatial equity is desired in the system, stations might be implemented and re-balancing strategies could be focused on where underprivileged people live. If the infrastructure is not being used, user-based discounts can be applied not only in the drop-off but in the pick-up.

People from the interviews feeling socially excluded perceived that BSS was for rich people, tourists, or students. They said it was certainly not for the poor. Moreover, it was identified that people living in a neighborhood with more traditional values and lifestyles are more likely to use less BSS, even though they have good access to the system. Traditional people with lower social status commonly dream of having an expensive car. They also search for constant safety feelings and therefore, a lifestyle of doing what they have been performing in the past. Finally, they feel they have been left behind by society (Sociovision, 2018). These social characteristics are in line with the cycling barriers presented by Transport for London (2011): 1) perception of risk, 2) resistance to change, and 3) social pressure: not knowing anyone else who cycle, worrying about what society would "say" about them if they cycle, fear of personal and social failure, fear they won't remember how to cycle or not knowing the "cycling etiquette".

Therefore, if the main value of the low social status targeted population is tradition, educational workshops and promotional campaigns can be useful (Transport for London, 2011). Social identification could be shaped by practicing cycling with people with the same characteristics and fears, or practicing cycling when others are not around. To overcome, the fear of safety, cycling should be motivated for leisure for example in green areas. Furthermore, cycling can be practiced with the family. In terms of BSS, workshops can be performed on teaching them how to access technology or campaigns for renting bikes with friends and families. Electric bicycles might also be a good option to promote cycling, because they have shown to decreased age differences due to the reduced physical effort (Haustein and Møller, 2016), positive self-image gained (Simsekoglu and Klöckner, 2019), traditionalist might perceive the system as convenient as driving.

The significance of classifying the different types of areas is to improve an existing system. Therefore, Table 8.2 summarized the suggested strategies for each type of area.

Furthermore, an indicator developed in this study was the deprivation index. It helped to identify the areas with higher needs in terms of access to opportunities and social status. This indicator can help to assess how equitable a system is. If areas with a higher deprived index are privileged with higher availability, a system follows a criterion of spatial equity. The deprivation index was defined as the rate of the prevalence of a low social-status population with the average of the accessibility to the opportunities to basic needs, such as healthcare, social and recreational facilities, education, transport, and proximity to the city center.

This index merges the concepts of accessibility with fairness. Usually, just sociodemographic characteristics are studied such as in (Fuller et al., 2011; Ursaki and Aultman-Hall, 2015) but accessibility to opportunities also is a potential indication of inequalities. The deprivation index helps to assess and visualize which areas are deprived in terms of accessibility to basic opportunities such as food, health, and education and also have those who have less economic or educational privileges. The more disadvantaged areas are potential areas where accessible mobility alternatives are sought to improve their socio-economic situation. However, this index does not include a weighting system for the basic opportunities. For example, food can be weighed higher than access to education systems. In this way, deprivation would be higher in areas without access to food services.

8.3.4 Application of quantitative and qualitative spatial fairness assessment

An application of the quantitative spatial fairness assessment was carried out in a hybrid bike-sharing system in Munich.

Sinus milieus (Sociovision, 2018) were used as social indicators to estimate the deprivation index. These are groups of people with similar values, orientation, and lifestyle, clustered according to the social status and basic orientation Flaig and Barth (2014). The German population was clustered into ten different milieus (Figure 7.4, pg. 111) by using a questionnaire based on 40 questions (Schwarz and Ernst, 2009) and around 24,000 interviews (Küppers, 2018). Sinus-Milieus® on a spatial scale are called Sinus-Geo-Milieus and are defined as the probability of every address in Germany to belong to a certain milieu group (Küppers, 2018). Sinus-Geo-Milieus use data from Sinus-Milieus® interviews, official national survey data, and data collected from the marketing company Microm (`https://www.microm.de/`) and applied a multinomial regression model using the addresses in Germany to calculate the probability of each house in Germany belonging to one of the ten milieus (Küppers, 2018). Sinus-Milieus® have been used in transport research e.g. for agent-based modeling (Schwarz and Ernst, 2009; Jensen et al., 2016), multiagent simulation (Soboll et al., 2011), marketing research (Diaz-Bone, 2004), as well as for understanding social changes (Manderscheid and Tröndle, 2008) and mobility preferences (Von Jens, 2018; Sinus Markt und Sozialforschung GmbH, 2019).

Results of the spatial fairness assessment show that bike availability was not prioritized in areas in terms of sociodemographics or social status but rather to basic values (e.g. tradition, adventure). By using milieus as a comparative social group, it was found that traditionalists have a lower priority in the availability of the system than areas where more progressive people live. If this study had focused on sociodemographics, there would have been a risk of not finding a population group that is excluded from bicycle availability.

The higher availability of shared bikes in Munich was slightly related to a higher deprivation index. In contrast, areas with a high concentration of traditionalist residents are negatively associated with the availability of shared bikes. Moreover, it was identified that the system in Munich serves around 75% of the total population, considering a service area and buffer of 500 meters from the stations. Regarding the population who live further than 500 meters from BSS services, 54% belong to the established and 31% of traditional and precarious population, in contrast to only 6% of the cosmopolitan population. The implementation of new BSS services has been prioritized in the county of Munich (Landkreis München, 2019) and not where this population lives in the city of Munich.

In this sense, traditional people are excluded from an opportunity for physical mobility and last-mile connection to public transport at low cost and the other benefits of BSS (see Chapter 2). Hence, traditional people in Munich might have resistance towards the implementation of these systems in the city, vandalism, or low political acceptance (Ariely and Uslaner, 2017; Wüstenhagen et al., 2007). The traditionalist population tends to feel left behind in a progressive society (Sociovision, 2018) and feeling socially excluded. Even though they might not use BSS, not having a "modern and innovative" transport system in their neighborhoods might increase these exclusion feelings. As Villeneuve and Kaufmann (2020) (pg.3) stated based on Lucas (2012), "lack of mobility traps some individuals in a vicious circle of social exclusion by denying them access to jobs and training, which in turn prevents them from earning an adequate salary and having the resources to participate in society."

Residential blocks in Munich inside the service area of the HBSS were classified into four types (Table 8.2) based on the availability and usage of bikes. Progressive milieus are prevalent in *type HH* areas. Mainstreamers and precarious in Munich live significantly more in *type LH* than in *type HH* areas. Moreover, established and liberal intellectuals do not seem to use the system. Even when they have a high level of availability in their residential areas, the observed demand is still low. In Munich, different strategies showed in Table 8.2 are proposed to be carried out for *type LH* and *type HL* areas.

Based on the different methods and analysis carried out in Munich, three classifications of HBSS were inferred:

1. Efficiency + Equity. Underprivileged and privileged people live in areas with higher availability. Therefore, the allocation is assumed to follow these two rules together.
2. Efficiency. Efficiency is present where the usage of the system is directly proportional to the availability, i.e. there is a higher availability where usage is higher and vice versa.
3. Distribution oriented to progressive values. Social status was not an indicator of the distribution of availability. However, the distribution of the infrastructure was associated with the ground values component of the milieus. Areas with residents belonging to social groups with an orientation to progressive values (especially cosmopolitan avant-garde) instead of traditional-oriented values (especially established) have a higher availability of bicycles.

After these three classifications, is this system in Munich fair? For some, it might be fair because where there was high demand, the system presents high availability. However, for others, it might be unfair, because BSS excludes the traditional population. It also might be unfair to some who believe the service should serve all social groups equally.

According to the qualitative assessment, based on data from 27 interviews with non-motorized households in Strasbourg (France) about mobility perceptions, BSS was perceived as not being oriented to the most disadvantaged population and not being served in the underprivileged neighborhoods. The perceived spatial inequality helps me understand that underprivileged people feel and perceive that the system is not for them. Inequality can lead to a negative image of BSS and not being publicly accepted, and thus, vandalism can occur. Social groups that were spatially linked to higher availability of bicycles were also perceived by the respondents as being the focus groups. Areas with a predominance of cosmopolitan avant-garde residents had higher availability of bicycles, which complements the statement in the interviews that BSS mainly serves students and the rich.

One limitation of the assessment is that the qualitative and quantitative assessments were not conducted in the same city. Although two different cities were used, they are somewhat comparable. The two cities used as case studies are located in Central Europe, they are not capitals but are representative of their countries, they have relatively well-developed bicycle infrastructure, and with regard to the urban structure, it is affected by the proximity of a river. Another limitation is that the calculation of the accessibility to opportunities in the estimation of the deprivation index was estimated with the distance 'As the Crow Flies' and not the distance based on the road network. Neither the topography was included in the application because of the relatively flat surface of Munich, which is recommended to be considered in further applications. Finally, the spatial fairness assessment focused on whom the bike-sharing service is targeted at within the business area in Munich. However, the social characteristics and their ability to access the system of people living outside the service area were not explored.

8.4 RQ3. Which spatial factors are associated with BSS usage?

8.4.1 Are the factors studied in one city associated with usage in another city or region?

Built environment factors associated spatio-temporally to BSS usage beyond geographic boundaries Stepwise linear regression (stepwise OLS), generalized linear models (GLM) with LASSO technique for variables selection, and gradient boosting machine (GBM) were selected to fit the usage of BSS in multiple cites with the built environment. Models performed better in cities with similar hourly demand distribution and comparable urban characteristics. Stepwise regression was parsimonious with fewer input arguments, and its results were easier to interpret. The three modeling techniques presented similar validation results. Generally, for the three regression methods, the logarithmic transformation performed a higher fit of the data in the validation phase. The advantage of stepwise OLS and GLM was that a variable selection process was implicit in the methods, but for GBM a variable selection process had to be developed to select those with more influence from the ranking list.

For further research, step-wise linear regression is recommended. It returns parsimonious results with a relatively high fit. The association of each variable is shown, and it can serve to use them in other areas. There was no black box of the results as in the case for GBM and therefore can be better explained to stakeholders. Finally, if an approach with multiple cities is willing to be carried out, choosing cities with similar urban characteristics is suggested (e.g. cities next to water bodies) and temporal travel patterns (same peak and off-peak hours).

In the application in multiple cities to identify built environment factors associated with BSS usage, mostly leisure activities were highly correlated such as parks, green areas, and bodies of water on the weekends, banks in the morning, gas stations, pubs, cinemas, clubs at night, shops on Saturdays, and memorials outside working hours. Regarding public transport, it was found that train stations were significantly associated with BSS usage in the German cases for weekday mornings, while the distance to bus stations was associated with usage in the international cases. The urban structure was found to play an important role in the international approach based on the distance from all stations to the marina and colleges and also land use represented by residential areas and parks. Summer and winter presented different factors, for example, bakeries, bus stations, and restaurants were more significant in summer than in winter.

The economically efficient design of BSS should be oriented not only but especially to the following variables associated with the usage beyond geographical boundaries (international and national level):

- Density:
  - High population density areas. Where there are more people more rentals can be performed.
- Diversity:
  - Green activities: parks, water bodies.
  - Touristic activities: memorials, artworks. BSS serving tourism.
  - Commercial areas: department stores and malls.
  - Evening leisure activities: restaurants, bars, pubs, cinemas, clubs. Due to the lack of transit at night, BSS are an opportunity to come back home where transit finished their services.
- Design:
  - Public transport stations: bus stations and railways. BSS serve as lat-mile connector to transit.
  - Car-sharing stations. Since car sharing stations are associated with the usage of BSS, it is inferred that car and bike-sharing infrastructure are placed in similar areas.
  - High density of cycle ways density. Cycling infrastructure is needed to use BSS.
  - Proximity to the city center. Closer to the city center might be more activities to perform, therefore more trips of BSS might be taken.

8.4.2 Are there factors from the social environment associated with the usage of BSS?

In Munich, progressive milieus were associated with the BSS usage in Munich (Germany) Residential areas where people with progressive orientation live such as cosmopolitan avant-gardes, performers, social ecologists, hedonists and adaptive navigators live were positively correlated to the usage of BSS. On the contrary, milieus with a traditional orientation such as established, liberal-intellectuals, traditionalists, precarious, and mainstreamers were negatively associated. At another spatial level, cosmopolitans and performers were positively associated with the usage of BSS in zones of analysis of the service areas. In conclusion, the usage of the system in Munich was oriented to the areas where the most progressive people with a tendency of high social status (e.g. junior employees in jobs with university degree requirement) live or perform their leisure activities, but not where the people with more traditional values lived.

This analysis was similar to market segmentation. To develop a more economically efficient system, a new supply of the BSS in Munich should be oriented where progressive people live and commute. If equity was required as well, areas should be prioritized, where more traditional people with low social status live. These results were complementary and therefore validated, with the survey by Stöckle et al. (2020), where the main value of BSS users in Munich was adventure (progressive values) but not tradition and security (traditionalist values).

8.4.3 Are the previously associated factors causal or indirectly associated with the usage of BSS?

A theoretical structure was created, including the factors previously associated with the usage of BSS in the literature and in the multiple cities' analysis. The links between factors were taken from theoretical models of land-use and transport interactions, and urban mobility cultures. Furthermore, these links were validated with Structural Equation models. These factors were modeled as latent variables representing the BSS observed demand, attractiveness, urban structure, mobility preferences, and milieus (social environment). To the best of the author's knowledge, this is the first time that has been merged the theoretical concepts of transport planning with mobility culture in transport modeling.

According to the modeled structure, the links between the factors were numerically validated using goodness-of-fit (CFI) and badness-of-fit diagnostic (RMSEA) tests. Figure 8.2 shows the results of the SEM applied in the hybrid BSS in Munich, Germany. The observed demand was linked directly to the attractiveness of an area. In other words, BSS drop-offs were directly associated with areas with activities such as department stores, food services, tourist attractions, cinemas, and theaters. The built environment variables that were identified previously were also part of the associated factors. It is inferred that parks and areas close to water bodies (e.g. lakes) were taken in the model as part of areas with high walkability density.

Observed demand was linked to the urban structure through activities. No direct link was found between the social environment and the usage of BSS, however, the social environment was directly linked to the urban structure. From the outcoming structure, it could be inferred that milieus chose their residence location based on the urban structure. Finally, mobility preferences were directly but weakly connected to the observed demand and milieus, however, the preferences were strongly connected to the urban structure.

Limitations of the application rely on the exclusion of the social environment and the relationships between the factors on a level beyond geographical borders. Moreover, spatial autocorrelation between zones of analysis was not considered, which could have helped to improve the good-of-fit of the model because areas would have been studied considering factors from their neighbors. Moreover, trips' destination were studied but not the trips between areas and the potential spatial factors associated with the trips such as distance, time, topography, infrastructure. In addition, non-censored demand could be potentially included as described in Gammelli et al. (2020). Finally, zones of analysis could have been clustered based on the temporal distribution of demand, and regression models could have been built per cluster to increase the prediction accuracy.

Even though it was not part of the main goals of the research and based on the results of the SEM, an expansion of the theoretical model of interactions of land-use and transport (Wulfhorst, 2003) is proposed, including the social environment represented by mobility preferences and milieus. The proposed structure theoretically connects the social environment with the urban structure through the concept of accessibility based on the resulting links shown in Figure 8.2.

"Accessibility can be seen as a key element in the complex system of land-use and transport dynamics" (Wulfhorst, 2008, 5) and "as an attribute of the land-use structure and of the transport supply" (Wulfhorst, 2008, 4). In this research, accessibility is understood 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) (at various times of the day)” (Geurs and Van Wee, 2004, 128). This concept of accessibility considers among others the individual component which is reflected by the needs, abilities, and opportunities of people. "These characteristics influence a person's level of access to transport modes and spatially distributed opportunities, and may strongly influence the total aggregate accessibility result." (Geurs and Van Wee, 2004, 128). Social factors can be at an individual level as described previously or at the level of the areas where groups of people live (Beckmann et al., 2008). On a spatial level, milieus are proposed to be considered as the social component of accessibility instead of individual needs, opportunities, or

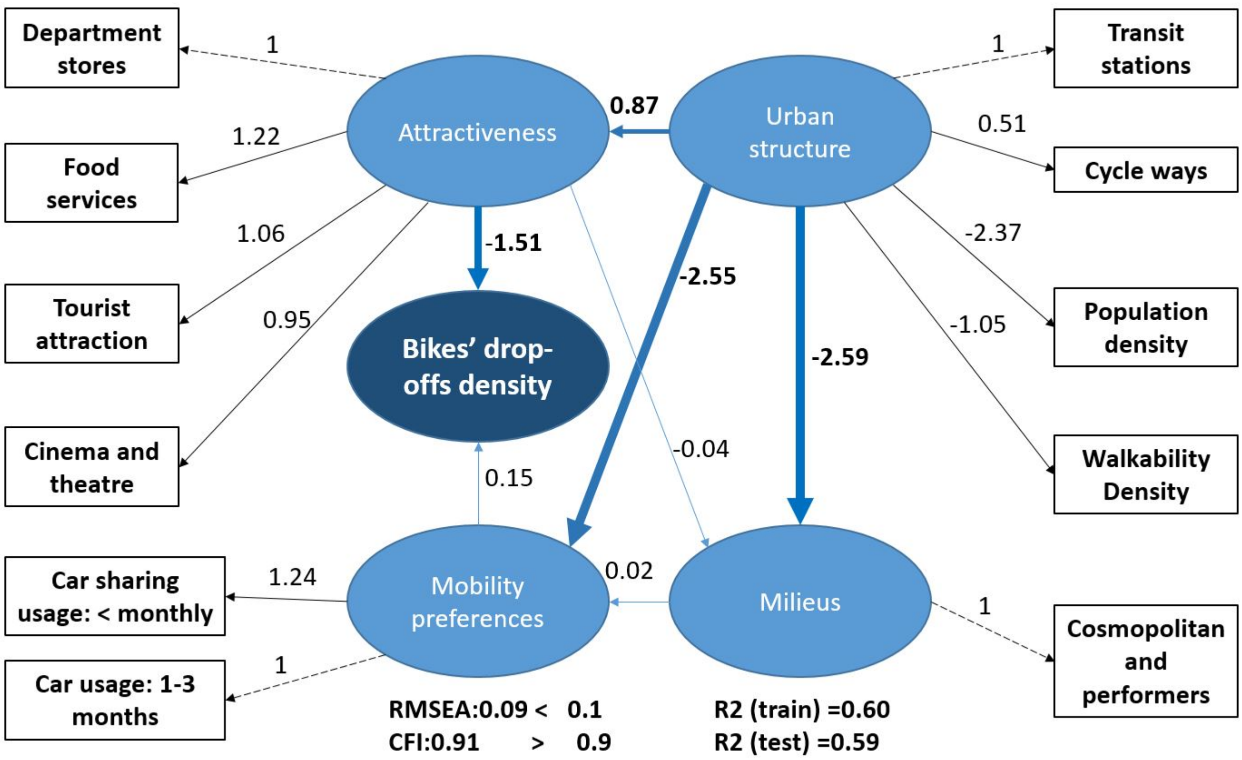


Figure 8.2: SEM results of factors associated to BSS usage

abilities because milieus are "characterized by groups with similar patterns of lifestyle by a high density of contact and a common spatial context" (Beckmann et al., 2008).

Figure 8.3 shows the proposed adaptation of the summarized theoretical structure of the interactions of land-use and transport (Wulfhorst, 2003) based on the results of Figure 8.2. The adaptation of this model will help to understand mobility deeper and not only as part of transport but as part of a "mobility culture". Milieus representing people's socioeconomics and values are in the center. People are the main component of transport and should be in "the center". Beckmann et al. (2008) explained that milieus spatial location dependent on the urban structure (Beckmann et al., 2008), however, in this model is it proposed to be understood that milieus are dependent on the accessibility of the urban structure. Moreover, in a long term, milieus also can influence the urban structure, for example, after a spatial fairness assessment, or gentrification. Mobility preferences are dependent on the milieus (Deffner et al., 2006) and the access to the transport supply and land use. Finally, if activities are required to be performed, transport demand is originated (see Table 7.2).

In summary, the simplified model proposes that mobility preferences emerge at the spatial level based on the accessibility of the urban structure (land use and transport supply) and the socio-spatial environment (milieus). Last but not least, transportation demand arises based on mobility preferences and when an activity needs to be performed.

8.5 RQ4. How can BSS be expanded or implemented based on spatial fairness?

Demand And/oR Equity (DARE) is a heuristic-based method that can serve as a decision-making method to allocate BSS stations and limit the service area which has as input the spatial fairness preferred criterion: spatial equity, efficiency, or a balance between them. DARE has mainly seven steps:

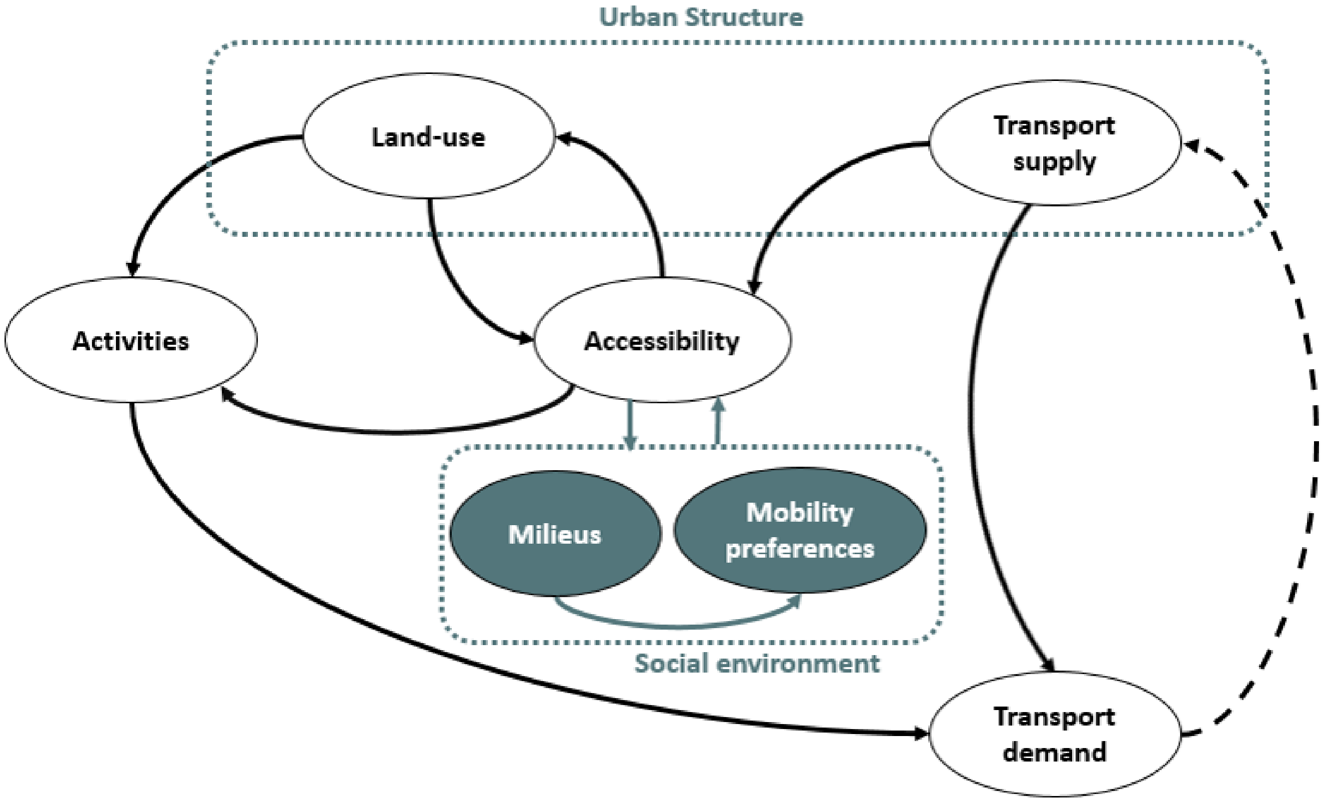


Figure 8.3: Adaptation of the land-use and transport interactions scheme and urban mobility cultures. Inspired and adapted from Wulfhorst (2003)

1. Selecting a study area, and dividing it into zones of analysis,
2. Collecting data from the built and social environment, generating features and aggregating them into categories,
3. Estimating deprivation in each analysis zone or an index showing where underprivileged people live,
4. Estimating potential ridership in each analysis zone or other variables related to “productivity" (e.g. systems’ earnings),
5. Ranking zones of analysis in terms of equity (step IV) and efficiency (step V),
6. Creating scenarios based on the number of (virtual) stations according to the available budget and the four algorithms previously presented (e.g. Top-n) for infrastructure allocation. For dockless systems, a service area is set using the collective buffer distance from the virtual stations.
7. Comparing scenarios in terms of density and coverage.

The decision-making method helps to locate stations and the service area for BSS. The method could be used for SBSS (physical stations) or FFBSS (virtual stations) to a) expand BSS after learning from an existing system, b) to relocate stations based on goals’ changes, and c) to implement new systems, after learning from a city with similar characteristics.

Planners can prioritize the distribution of infrastructure considering spatial equity and efficiency weights according to the BSS goals and preferred fairness criterion. For example, if efficiency is preferred, then areas with higher potential demand are chosen to have stations. If pure equity is desired, the most deprived areas are prioritized with infrastructure. Furthermore, a balance between efficiency and equity can potentially be achieved in which disadvantaged areas are not abandoned, and the system can also be economically efficient. The different scenarios with different weights can be communicated to the public and stakeholders to analyze which scenario(s) meet(s) the needs of the people and the desired goals of the system. This approach can help planners be transparent about whom they have and have not prioritized when allocating resources.

The decision-making method is a "semi-automated" heuristic process. Setting the zones of analysis, estimating potential demand and the deprivation of each zone is practically an automated process. The few "manual" procedures are the data collection and the inputs of the design such as the size of the areas, and spatial factors to be considered. In addition, different scenarios can be created with different weights and parameters, allowing decision-makers to analyze and select the scenario that meets the desired goals of the system.

The "semi-automated" process can help to mitigate the BSS's drawback related to the "inconvenient system design" and over or undersupply. This process can help to reduce human efforts by developing multiple scenarios compared to GIS approaches. Variables included in the literature that are related to the usage of BSS are present in the design, and also deprivation is considered to mix the advantages of social and economic efficiencies. This approach has the potential to plan systems efficiently yet equitably by allowing infrastructure to be placed where high demand is expected and also where the neediest population lives.

The method could be improved by adding in the rank index an extra parameter from crowdsourcing or community workshops. Most voted zones could be another weighting input for the estimation of the rank index and thus, include public participation in the planning. In addition, an environmental parameter can also be included in the ranking index, giving additional weight to areas with high emissions, for example.

Four algorithms were developed to suggest the location of BSS supply after being ranked according to weights given to the expected usage and/or deprivation and the desired number of (virtual) stations.

1. Top-n. The top-ranked areas are prioritized
2. Neighbor. The top-1 ranked area is assigned a (virtual) station and then, the neighboring area with the highest ranking. The procedure continues until all the required stations are located
3. Island. The $top - i$ ranked areas are assigned (virtual) stations, where "i" is the number of islands desired. The remaining number of stations is distributed equally among the islands using the neighbor method.
4. Island-weighted. It differs from the "Island" algorithm by distributing the remaining stations among the islands with a weighting function.

By having four different algorithms, different scenarios can be developed based on BSS goals. The top-n method might have a big coverage but a low density because of the randomness of the location of the higher-ranked areas. On the contrary, the neighbor method might have a high density but low coverage because it is based on contiguous areas. The island method has an equilibrium between coverage and density. These multiple scenarios give opportunities to meet the goals desired for a system based on the fairness or prioritization criteria desired.

Coverage of the supply and its density are outputs of different scenarios, which can help to identify an optimal number of (virtual) stations. Coverage is an indicator that more people have access to BSS, and density allows that users have higher availability of supply, and also balancing procedures would require fewer efforts. The optimal system, if the resources are limited, would be a system with the highest possible coverage at the highest possible density. After estimating coverage and density, different scenarios can be evaluated and compared. The balance between them is a way to have an idea of an ideal initial number of (virtual) stations to be implemented.

Limitations of the method include the lack of feedback from stakeholders. DARE was built based on needs identified in the scientific literature and public opinion. However, stakeholders' inputs were not included in the design of the method. Stakeholders could use the method and analyze the methodology in order to validate its usefulness, feasibility, complexity, and relevance to real-world practice. In addition, DARE could be improved based on the experiences of practitioners facing real-life planning decisions through their feedback. This limitation is relevant to the practical application and practitioner acceptance of DARE, and it should be considered in future research. Other limitations are that the balancing strategies are not part of the supply allocation decision and trip distributions were not considered but Only destination density. Trips connecting zones can be used as part of the allocation algorithms.

DARE was implemented in Munich, Germany, in the coverage area of the existing hybrid system. We applied the two extreme cases of spatial equity and spatial efficiency with a budget of 100 stations. When spatial equity was sought, disadvantaged areas were given preference in station allocation. However, in these cases there were only a very limited number of stations in the city center, making it difficult for people in disadvantaged areas to cycle to and from the city center. In contrast, with spatial efficiency, the stations are concentrated in the city center and disadvantaged areas are poorly served. Furthermore, DARE was also applied in the peripheral region of Munich with different weights for equity and efficiency. When the equity weighting was lower, stations were located closer to the city of Munich. The top-n algorithm with a high-efficiency weighting had similarities to the existing station distribution, which gives us an idea of the equity criterion chosen for the station distribution. Furthermore, it should be noted that the top-n algorithm is similar to the island algorithm when the number of islands is equal to the number of stations. When the number of stations is small, the neighborhood algorithm is similar to the island algorithm because the populated edge area is very sparse.

8.6 Thesis contributions

In order to sum up, this research included contributions to theoretical, methodological, and practical levels.

Theoretical contributions

1. Syntheses of the literature
   - (a) BSS: Types, advantages and disadvantages.
   - (b) BSS planning methods.
   - (c) Collection of terms in English referring to BSS.
   - (d) Conceptual framework of spatial fairness.
   - (e) Theoretical framework of interactions between factors associated with BSS usage, after linking the theories of land-use and transport interactions and urban mobility cultures.
2. Own Concepts
   - (a) Deprivation index.
   - (b) Bike availability.
   - (c) Rank index concept to allocate BSS (virtual) stations.

Methodological contributions

1. Mixed methods approach for understanding a public discussion.
2. Method for quantitative assessment of spatial fairness on BSS.
3. Identification of spatial factors associated with BSS usage beyond geographical boundaries.
4. Estimation of the potential use of BSS using structural equation models and factors from theories of land use and transport theory interactions, and urban mobility cultures.
5. Demand And/oR Equity (DARE) Heuristic Method for planning BSS.
6. Four algorithms for the location of (virtual) stations.
7. Optimization of the number of (virtual) stations based on the Gaussian Kernel Density Estimate (KDE) of the stations and their coverage area.

8. Considering milieus as input for BSS planning

Practical contributions

1. Topics related to the public discussion on the BSS dilemma.
2. Perception of the spatial fairness of the bike-sharing system in Strasbourg (France).
3. Quantitative spatial fairness assessment of the bike-sharing system in Munich (Germany).
4. Associated built environment parameters with the usage of BSS in six cities in Germany (Hamburg, Frankfurt am Main, Stuttgart, Darmstadt, Marburg, Kassel) and three cities in three countries and three continents (Hamburg, Chicago, Montreal).
5. Associated built and social environment parameters with the usage of the hybrid BSS in Munich, Germany.
6. Application of DARE method in the service area of the hybrid system in Munich (Germany) and its periphery.

Chapter 9

Conclusions

> *"If the bike share in the Bronx would expand towards the entire borough, I would ride to the Mall at Bay Plaza often. That service area is just too small. BTW, it seems the service area should have started from the southern part of the borough."* @MyratheP-igeon, 26 Nov. 2018

This tweet represents a summary of the main objective of the study. There is a need to expand bike-sharing and making it accessible in underprivileged areas such as the South Bronx, a poor urban community in New York. This study presented a methodology for expanding or implementing bike-sharing that includes spatial fairness as an input.

Transportation planners have now access to a method for creating scenarios for the allocation of BSS infrastructure based on observed demand and fairness criteria using the built and social environment. In other words, systems can be planned in terms of economic efficiency also socioeconomic efficiency. Hence, this research offers the opportunity to incorporate fairness by providing the possibility that *"the service area **can** start from the southern part of the borough".*

9.1 Recommendations for implementation or expansion of BSS

To conclude this study, the steps recommended when planning the extension or implementation of BSS are summarized based on the results of the study. The methods proposed in the research are applicable all over the world. The requirements are to learn from an existing bike-sharing system in the same city or a city with similar urban structure characteristics, and to collect built and social environment factors. The following steps focus on the lessons learned from this research. Strategies were not considered in the fields of governance, operations (e.g. balancing), financial, maintenance, and policy strategies.

9.1.1 Setting BSS goals

To set the goals for a system, it should be first asked: why is a BSS system needed in the city? This question might be answered with help of the summary in Section 2.1.1 concerning the main benefits of BSS shown in practice including I) cycling benefits (e.g. improve health, shift motorized transport trips to alternative mobility), II) access-economy benefits (e.g. monetary saving, access to a bike on an as-needed basis), III) mobility benefits (e.g. greater transit usage, transport resilience), and/or IV) sustainability benefits (e.g. economic development, greater environmental awareness, potential reduction of emissions, and energy consumption). Furthermore, perceived benefits identified on Twitter (Table 8.1) could help to set goals, such as BSS being good for the environment (e.g. less congestion), society (e.g. equitable, help to explore cities), economy (e.g. affordable), and mobility (e.g. fast, fun, practical, easy to use, good for transit last-mile connection).

Goals could be also oriented to avoid BSS shown barriers (see Section 4.4.1) such as cycling barriers (e.g. safety), administrative barriers (e.g. lack of integration and information), infrastructure barriers (poor cycling infrastructure), equity barriers (e.g. prioritization of privileged social groups). In addition, drawbacks perceived by people on Twitter (Table 8.1) could be avoided such as environmental (e.g. bikes dumps), societal (e.g. not being oriented to the people with need), economic (e.g. costly), mobility-related (e.g. conflicts with other modes).

In order to avoid falling into some BSS common drawback, it is recommended to check whether the city for implementing BSS already has a coherent, direct, attractive, comfortable, and above all safe cycling infrastructure and cycling population. Even though BSS could be the first initiative of a city to promote cycling, being a cycling community first will help that a bike-sharing system could be the element that makes cycling accessible to all and (re)launch a "bike-culture". In addition, searching for regional alliances and also analyzing the possibilities for public and private alliances can help to expand the system faster and with fewer risks, including not only monetary goals but also social and environmental ones.

These perceived benefits and drawbacks could be updated with interviews, surveys, and social media analysis in order that they are closely related to the city of study. A social media analysis in cities with similar characteristics might give an idea of what people expect and what should be avoided. This analysis could follow a quantitative and qualitative approach following the guidelines presented in section 4.3. It includes a data collection, in which the terms "bike share", "bike sharing", "bike-sharing and "bikesharing" should be included because they represented 70% of the tweets collected in the study. Sentiment analysis is followed to cluster the main post quantitatively and qualitatively. Moreover, interviews, workshops, and surveys could help in having a deeper understanding of the perception and interests of the population.

For matching the desired goals of the scheme, the proper type of BSS should be selected including the type of service, type of shared-economy concept, presence or not from stations, type of bicycles, access technology, and business model (see Table 2.1). According to Chapter 4, people who tweeted in English preferred hybrid systems combining dockless with docked services in an electric version.

9.1.2 DARE: Demand And/Or Equity method for allocating BSS stations and limiting the service area.

DARE is a heuristic-based method for planning the allocation of BSS stations and their service area based on spatial equity, spatial efficiency, or a balance of them both. Generally, DARE includes the following seven main steps:

1. **Setting a study area and zones of analysis.** This area is for learning from previous experience in order to estimate behavior in the area of implementation. Based on the results of Chapter 6, this area is recommended to have comparable urban structures (e.g. rivers, universities, seaports, public transport, leisure activities), such as historical urban developments, physical geography, cultural backgrounds, etc. You can see the example of Montreal, Chicago, and Hamburg in Chapter 6.

   The learning area and the implementation area should be split into smaller areas. As shown in this research, a good alternative is based on the existing network. This approach helps to delimit regions based on physical barriers, as water bodies or highways. The distance for delimiting the areas should be in concordance with the stations' density desired and maximum distance that a user is willing to walk to access the system. According to the literature review in Chapter 7, the most common distance range from 200 meters to 400 meters.

2. **Data collection and processing.** Data from the built and social environment should be collected for a further generation of features and their aggregation into categories.

3. **Estimating the potential demand.** Different regression methods can be used to estimate potential demand in each zone of analysis. The indicator for observed ridership is recommended to be the density of arrivals in a zone of analysis because they are closer to the spatial factors associated with the trips rather than the departures, which can be further than the origin of the trip. The density of arrivals commonly presents a skewed distribution, as many built and social environment factors. Spatial predictors are recommended to be chosen from Chapter 6, which studied associated factors beyond geographic boundaries (e.g. public transport stations, leisure activities), and from Chapter 7 which includes the built and social environment (e.g. car usage, cosmopolitan population).

   Because of the vast number of possible variables and to avoid multicollinearity between variables with similar characteristics (e.g. restaurants and cafés), spatial variables could be clustered into categories (e.g. leisure food) using, for example, hierarchical clustering as shown in Chapter 7. When variables are independent of each other, stepwise regression showed the best fit of the data and a lower number of predictors selected. However, when exploring multiple types of variables with high associations between them and which logically should be clustered (e.g. restaurants' density and cosmopolitan residents). It is recommended to use SEM with the structure shown in Chapter 7 because these types of models help to predict behavior using multiple types of variables searching for causal relationships, which can be more helpful for generalization and transferability of the model (shown in Chapter 7).

   In this study, milieus were considered as a categorization of social groups. They have the advantage that, in addition to sociodemographic parameters, they also include the main values of the inhabitants, e.g., tradition, adventure, modernization. Sociodemographics have the limitation of the so-called "sociodemographic twins". This means that areas with the same sociodemographic parameters are expected to behave similarly. The prominent orientation or values helped to further categorize and further divide the social environment and better understand the social environment of an area. Values were found to have a higher relationship with BSS use than sociodemographics (see Chapter 5). The drawback, however, is that collecting this information is difficult due to the complexity of estimating it. Therefore, in the absence of milieus, sociodemographic characteristics, perceptions, or attitudes can be included as social environments as an approximation.

4. **Estimating the neediest population with regard to opportunities and social status**. A deprivation index, defined in Chapter 5, can be calculated in each zone of analysis. This index is the ratio of the underprivileged population (with regard to income, occupation, education) and the accessibility to basic opportunities (e.g. food, education, health). Areas with higher deprivation index are assumed to include the underprivileged population.

5. **Ranking potential areas** At this point, each zone of analysis should have an estimated potential demand and deprivation index. After setting policies, regulations, system operation strategies, financial models (Yanocha et al., 2018), design inputs should be established (Table 2.2).

   The main design input for DARE is the weights from 0 to 1 on how to focus the allocation of infrastructure: efficiency and/or equity. Efficiency is related to the estimated demand and equity to the deprivation index. A weight of 0 for efficiency means an allocation privileging deprived areas, and a weight of zero for equity means privileging areas where it is estimated to have higher BSS usage.

6. **Building scenarios** Different scenarios can be built for potential locations of stations and boundaries of service areas. Based on the rank of areas based on efficiency and equity and their respective weights, different scenarios can be created for the distribution of the allocation of infrastructure. Four algorithms were created (see Chapter 7) to allocate the

infrastructure and limit service area based on this ranking index: Top-n, neighbor, island, and island weighted.

7. **Assessing scenarios** Coverage and density of stations are indicators suggested for comparing the different scenarios (see Chapter 7). Top-n presented higher coverage, neighbor presented higher density and the island algorithms is in between them both. Higher coverage is recommended for the dense urban setting because of the potential higher accessibility to more areas, and high density is suggested for the easiness for the user to find stations and for the operator to balance the bicycles.

   In sum, DARE can show different scenarios based on coverage and density of the infrastructure, and demand and/or people's needs. Also, DARE allows transparency while taking decisions and therefore, weights and the chosen scenario can be set by the actors involved in BSS such as users, non-users, stakeholders, politicians, planners, partner organizations, interest groups, individual members of the "general public", and particularly disadvantaged groups (Elvy, 2014). Methods for public participation can include online map-based commenting, smartphone app crowdsourcing platform, public hearings, public opinion survey, consensus conference, citizens' panels, focus groups, among others (Rowe and Frewer, 2000; Griffin and Jiao, 2019).

   Further recommendations are to integrate the system physically, technologically, and monetarily with public transportation and other shared means of transport and to check whether the design is geared to the desired goals.

   Finally, the fixed location of the stations could be determined after site visits and involving the general public and stakeholders.

9.1.3 Spatial fairness assessment

Assessment of the performance is suggested to improve future optimization or expansion of the system. Social and spatial fairness assessments (see Chapter 5) could help to determine if the system is efficient, or who does the system serves and who is excluded.

Spatial fairness assessment could be carried out qualitatively by talking to people who are the experts. It can be further complemented with quantitative data (with the concept of availability of the bicycles in a respective area, which represents the accessibility to the system. If a system follows equity, equality, efficiency, or a balance of both is suggested to be estimated through the calculation of Gini coefficients based on the availability of bicycles, correlation of the availability of bicycles and deprivation index, or statistical independence tests between different social groups and availability (see Figure 5.5, p. 64).

After this assessment if the bike-sharing system is not considered fair, i.e. nor serving the targeted population, new goals for the system can be set and DARE could be applied once more.

9.2 Main reflections on the research

Three main considerations emerged from this research: 1) Should the consideration of fairness as an input be exclusive to public systems, or should it also apply to private systems?, 2) the advantages of exploring causal relationships, and 3) the importance of including societal aspects and interdisciplinary approaches in the planning of transportation systems.

9.2.1 Should private or public BSS consider spatial fairness in their planning?

Whether public or private, BSS occupy our public space that belongs to all. We have the right to know who is being prioritized in projects developed in our public space or with our tax money. Moreover, if a project is private, it does not mean that it cannot be fair and equitable. For some stakeholders, a project can be fair if it is economically efficient with a narrow justice focus. Perhaps private companies do not consider profit the fairest way to distribute resources, and they can broaden their focus on equity by giving priority to those most in need. Companies with a wider justice focus can have a better image in the population, which can serve not only to contribute to social justice in a city but also to have trust and appreciation of the public. Contributing to social justice means reducing social gaps and exclusion, crime rates, poverty, and raising life quality of a place(Baudot, 2006).

Remember that prioritizing the neediest does not mean that a project is not serving those that contribute the most. Private or public systems can be developed more economically effective, where spatial factors allow for potentially higher demand. Moreover, both can also promote social benefits by providing access to those who have the greatest needs or at least allowing them to participate in new transport trends. Those most in need can become major customers if they are provided with information and incentives. If people do not want to own conventional bicycles, an affordable electric version may help to enter the cycling community.

9.2.2 Advantages of exploring causal relationships

This study distinguished features that have causal impacts from those that are purely correlational. Then, generalization could be inferred beyond the original dataset. SEM allowed to forecast potential demand using different types of variables from the built and social environment, and also to estimate direct and indirect associations among the predictors. Therefore, SEM helps to understand the problem deeply, and gives an idea of which variables have a causal relationship with the usage of BSS. In addition, causal relationships could explain how the variables are related to each other, which is an advantage when learning from one system (learning area) and transferring the knowledge gained to another (implementation area). Causality is suggested to be further considered in regression models such as in SEM because it involves behavior, supply-demand effects, and the need to predict "interventions" in new areas.

9.2.3 Planning with mobility engineering glasses

Planning for transportation systems goes beyond the observed behavior and the provided infrastructure. Transportation planning should enable people the opportunity to move, to have fun, to go to work, to be healthy, to fulfill needs. Not all people move similarly, or even do not all want to move at all. When transportation is planned, the infrastructure is taken into account, and also service is being provided. The key is to know what is being served, for whom, and if there is a need for it. Therefore, the main focus of this project was to plan and design BSS based on firstly understanding how bike-sharing works and how it is perceived.

Reading posts of people feeling that BSS are not for them was the motivation to incorporate the fairness approach into this project, which began by focusing on the efficiency and the built environment. In addition, identifying social groups that were excluded from a new form of mobility that can improve their last-mile connectivity to public transport and enhance their physical condition served as an inspiration to include them in future plans of BSS. Exclusion of populations based on where they live, their social status, or their attitudes can be enhanced if the planning of a transport system is based only on predicting demand, the unfair cycle may never be broken. Therefore, the need to include social sciences in transport research. They can help together with the traditional transport concepts (e.g. modeling, simulation, optimization) to build a fairer society and make transport planning solutions based on the neediest population.

Mobility is a social science that works with transport engineering concepts and has two pillars: the infrastructure and the people who use it. Without the people, the infrastructure is not needed, and people cannot move without the infrastructure. This research was a mobility engineering project. Mobility engineering is understood in this research as studying a transport planning problem using quantitative techniques and complementing them with qualitative approaches to understand deeper the problem and possible solutions and if systems might work or not.

The complexity of this mobility engineering research was the interdisciplinary focus. Multidisciplinary topics were included civil engineering, data mining, statistics, machine learning, transport theory, GIS, psychology, marketing, and sociology. It is therefore worth emphasizing the importance of interdisciplinary teams in solving transportation problems and infrastructure planning. A holistic understanding of transport requires both infrastructure and "models" as well as people (including users, non-users, politicians, optimists, and pessimists).

Regarding the lessons learned from including qualitative and quantitative approaches to solve a research question focused on transport planning, it is recommended interdisciplinary teams in practice and research. Teams of people from different backgrounds with a common theme for planning mobility systems. Mobility engineering departments could then solve traditional engineering problems, including the social aspect of mobility.

9.3 Further research

To conclude this study, future research questions are presented to continue this study. They are summarized as new applications, DARE enhancements, applications during the COVID-19 pandemic, integration of BSS with e-commerce, and traffic justice education for traffic engineers.

How can the public discussion, the associated spatial factors, the spatial fairness assessment, and DARE be applied in other areas and transportation systems? Further research could include a comparison of the public discussion on tweets regarding BSS to other shared modes such as car-sharing, scooter, ride-sharing, or autonomous mobility. The dilemma of being good or bad can be explored and compared to analyze which modes are more or less accepted by the public and how can they be improved.

In this research, spatial factors associated with BSS origins and destinations were identified. However, there is a lack in the literature of estimating trips between stations or zones of analysis, considering associated spatial factors. In other words, further research that relies on the estimation of the O-D matrix of bicycle trips based on the built and social environment of the trip (e.g. the shortest path) is needed.

Furthermore, equity and adventure, and progressive orientation with high social status were associated with the usage of BSS. Is this the case of only Munich? or can these values be generalized to other regions of Germany and in the world. Then, the implementation of BSS can be oriented to this population and to optimize the economic efficiency of BSS worldwide.

The theoretical structure that integrated the concept of interactions of transport and land use with urban mobility cultures can be validated with SEM by carrying out similar approaches with other transport modes and in other cities. For example, structural equation models can be built with observed demand from public transport or other shared modes to validate if the significant relationships are similar.

Finally, DARE and spatial fairness assessment is purposed to be applied in other shared mobility vehicles, and also in public transport stations adding a spatiotemporal component with transit frequencies. Moreover, beyond transport, the method can be extended for other logistic and operational services which aim for spatial fairness.

How can DARE be improved? After assessing how fair a bike-sharing system is, the rights of the environment were not considered. Justice, equality, or efficiency can be unfair to the environment.

For example, serving those most in need may require a greater balancing effort, and emissions from the trucks that are responsible for balancing may be unfair to the environment. Additionally, public participation may be another contribution to determining where people want BSS supply. Therefore, weights related to public participation or environmental impacts could be included in the ranking index.

DARE could be expanded by include balancing strategies. The algorithms in DARE do not include trip distribution that can connect areas, but only the destination or starting point of the trips. The inclusion of trips in the infrastructure assignment can be carried out as follows: If the trips from area A to area B are high and area A is selected to implement BSS supply, then area B would immediately be selected for BSS supply as well.

A limitation of this research was that there was no stakeholder feedback for the decision-making tool. Therefore, further research included the adaptation of DARE with feedback from stakeholders. In addition, possible weights for the ranking index can be suggested by stakeholders from different cities to obtain an average score and different scenarios can be chosen by the stakeholders to analyze their perception of fairness for BSS.

What is the public discussion about BSS and the built and social environment factors associated with BSS usage during the COVID -19 pandemic? Bike-sharing helps people travel safely without public transit" versus "Bike sharing = germ sharing". During the COVID-19 pandemic, BSS served as a substitute for public transport but were also accused of supporting the spread of the virus. Following this dilemma that BSS were "friend or foe" during the pandemic, further research is based on the identification of issues, their links and the narrative associated with this dilemma. What do the general public, journalists, activists, news, etc. think, report, complaint, or thank BSS during the pandemic in social media?

Moreover, the COVID-19 pandemic has led to devastating impacts on the society, economy, and the urban systems. Changes in mobility administration and behavior have been correlated to the spatio-temporal spread of the virus around the world (Qu et al., 2020). Some cities limited the supply and number of passengers of public transportation (PT) because it may be a way of spreading influenza-like viruses such as COVID-19 (Sun et al., 2013). Moreover, people became afraid of using public transport and the risk of being infected (Qu et al., 2020).

These circumstances led to a decrease in PT usage and an increase in other transport means. For instance, the city of New York reported a decrease in transit usage (-1.00%) and an increment of driving (+3.12%), walking (+2.80%), and cycling (+1.50%) (Wang et al., 2020). An increase in bike-sharing usage has been also reported and evidenced possible future modal change from the subway to cycling (Teixeira and Lopes, 2020).

The limited PT access during the lockdown and the consequent change of transport behavior created a scenario that might help us identify spatial factors where BSS and cycling, in general, can be enhanced. Hence, identification of spatial factors associated with BSS usage is suggested to be identified during the lockdown and compared with the factors before the COVID-19 pandemic. The results may show potential spatial factors where areas for potential improvement could be identified for BSS and cycling in general, as they are only accessible when other options are not available, such as in times of a pandemic.

How can BSS be planned together with parcel lockers? In the past years and especially during the COVID-19 pandemic, e-commerce has increased remarkably. This has led to a consequent increase in the demand for the freight last-mile connection (Vakulenko et al., 2019). Delivery over the last mile is costly and provokes a higher volume of commercial vehicles, which is why e-retailers offered an innovative solution: parcel lockers (Vakulenko et al., 2019). They are systems that automatically enable users or customers to pick up goods purchased online. Customers can access their packages seven days per week, 24 hours per day, and they are informed when their goods arrived via apps, text, or e-mail when their goods have arrived (Iwan et al., 2016).

One of the weaknesses of parcel lockers is the last mile covered by the customer (Iwan et al., 2016). Especially if the last mile is covered by private vehicles, emissions may not be reduced. Therefore, the integration of cargo bikes into the existing bike-sharing infrastructure is recommended to make cycling to parcel lockers more competitive. Not only would cycling bring health and environmental benefits, but it would also increase the catchment area for last-mile connections and more people would benefit from parcel lockers. If cargo bike-sharing would be integrated, who would be advantaged by integrating cargo bikes in the bike-sharing stations close to parcel lockers?

How to teach and motivate to learn transport justice to transport engineers? Transport justice is more than social concepts. As this research showed, fairness can be evaluated numerically and applied in the planning process of a transport system. There is a need to integrate fairness concepts into traditional transport models, simulations, and optimizations. Therefore, the integration of transport justice principles is highly suggested in the protocols of transport engineering studies, to motivate scholars to develop fairer transportation systems in their practical work.

Bibliography

Acquier, A., Daudigeos, T., and Pinkse, J. (2017). Promises and paradoxes of the sharing economy: An organizing framework. *Technological Forecasting and Social Change*, 125:1–10.

Adminaité-Fodor, D. and Jost, G. (2020). How safe is walking and cycling in europe? pin flash report 38.

Aeroe, T. (2001). *Residential preferences, choice of housing, and lifestyle*. PhD thesis, PhD dissertation (English summary), Aalborg University.

Akaike, H. (1973). Maximum likelihood identification of gaussian autoregressive moving average models. *Biometrika*, 60(2):255–265.

Albiński, S., Fontaine, P., and Minner, S. (2018). Performance analysis of a hybrid bike sharing system: A service-level-based approach under censored demand observations. *Transportation Research Part E: Logistics and Transportation Review*, 116:59 – 69.

Aldred, R. (2015). A matter of utility? rationalising cycling, cycling rationalities. *Mobilities*, 10(5):686–705.

Ambec, S., Garapin, A., Muller, L., and Rahali, B. (2019). How institutions shape individual motives for efficiency and equity: Evidence from distribution experiments. *Journal of Behavioral and Experimental Economics*, 81:128 – 138.

Anaya Boig, E. and para la Diversificación y Ahorro de la Energía, I. (2007). *Guía metodológica para la implantación de sistemas de bicicletas públicas en España*.

Andreotta, M., Nugroho, R., Hurlstone, M. J., Boschetti, F., Farrell, S., Walker, I., and Paris, C. (2019). Analyzing social media data: A mixed-methods framework combining computational and qualitative text analysis. *Behavior research methods*, 51(4):1766–1781.

Ariely, G. and Uslaner, E. M. (2017). Corruption, fairness, and inequality. *International Political Science Review*, 38(3):349–362.

Bachand-Marleau, J., Lee, B. H., and El-Geneidy, A. M. (2012). Better understanding of factors influencing likelihood of using shared bicycle systems and frequency of use. *Transportation Research Record*, 2314(1):66–71.

Bakogiannis, E., Vassi, A., Christodoulopoulou, G., and Siti, M. (2018). Bike sharing systems as a tool to increase sustainable coastal and maritime tourism. the case of piraeus. *Regional Science Inquiry*, 10(3):57–70.

Banerjee, S., Kabir, M. M., Khadem, N. K., and Chavis, C. (2020). Optimal locations for bike-share stations: A new gis based spatial approach. *Transportation Research Interdisciplinary Perspectives*, 4:100101.

Banister, D. (2008). The sustainable mobility paradigm. *Transport Policy*, 15(2):73 – 80. New Developments in Urban Transportation Planning.

Barajas, J. M. and Drive, L. (2018). How equitable is bikesharing? exploring population characteristics and access to employment. Technical report.

Barter, P. A. (1999). Transport and urban poverty in asia: a brief introduction to the key issues. *Regional Development Dialogue*, 20(1):143–163.

Barth, B., Flaig, B. B., Schäuble, N., and Tautscher, M. (2017). *Praxis der Sinus-Milieus®: Gegenwart und Zukunft eines modernen Gesellschafts-und Zielgruppenmodells*. Springer-Verlag.

Baudot, J. (2006). Social justice in an open world the role of the united nations. *New York: United Nations*.

Bauman, A., Crane, M., Drayton, B. A., and Titze, S. (2017). The unrealised potential of bike share schemes to influence population physical activity levels–a narrative review. *Preventive medicine*, 103:S7–S14.

Beckmann, K. J., Hesse, M., Holz-Rau, C., and Hunecke, M. (2008). *StadtLeben-Wohnen, Mobilität und Lebensstil: neue Perspektiven für Raum-und Verkehrsentwicklung*. Springer-Verlag.

Berger, R. (2018). Bike sharing 5.0-market insights and outlook. *Roland Berger: Berlin, Germany*.

Bhuyan, I. A., Chavis, C., Nickkar, A., and Barnes, P. (2019). GIS-Based Equity Gap Analysis: Case Study of Baltimore Bike Share Program. *Urban Science*, 3(2):42.

Bikes, D. (2018). Divvy data. https://www.divvybikes.com/system-data. Accessed on: 15.01.2018.

Bishara, A. and Hittner, J. (2012). Testing the significance of a correlation with nonnormal data: comparison of pearson, spearman, transformation, and resampling approaches. *Psychological methods*, 17(3):399.

BIXI-MONTREAL (2017). Open data - bixi montréal. www.bixi.com/en/open-data. Accessed on 17.12.2017.

Böckmann, M. (2013). The shared economy: It is time to start caring about sharing; value creating factors in the shared economy. *University of Twente, Faculty of Management and Governance*.

Bonilla, S. H., Silva, H. R., Terra da Silva, M., Franco Gonçalves, R., and Sacomano, J. B. (2018). Industry 4.0 and sustainability implications: A scenario-based analysis of the impacts and challenges. *Sustainability*, 10(10):3740.

Box, G. E. P. and Cox, D. R. (1964). An analysis of transformations. *Journal of the Royal Statistical Society. Series B (Methodological)*, 26(2):211–252.

Bregman, S. (2012). *Uses of social media in public transportation*. Number 99. Transportation Research Board.

Brown, A., Klein, N. J., Thigpen, C., and Williams, N. (2020). Impeding access: The frequency and characteristics of improper scooter, bike, and car parking. *Transportation research interdisciplinary perspectives*, 4:100099.

Brömmelstroet, M. t., Nikolaeva, A., Glaser, M., Nicolaisen, M. S., and Chan, C. (2017). Travelling together alone and alone together: mobility and potential exposure to diversity. *Applied Mobilities*, 2(1):1–15.

Buck, D. (2013). Encouraging equitable access to public bikesharing systems. *ITE Journal*, 83(3):24–27.

Buckley, G., Card, J., Norris, M., and Hinkle, J. (2014). Planning for a eugene bike share program: A review of programs in the united states.

Buehler, R., Hamre, A., et al. (2014). Economic benefits of capital bikeshare: A focus on users and businesses. Technical report, Mid-Atlantic Universities Transportation Center.

Büttner, B., Kinigadner, J., Ji, C., Wright, B., and Wulfhorst, G. (2018). The tum accessibility atlas: Visualizing spatial and socioeconomic disparities in accessibility to support regional land-use and transport planning. *Networks and Spatial Economics*, 18(2):385–414.

Büttner, J. and Petersen, T. (2011). *Optimising Bike Sharing in European Cities: A Handbook*. OBIS.

Caggiani, L., Camporeale, R., Dimitrijević, B., and Vidović, M. (2020). An approach to modeling bike-sharing systems based on spatial equity concept. *Transportation Research Procedia*, 45:185–192.

Caggiani, L., Camporeale, R., and Ottomanelli, M. (2017). Planning and Design of Equitable Free-Floating Bike-Sharing Systems Implementing a Road Pricing Strategy. *Journal of Advanced Transportation*, 2017:1–18.

Caggiani, L., Camporeale, R., Ottomanelli, M., and Szeto, W. Y. (2018). A modeling framework for the dynamic management of free-floating bike-sharing systems. *Transportation Research Part C: Emerging Technologies*, 87:159–182.

Camargo, B. V. and Justo, A. M. (2013). Iramuteq: um software gratuito para análise de dados textuais. *Temas em psicologia*, 21(2):513–518.

Cantelmo, G., Kucharski, R., and Antoniou, C. (2020). Low-dimensional model for bike-sharing demand forecasting that explicitly accounts for weather data. *Transportation research record*, 2674(8):132–144.

Casas, I. and Delmelle, E. C. (2017). Tweeting about public transit—gleaning public perceptions from a social media microblog. *Case Studies on Transport Policy*, 5(4):634–642.

Caspi, O. and Noland, R. B. (2019). Bikesharing in philadelphia: Do lower-income areas generate trips? *Travel behaviour and society*, 16:143–152.

Caulfield, B., O'Mahony, M., Brazil, W., and Weldon, P. (2017). Examining usage patterns of a bike-sharing scheme in a medium sized city. *Transportation Research Part A: Policy and Practice*, 100:152 – 161.

Cavill, N. and Davis, A. (2007). Cycling and health-what's the evidence?

Cervero, R. and Kockelman, K. (1997). Travel demand and the 3ds: Density, diversity, and design. *Transportation research. Part D, Transport and environment*, 2(3):199–219.

Chaniotakis, E. and Antoniou, C. (2015). Use of geotagged social media in urban settings: Empirical evidence on its potential from twitter. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, pages 214–219. IEEE.

Chaniotakis, E., Antoniou, C., and Pereira, F. (2016). Mapping social media for transportation studies. *IEEE Intelligent Systems*, 31(6):64–70.

Chardon, C. M. D., Caruso, G., and Thomas, I. (2017). Bicycle sharing system 'success' determinants. *Transportation Research Part A: Policy and Practice*, 100:202 – 214.

Chatterjee, S. and Hadi, A. (2015). *Regression analysis by example*. John Wiley and Sons.

Chen, C.-F. and Huang, C.-Y. (2020). Investigating the effects of a shared bike for tourism use on the tourist experience and its consequences. *Current Issues in Tourism*, pages 1–15.

Chen, F., Turoń, K., Kłos, M., Czech, P., Pamuła, W., and Sierpiński, G. (2018). Fifth-generation bike-sharing systems: examples from poland and china. *Zeszyty Naukowe. Transport/Politechnika Śląska*.

Chen, L., Zhang, D., Pan, G., Ma, X., Yang, D., Kushlev, K., Zhang, W., and Li, S. (2015). Bike sharing station placement leveraging heterogeneous urban open data. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 571–575.

Chen, Z., Guo, Y., Stuart, A. L., Zhang, Y., and Li, X. (2019). Exploring the equity performance of bike-sharing systems with disaggregated data: A story of southern Tampa. *Transportation Research Part A: Policy and Practice*, 130:529–545.

Cheng, M. (2016). Sharing economy: A review and agenda for future research. *International Journal of Hospitality Management*, 57:60 – 70.

Chretien, K. C., Tuck, M. G., Simon, M., Singh, L. O., and Kind, T. (2015). A digital ethnography of medical students who use twitter for professional development. *Journal of general internal medicine*, 30(11):1673–1680.

Cintrano, C., Chicano, F., and Alba, E. (2020). Using metaheuristics for the location of bicycle stations. *Expert Systems with Applications*, 161:113684.

Clark, J. and Curl, A. (2016). Bicycle and Car Share Schemes as Inclusive Modes of Travel? A Socio-Spatial Analysis in Glasgow, UK. *Social Inclusion*, 4(3):83–99.

Cohen, A. and Shaheen, S. (2018). *Planning for Shared Mobility*.

Cohen, A. P. and Shaheen, S. A. (2016). *Planning for shared mobility*. American Planning Association.

Collins, C., Hasan, S., and Ukkusuri, S. V. (2013). A novel transit rider satisfaction metric: Rider sentiments measured from online social media data. *Journal of Public Transportation*, 16(2):2.

Commission, E. et al. (2019). Annual european union greenhouse gas inventory 1990–2017 and inventory report 2019.

Conrow, L., Murray, A. T., and Fischer, H. A. (2018). An optimization approach for equitable bicycle share station siting. *Journal of Transport Geography*, 69:163–170.

Contardo, C., Morency, C., and Rousseau, L.-M. (2012). *Balancing a dynamic public bike-sharing system*, volume 4. Cirrelt Montreal, Canada.

Couch, S. and Smalley, H. K. (2019). Encouraging Equitable Bikeshare: Implications of Docked and Dockless Models for Spatial Equity. *arXiv:1906.00129 [stat]*. arXiv: 1906.00129.

Cox, D. R. and Wermuth, N. (2004). Causality: A statistical view. *International Statistical Review*, 72(3):285–305.

Cropanzano, R., Fortin, M., and Kirk, J. F. (2015). How do we know when we are treated fairly? justice rules and fairness judgments. In *Research in personnel and human resources management*, pages 279–350. Emerald Group Publishing Limited.

Daley, M. and Rissel, C. (2011). Perspectives and images of cycling as a barrier or facilitator of cycling. *Transport policy*, 18(1):211–216.

Das, S., Dutta, A., Medina, G., Minjares-Kyle, L., and Elgart, Z. (2019). Extracting patterns from twitter to promote biking. *IATSS research*, 43(1):51–59.

de Chardon, C. M. (2019). The contradictions of bike-share benefits, purposes and outcomes. *Transportation research part A: policy and practice*, 121:401–419.

Deboosere, R. and El-Geneidy, A. (2018). Evaluating equity and accessibility to jobs by public transport across canada. *Journal of Transport Geography*, 73:54–63.

Deffner, J., Götz, K., Schubert, S., Potting, C., Stete, G., Tschann, A., Loose, W., Janowicz, C., Klein-Hitpaß, A., and Oßwald, S. (2006). Entwicklung eines integrierten konzepts der planung, kommunikation und implementierung einer nachhaltigen, multioptionalen mobilitätskultur. *Schlussbericht. Frankfurt*.

DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of public transportation*, 12(4):3.

Deutsche Bahn AG (2017). Das smarte leihfahrrad der deutschen bahn | call a bike. https://www.callabike-interaktiv.de/de. Accessed on: 31.10.2017.

Deutsche Bahn (DB) (2017). Call a bike - open-data-portal – deutsche bahn datenportal. http://data.deutschebahn.com/dataset/data-call-a-bike. Accessed on: 31.10.2017.

Diaz-Bone, R. (2004). Milieu models and milieu instruments in market research. In *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research*, volume 5, pages 1–17.

Duran, A. C., Anaya-Boig, E., Shake, J. D., Garcia, L. M. T., Rezende, L. F. M. d., and Hérick de Sá, T. (2018). Bicycle-sharing system socio-spatial inequalities in Brazil. *Journal of Transport & Health*, 8:262–270.

Duran-Rodas, D., Chaniotakis, Wulfhorst, G., and Constantinos, A. (2019a). Identification of spatio-temporal factors affecting bike sharing demand: a multiple city approach based on a local level. In *Mapping the Travel Behavior Genome*. Elsevier.

Duran-Rodas, D., Chaniotakis, E., and Antoniou, C. (2019b). Built environment factors affecting bike sharing ridership: Data-driven approach for multiple cities. *Transportation Research Record*, page 0361198119849908.

Duran-Rodas, D., Villeneuve, D., Pereira, F. C., and Wulfhorst, G. (2020a). How fair is the allocation of bike-sharing infrastructure? framework for a qualitative and quantitative spatial fairness assessment. *Transportation Research Part A: Policy and Practice*, 140:299–319.

Duran-Rodas, D., Villeneuve, D., and Wulfhorst, G. (2020b). Bike-sharing: the good, the bad, and the future. *European Journal of Transport and Infrastructure Research*, 20(4):38–58.

Duran-Rodas, D., Wright, B., Pereira, F. C., and Wulfhorst, G. (2021). Demand and/or equity (dare) method for planning bike-sharing. *Transportation Research Part D: Transport and Environment*, 97:102914.

EC (2016). Statistical pocketbook 2016 - mobility and transport. Technical report, European Commission.

Eckhardt, G. M. and Bardhi, F. (2015). The sharing economy isn't about sharing at all. *Harvard business review*, 28(1):2015.

Eckhardt, G. M. and Bardhi, F. (2016). The relationship between access practices and economic systems. *Journal of the Association for Consumer Research*, 1(2):210–225.

Efthymiou, D., Antoniou, C., and Waddell, P. (2013). Factors affecting the adoption of vehicle sharing systems by young drivers. *Transport Policy*, 29:64 – 73.

Eibner, C. and Sturm, R. (2006). Us-based indices of area-level deprivation: results from healthcare for communities. *Social science & medicine*, 62(2):348–359.

El-Assi, W., Mahmoud, M., and Habib, K. (2017). Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in toronto. *Transportation*, 44(3):589–613.

Elvy, J. (2014). Public participation in transport planning amongst the socially excluded: An analysis of 3rd generation local transport plans. *Case studies on transport policy*, 2(2):41–49.

Everitt, B. S., Landau, S., Leese, M., and Stahl, D. (2011). Hierarchical clustering. *Cluster analysis*, 5:71–110.

Faghih-Imani, A. and Eluru, N. (2016). Incorporating the impact of spatio-temporal interactions on bicycle sharing system demand: A case study of new york citibike system. *Journal of Transport Geography*, 54:218 – 227.

Faghih-Imani, A., Eluru, N., El-Geneidy, A. M., Rabbat, M., and Haq, U. (2014). How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (bixi) in montreal. *Journal of Transport Geography*, 41:306 – 314.

Faghih-Imani, A., Hampshire, R., Marla, L., and Eluru, N. (2017). An empirical analysis of bike sharing usage and rebalancing: Evidence from barcelona and seville. *Transportation Research Part A: Policy and Practice*, 97(Supplement C):177 – 191.

Fainstein, S. S. (2009). Planning and the Just City. *Searching for the just city: debates in urban theory and practice*, page 19.

Ferrando, H., Anaya, E., and Arauzo, I. (2007). Guía metodológica para la implantación de sistemas de bicicletas públicas en españa. *Intituto para la Diversificación y Ahorro de la Energía*.

Firnkorn, J. and Shaheen, S. (2016). Generic time- and method-interdependencies of empirical impact-measurements: A generalizable model of adaptation-processes of carsharing-users' mobility-behavior over time. *Journal of Cleaner Production*, 113:897 – 909.

Fishman, E. (2016). Bikeshare: A Review of Recent Literature. *Transport Reviews*, 36(1):92–113.

Fishman, E., Washington, S., and Haworth, N. (2012). Barriers and facilitators to public bicycle scheme use: A qualitative approach. *Transportation research part F: traffic psychology and behaviour*, 15(6):686–698.

Fishman, E., Washington, S., and Haworth, N. (2013). Bike share: A synthesis of the literature. *Transport Reviews*, 33(2):148–165. cited By 98.

Fishman, E., Washington, S., and Haworth, N. (2014a). Bike share's impact on car use: evidence from the united states, great britain, and australia. *Transportation Research Part D: Transport and Environment*, 31:13–20.

Fishman, E., Washington, S., Haworth, N., and Mazzei, A. (2014b). Barriers to bikesharing: an analysis from melbourne and brisbane. *Journal of Transport Geography*, 41:325–337.

Fishman, E., Washington, S., Haworth, N., and Watson, A. (2015). Factors influencing bike share membership: An analysis of Melbourne and Brisbane. *Transportation Research Part A: Policy and Practice*, 71:17–30.

Flaig, B. B. and Barth, B. (2014). Die sinus-milieus® 3.0–hintergründe und fakten zum aktuellen sinus-milieu-modell. In *Zielgruppen im Konsumentenmarketing*, pages 105–120. Springer.

Frade, I. and Ribeiro, A. (2015). Bike-sharing stations: A maximal covering location approach. *Transportation Research Part A: Policy and Practice*, 82:216–227.

Friedman, J. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5):1189–1232. cited By 2353.

Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, volume 1. Springer series in statistics New York.

Fuller, D., Gauvin, L., Kestens, Y., Daniel, M., Fournier, M., Morency, P., and Drouin, L. (2011). Use of a New Public Bicycle Share Program in Montreal, Canada. *American Journal of Preventive Medicine*, 41(1):80–83.

Gal-Tzur, A., Grant-Muller, S. M., Kuflik, T., Minkov, E., Nocera, S., and Shoor, I. (2014). The potential of social media in delivering transport policy goals. *Transport Policy*, 32:115–123.

Gammelli, D., Peled, I., Rodrigues, F., Pacino, D., Kurtaran, H. A., and Pereira, F. C. (2020). Estimating latent demand of shared mobility through censored gaussian processes. *Transportation Research Part C: Emerging Technologies*, 120:102775.

García-Palomares, J. C., Gutiérrez, J., and Latorre, M. (2012). Optimizing the location of stations in bike-sharing programs: A gis approach. *Applied Geography*, 35(1):235 – 246.

Gauthier, A., Huges, C., Kost, C., Li, S., Linke, C., Lotshaw, S., Mason, J., Pardo, C., Rasore, C., Schroeder, B., et al. (2014). ITDP Bike Share Planning Guide. *New York*.

Gavalas, D., Konstantopoulos, C., and Pantziou, G. (2016). Design and management of vehicle-sharing systems: A survey of algorithmic approaches. In *Smart cities and homes*, pages 261–289. Elsevier.

Gehrke, S. R. and Welch, T. F. (2019). A bikeshare station area typology to forecast the station-level ridership of system expansion. *Journal of Transport and Land Use*, 12(1):221–235.

Gentry, J. (2015). *twitteR: R Based Twitter Client*. R package version 1.1.9.

Geurs, K. T. and Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 12(2):127 – 140.

Gibbs, G. R. (2007). Thematic coding and categorizing. *Analyzing qualitative data*, 703:38–56.

Gilbert, C. and Hutto, E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth International Conference on Weblogs and Social Media (ICWSM-14). Available at (20/04/16) http://comp. social. gatech. edu/papers/icwsm14. vader. hutto. pdf*, volume 81, page 82.

Gini, C. (1936). On the measure of concentration with special reference to income and statistics. *Colorado College Publication, General Series*, 208:73–79.

Goldman, B. and Cropanzano, R. (2015). “Justice" and “fairness" are not the same thing. *Journal of Organizational Behavior*, 36(2):313–318.

Goodman, A. and Cheshire, J. (2014). Inequalities in the London bicycle sharing system revisited: impacts of extending the scheme to poorer areas but then doubling prices. *Journal of Transport Geography*, 41:272–279.

Gössling, S. (2016). Urban transport justice. *Journal of transport Geography*, 54:1–9.

Grace, J. B. and Keeley, J. E. (2006). A structural equation model analysis of postfire plant diversity in california shrublands. *Ecological Applications*, 16(2):503–514.

Grant-Muller, S. M., Gal-Tzur, A., Minkov, E., Nocera, S., Kuflik, T., and Shoor, I. (2014). Enhancing transport data collection through social media sources: methods, challenges and opportunities for textual data. *IET Intelligent Transport Systems*, 9(4):407–417.

Griffin, G. P. and Jiao, J. (2019). The geography and equity of crowdsourced public participation for active transportation planning. *Transportation Research Record*, 2673(1):460–468.

Gu, Y., Qian, Z. S., and Chen, F. (2016). From twitter to detector: Real-time traffic incident detection using social media data. *Transportation research part C: emerging technologies*, 67:321–342.

Haas, B. (2017). Chinese bike share graveyard a monument to industry's "arrogance". *The Guardian*, 25.

Hamann, T. K. and Güldenberg, S. (2017). Overshare and collapse: How sustainable are profit-oriented company-to-peer bike-sharing systems?

Hamann, T. K., Güldenberg, S., and Renzl, B. (2019). Overshare and collapse: How sustainable are profit-oriented company-to-peer bike-sharing systems? *Die Unternehmung*, 73(4):345–373.

Handy, S., Cao, X., and Mokhtarian, P. (2005). Correlation or causality between the built environment and travel behavior? evidence from northern california. *Transportation Research Part D: Transport and Environment*, 10(6):427–444.

Hannig, J. (2015). Perceptions of bike sharing in underserved communities within milwaukee and the twin cities.

Hardaker, C. (2010). Trolling in asynchronous computer-mediated communication: From user discussions to academic definitions. *Journal of politeness research*, 6(2):215–242.

Haustein, S. and Møller, M. (2016). Age and attitude: Changes in cycling patterns of different e-bike user segments. *International journal of sustainable transportation*, 10(9):836–846.

Hirsch, J. A., Stratton-Rayner, J., Winters, M., Stehlin, J., Hosford, K., and Mooney, S. J. (2019). Roadmap for free-floating bikeshare research and practice in North America. *Transport Reviews*, 39(6):706–732.

Hoe, N. (2015). Bike sharing in low-income communities: Results from a spring 2015 baseline survey. *Philadelphia, PA: Temple University Institute for Survey Research*.

Hoffmann, M. L. (2016). *Bike lanes are white lanes: Bicycle advocacy and urban planning*. U of Nebraska Press.

Hooper, D., Coughlan, J., and Mullen, M. (2008). Evaluating model fit: a synthesis of the structural equation modelling literature. In *7th European Conference on research methodology for business and management studies*, pages 195–200.

Hosford, K. and Winters, M. (2018). Who are public bicycle share programs serving? an evaluation of the equity of spatial access to bicycle share service areas in canadian cities. *Transportation research record*, 2672(36):42–50.

Howland, S. Current Efforts to Make Bike Share More Equitable: A Survey of System Owners and Operators. page 18.

Hsieh, H.-F. and Shannon, S. E. (2005). Three approaches to qualitative content analysis. *Qualitative Health Research*, 15(9):1277–1288. 07758 PMID: 16204405.

Hu, M. and Liu, B. (2004). Mining opinion features in customer reviews. In *AAAI*, volume 4, pages 755–760.

Huang, R. (2016). RQDA: R-based Qualitative Data Analysis.

Hunecke, M. (2002). Umweltbewusstsein, symbolische bewertung der mobilität und mobilitätsverhalten. In *Mobilität von Jugendlichen*, pages 47–63. Springer.

INTEGRAL (2018). Sinus-milieus. https://www.sinus-institut.de/en/sinus-solutions/sinus-milieus/.

Iwan, S., Kijewska, K., and Lemke, J. (2016). Analysis of parcel lockers' efficiency as the last mile delivery solution–the results of the research in poland. *Transportation Research Procedia*, 12:644–655.

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An introduction to statistical learning*, volume 112. Springer.

Jensen, T., Holtz, G., Baedeker, C., and Chappin, É. J. (2016). Energy-efficiency impacts of an air-quality feedback device in residential buildings: an agent-based modeling assessment. *Energy and Buildings*, 116:151–163.

Jones, P. and Lucas, K. (2012). Social impacts and equity issues in transport: an introduction. *Journal of Transport Geography*, 21.

Kabra, A., Belavina, E., and Girotra, K. (2019). Bike-share systems: Accessibility and availability. *Management Science*.

Kelle, U. (2006). Combining qualitative and quantitative methods in research practice: purposes and advantages. *Qualitative research in psychology*, 3(4):293–311.

Kinigadner, J., Büttner, B., Wulfhorst, G., and Vale, D. (2020). Planning for low carbon mobility: Impacts of transport interventions and location on carbon-based accessibility. *Journal of Transport Geography*, 87:102797.

Klinger, T., Kenworthy, J. R., and Lanzendorf, M. (2013). Dimensions of urban mobility cultures–a comparison of german cities. *Journal of Transport Geography*, 31:18–29.

Kodransky, M. and Lewenstein, G. (2014). Connecting low-income people to opportunity with shared mobility. *Institute for Transportation and Development Policy and Living Cities*.

Koglin, T. and Rye, T. (2014). The marginalisation of bicycling in modernist urban transport planning. *Journal of Transport & Health*, 1(4):214–222.

König, V. (2017). Einführung in die luxus-und premiummarkenführung. In *Grundlagen der Luxus- und Premiummarkenführung*, pages 3–35. Springer.

Koning, R. d., Tan, W. G. Z., and van Nes, A. (2020). Assessing spatial configurations and transport energy usage for planning sustainable communities. *Sustainability*, 12(19):8146.

Kuhnimhof, T. and Wulfhorst, G. (2013). The reader's guide to mobility culture. In *Megacity Mobility Culture*, pages 55–64. Springer.

Kuipers, G. (2013). The rise and decline of national habitus: Dutch cycling culture and the shaping of national similarity. *European journal of social theory*, 16(1):17–35.

Kumar, A. and Garg, G. (2019). Sentiment analysis of multimodal twitter data. *Multimedia Tools and Applications*, 78(17):24103–24119.

Küppers, V. R. (2018). *Übertragung in den Raum: Die Sinus-Geo-Milieus®*, pages 95–102. Springer Fachmedien Wiesbaden, Wiesbaden.

Kwak, H., Lee, C., Park, H., and Moon, S. (2010). What is twitter, a social network or a news media? In *Proceedings of the 19th international conference on World wide web*, pages 591–600.

Landkreis München (2019). Landkreis münchen: Ein jahr mvg rad im landkreis münchen.

Larsen, J., Urry, J., and Axhausen, K. (2006). Mobilities. *Networks, Geographies*, 30.

Lefcheck, J. S. (2016). piecewisesem: Piecewise structural equation modelling in r for ecology, evolution, and systematics. *Methods in Ecology and Evolution*, 7(5):573–579.

Lesser, J. A. and Hughes, M. A. (1986). The generalizability of psychographic market segments across geographic locations. *Journal of Marketing*, 50(1):18–27.

Leventhal, G. S. (1976). The distribution of rewards and resources in groups and organizations. In *Advances in experimental social psychology*, volume 9, pages 91–131. Elsevier.

Leventhal, G. S. (1980). What should be done with equity theory? In *Social exchange*, pages 27–55. Springer.

Li, R., Lei, K. H., Khadiwala, R., and Chang, K. C.-C. (2012). Tedas: A twitter-based event detection and analysis system. In *2012 IEEE 28th International Conference on Data Engineering*, pages 1273–1276. IEEE.

Li, Z., Zhang, J., Gan, J., Lu, P., Gao, Z., and Kong, W. (2019). Large-scale trip planning for bike-sharing systems. *Pervasive and Mobile Computing*, 54:16–28.

Lin, D., Foster, D. P., and Ungar, L. H. (2011). Vif regression: A fast regression algorithm for large data. *Journal of the American Statistical Association*, 106(493):232–247.

Lin, J.-R. and Yang, T.-H. (2011). Strategic design of public bicycle sharing systems with service level constraints. *Transportation research part E: logistics and transportation review*, 47(2):284–294.

Lin, J.-R., Yang, T.-H., and Chang, Y.-C. (2013). A hub location inventory model for bicycle sharing system design: Formulation and solution. *Computers & Industrial Engineering*, 65(1):77–86.

Lin, P., Weng, J., Hu, S., Alivanistos, D., Li, X., and Yin, B. (2020). Revealing spatio-temporal patterns and influencing factors of dockless bike sharing demand. *IEEE Access*, 8:66139–66149.

Litman, T. (1999). *Evaluating transportation equity*. Victoria Transport Policy Institute Victoria, BC, Canada.

Litman, T. and Burwell, D. (2006). Issues in sustainable transportation. *International Journal of Global Environmental Issues*, 6(4):331–347.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies*, 5(1):1–167.

Liu, J., Li, Q., Qu, M., Chen, W., Yang, J., Xiong, H., Zhong, H., and Fu, Y. (2015). Station site optimization in bike sharing systems. In *2015 IEEE International Conference on Data Mining*, pages 883–888. IEEE.

Liu, W., Al Zamal, F., and Ruths, D. (2012). Using social media to infer gender composition of commuter populations. In *Proceedings of the when the city meets the citizen workshop, the international conference on weblogs and social media*.

Lucas, K. (2012). Transport and social exclusion: Where are we now? *Transport policy*, 20:105–113.

Lucas, K. (2019). A new evolution for transport-related social exclusion research? *Journal of transport geography*, 81:102529.

Lucas, K., Mattioli, G., Verlinghieri, E., and Guzman, A. (2016). Transport poverty and its adverse social consequences. In *Proceedings of the institution of civil engineers-transport*, volume 169, pages 353–365. Thomas Telford Ltd.

Lucy, W. (1981). Equity and Planning For Local Services. *Journal of the American Planning Association*, 47(4):447–457.

Ma, X., Yuan, Y., Van Oort, N., and Hoogendoorn, S. (2020). Bike-sharing systems' impact on modal shift: A case study in delft, the netherlands. *Journal of Cleaner Production*, 259:120846.

Ma, Y., Lan, J., Thornton, T., Mangalagiu, D., and Zhu, D. (2018). Challenges of collaborative governance in the sharing economy: The case of free-floating bike sharing in shanghai. *Journal of cleaner production*, 197:356–365.

MacArthur, J., McNeil, N., Cummings, A., and Broach, J. (2020). Adaptive bike share: expanding bike share to people with disabilities and older adults. *Transportation research record*, 2674(8):556–565.

Manca, F., Sivakumar, A., and Polak, J. W. (2019). The effect of social influence and social interactions on the adoption of a new technology: The use of bike sharing in a student population. *Transportation Research Part C: Emerging Technologies*, 105:611–625.

Manderscheid, M. and Tröndle, C. (2008). People's churches in germany in the midst of social changes: Die sinus-milieus und andere soziologische erklärungsversuche als ansätze für eine neue pastorale praxis. *European Journal of Mental Health*, 3(1):21–34.

Mann, H. B. and Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The annals of mathematical statistics*, pages 50–60.

Markt, S. (2017). und Sozialforschung GmbH (2011): Informationen zu den Sinus-Milieus® 2011. *Verfügbar unter http://www. sinus-institut. de/fileadmin/user_data/sinus-institut/Dokumente/downloadcenter/Sinus_Milieus/2017-01-01_Informationen_zu_den_Sinus-Milieus. pdf, aufgerufen am*, 31.

Martens, K. (2007). Promoting bike-and-ride: The dutch experience. *Transportation Research Part A: Policy and Practice*, 41(4):326–338.

Marwick, A. E. (2014). Ethnographic and qualitative research on twitter. *Twitter and society*, 89:109–121.

Marwick, A. E. and Boyd, D. (2011). I tweet honestly, i tweet passionately: Twitter users, context collapse, and the imagined audience. *New media & society*, 13(1):114–133.

Mattson, J. and Godavarthy, R. (2017). Bike share in fargo, north dakota: Keys to success and factors affecting ridership. *Sustainable Cities and Society*, 34:174 – 182.

McCray, T. and Brais, N. (2007). Exploring the Role of Transportation in Fostering Social Exclusion: The Use of GIS to Support Qualitative Data. *Networks and Spatial Economics*, 7(4):397–412.

McNeil, N., Broach, J., and Dill, J. (2018). Breaking barriers to bike share: Lessons on bike share equity. *Institute of Transportation Engineers. ITE Journal*, 88(2):31–35.

McNeil, N., Dill, J., MacArthur, J., and Broach, J. (2017). Breaking barriers to bike share: Insights from bike share users.

Meddin, R. and DeMaio, P. (2020). The bike-sharing world map. http://www. metrobike. net.

Messer, L. C., Laraia, B. A., Kaufman, J. S., Eyster, J., Holzman, C., Culhane, J., Elo, I., Burke, J. G., and O'campo, P. (2006). The development of a standardized neighborhood deprivation index. *Journal of Urban Health*, 83(6):1041–1062.

Miramontes, M. (2018). *Assessment of mobility stations. Success factors and contributions to sustainable urban mobility*. PhD thesis, PhD thesis, München.

Mögele, M. and Rau, H. (2020). Cultivating the "car state": a culturally sensitive analysis of car-centric discourses and mobility cultures in southern germany. *Sustainability: Science, Practice and Policy*, 16(1):15–28.

Molina-García, J., Castillo, I., Queralt, A., and Sallis, J. F. (2015). Bicycling to university: evaluation of a bicycle-sharing program in spain. *Health promotion international*, 30(2):350–358.

Montiel, L. M., Nathan, R. P., and Wright, D. J. (2004). *An update on urban hardship*. Nelson A. Rockefeller Institute of Government, State University of New York ....

Moon-Miklaucic, C., Bray-Sharpin, A., De La Lanza, I., Khan, A., Re, L. L., and Maassen, A. (2018). The evolution of bike sharing: 10 questions on the emergence of new technologies, opportunities, and risks. Technical report, Working Paper. Washington, DC: World Resources Institute. Available online ....

Mooney, S. J., Hosford, K., Howe, B., Yan, A., Winters, M., Bassok, A., and Hirsch, J. A. (2019). Freedom from the station: Spatial equity in access to dockless bike share. *Journal of Transport Geography*, 74:91–96.

Moudon, A. V., Hess, P. M., Snyder, M. C., and Stanilov, K. (1997). Effects of site design on pedestrian travel in mixed-use, medium-density environments. *Transportation Research Record*, 1578(1):48–55.

Murphy, E. and Usher, J. (2011). An analysis of the role of bicycle-sharing in a european city: the case of dublin. In *Paper presented at the Irish Transport Research Network (ITRN), August 31st-September 1st, University College Cork, Ireland*. IRTN.

Murphy, E. and Usher, J. (2015). The role of bicycle-sharing in the city: Analysis of the irish experience. *International Journal of Sustainable Transportation*, 9(2):116–125.

MVG Rad (2019). Das rad der stadt und des landkreises. https://www.mvg.de/dam/mvg/services/mobile-services/mvg-rad/folder-mvg-rad.pdf, 21 2019. accessed on: 30.07.2019.

Natekin, A. and Knoll, A. (2013). Gradient boosting machines, a tutorial. *Frontiers in neurorobotics*, 7:21.

Nickkar, A., Banerjee, S., Chavis, C., Bhuyan, I. A., and Barnes, P. (2019). A spatial-temporal gender and land use analysis of bikeshare ridership: The case study of baltimore city. *City, Culture and Society*, 18:100291.

Nikitas, A. (2017). Bike-sharing fiascoes and how to avoid them – an expert's guide. https://theconversation.com/bike-sharing-fiascoes-and-how-to-avoid-them-an-experts-guide-84926 . Accessed on: 17.07.2018.

Nobis, C. and Kuhnimhof, T. (2018). Mobilität in deutschland- mid: Ergebnisbericht.

Noland, R. B., Smart, M. J., and Guo, Z. (2016). Bikeshare trip generation in new york city. *Transportation Research Part A: Policy and Practice*, 94:164 – 181.

Ogilvie, F. and Goodman, A. (2012). Inequalities in usage of a public bicycle sharing scheme: Socio-demographic predictors of uptake and usage of the london (uk) cycle hire scheme. *Preventive Medicine*, 55(1):40 – 45.

Oh, H., Assaf, A. G., and Baloglu, S. (2016). Motivations and goals of slow tourism. *Journal of Travel Research*, 55(2):205–219.

Oja, P., Titze, S., Bauman, A., De Geus, B., Krenn, P., Reger-Nash, B., and Kohlberger, T. (2011). Health benefits of cycling: a systematic review. *Scandinavian journal of medicine & science in sports*, 21(4):496–509.

OpenStreetMap-contributors (2017). Planet dump retrieved from https://planet.osm.org . https://www.openstreetmap.org . Accessed on: 31.10.2017.

Pal, A. and Zhang, Y. (2017). Free-floating bike sharing: Solving real-life large-scale static rebalancing problems. *Transportation Research Part C: Emerging Technologies*, 80:92–116.

Pampalon, R., Hamel, D., Gamache, P., Philibert, M. D., Raymond, G., and Simpson, A. (2012). An area-based material and social deprivation index for public health in québec and canada. *Canadian Journal of Public Health/Revue Canadienne de Sante'e Publique*, pages S17–S22.

Papacharissi, Z. (2012). Without you, i'm nothing: Performances of the self on twitter. *International journal of communication*, 6:18.

Pearce, J., Blakely, T., Witten, K., and Bartie, P. (2007). Neighborhood deprivation and access to fast-food retailing: a national study. *American journal of preventive medicine*, 32(5):375–382.

Pereira, F. C., Rodrigues, F., and Ben-Akiva, M. (2013). Text analysis in incident duration prediction. *Transportation Research Part C: Emerging Technologies*, 37:177 – 192.

Perrin, A. (2015). Social media usage. *Pew research center*, 125:52–68.

Pochet, P. and Cusset, J.-M. (1999). Cultural barriers to bicycle use in western african cities.

Prelog, R. (2015). Equity of access to bicycle infrastructure. *Washington, DC: League of American Bicyclists*.

Pucher, J. and Buehler, R. (2017). Cycling towards a more sustainable transport future.

Qiu, L.-Y. and He, L.-Y. (2018). Bike sharing and the economy, the environment, and health-related externalities. *Sustainability*, 10(4):1145.

Qu, X., Gao, K., and Li, X. S. (2020). Impacts of covid-19 on the transport sector and measures as well as recommendations of policies and future research: A report on sig-c1 transport theory and modelling. *Available at SSRN 3689209*.

R Core Team (2014). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Rahim Taleqani, A., Hough, J., and Nygard, K. E. (2019). Public opinion on dockless bike sharing: A machine learning approach. *Transportation research record*, 2673(4):195–204.

Ranaiefar, F. and Rixey, R. A. (2016). Bike sharing ridership forecast using structural equation modeling. In *Transportation Research Board 95th Annual Meeting*, number 16-6573.

Ratinaud, P. (2009). IRAMUTEQ: Interface de R pour les Analyses Multidimensionnelles de Textes et de Questionnaires [Computer software].

Rau, A. (2018). Bye Bye, Obikes! | The Munich Eye . https://themunicheye.com/bye-bye-obikes-3604.

Reinert, A. (1983). Une méthode de classification descendante hiérarchique: application à l'analyse lexcicale par contexte. *Les cahiers de l'analyse des données*, 8(2):187–198.

Reinert, p. M. (1987). Classification descendante hierarchique et analvse lexicale par contexte-application au corpus des poesies d'a. rihbaud. *Bulletin of Sociological Methodology/Bulletin de Méthodologie Sociologique*, 13(1):53–90.

Reiss, S. and Bogenberger, K. (2015). Gps-data analysis of munich's free-floating bike sharing system and application of an operator-based relocation strategy. In *2015 IEEE 18th international conference on intelligent transportation systems*, pages 584–589. IEEE.

Reiss, S. and Bogenberger, K. (2017). A relocation strategy for munich's bike sharing system: Combining an operator-based and a user-based scheme. *Transportation Research Procedia*, 22:105–114.

Reynaud, F., Faghih-Imani, A., and Eluru, N. (2018). Modelling bicycle availability in bicycle sharing systems: A case study from montreal. *Sustainable cities and society*, 43:32–40.

Ribeiro, F. N., Araújo, M., Gonçalves, P., Gonçalves, M. A., and Benevenuto, F. (2016). Sentibench-a benchmark comparison of state-of-the-practice sentiment analysis methods. *EPJ Data Science*, 5(1):1–29.

Ricci, M. (2015). Bike sharing: A review of evidence on impacts and processes of implementation and operation. *Research in Transportation Business & Management*, 15:28–38.

Roca-Riu, M., Menendez, M., Dakic, I., Buehler, S., and Ortigosa, J. (2020). Urban space consumption of cars and buses: an analytical approach. *Transportmetrica B: Transport Dynamics*, 8(1):237–263.

Rochat, P., Dias, M. D., Liping, G., Broesch, T., Passos-Ferreira, C., Winning, A., and Berg, B. (2009). Fairness in distributive justice by 3-and 5-year-olds across seven cultures. *Journal of Cross-Cultural Psychology*, 40(3):416–442.

Rodrigue, J.-P., Comtois, C., and Slack, B. (2016). *The geography of transport systems*. Taylor & Francis.

Roesler, V., Barrére, E., and Willrich, R. (2020). *Special Topics in Multimedia, IoT and Web Technologies*. Springer.

Rosseel, Y. (2012). Lavaan: An r package for structural equation modeling and more. version 0.5–12 (beta). *Journal of statistical software*, 48(2):1–36.

Rowe, G. and Frewer, L. J. (2000). Public participation methods: a framework for evaluation. *Science, technology, & human values*, 25(1):3–29.

Rube, S. (2018). Das fahrradverleihsystem mvg-rad ein wichtiger beitrag zur multimodalitaet. https://bn-muenchen.de/, 2019. accessed on: 30.07.2019.

Ruiz Bueno, A. (2017). Trabajar con iramuteq: Pautas.

Schmitt, M., Barbacsy, R., Binz, S., Buttgereit, C., Heinz, J., Hesse, J., Kraft, S., Kuhlmann, N., Lischetzke, T., Nisslmüller, K., et al. (1994). Distributive justice research from an interactionist perspective.

Schmöller, S. and Bogenberger, K. (2014). Analyzing external factors on the spatial and temporal demand of car sharing systems. *Procedia - Social and Behavioral Sciences*, 111:8 – 17.

Schmöller, S., Weikl, S., Müller, J., and Bogenberger, K. (2015). Empirical analysis of free-floating carsharing usage: The munich and berlin case. *Transportation Research Part C: Emerging Technologies*, 56:34 – 51.

Schönberg, A., Dyskin, A., and Ewer, K. (2018). Bike sharing 5.0: Market insights and outlook. *Berlin: Roland Berger*.

Schoner, J., Harrison, R. A., and Wang, X. (2012). Sharing to grow: Economic activity associated with nice ride bike share stations.

Schulz, A., Ristoski, P., and Paulheim, H. (2013). I see a car crash: Real-time detection of small scale incidents in microblogs. In *Extended semantic web conference*, pages 22–33. Springer.

Schwarz, G. (1978). Estimating the dimension of a model. *The annals of statistics*, 6(2):461–464.

Schwarz, N. and Ernst, A. (2009). Agent-based modeling of the diffusion of environmental innovations—an empirical approach. *Technological forecasting and social change*, 76(4):497–511.

Schweitzer, L. (2014). Planning and social media: a case study of public transit and stigma on twitter. *Journal of the American Planning Association*, 80(3):218–238.

Schönfelder, S. and Axhausen, K. W. (2003). Activity spaces: measures of social exclusion? *Transport Policy*, 10(4):273–286.

Shaheen, S. and Chan, N. (2015). Mobility and the sharing economy: Impacts synopsis. *Berkeley, CA: Transportation Sustainability Research Center, University of California*.

Shaheen, S., Chan, N., Bansal, A., and Cohen, A. (2015). Shared mobility: Definitions, industry developments, and early understanding. *University of California Berkeley Transportation Sustainability Research Center, Berkeley. http://innovativemobility. org/wp-content/uploads/2015/11/SharedMobility_WhitePaper_FINAL. pdf*.

Shaheen, S. and Cohen, A. (2019). Shared micromoblity policy toolkit: Docked and dockless bike and scooter sharing.

Shaheen, S., Cohen, A., Chan, N., and Bansal, A. (2020). Sharing strategies: carsharing, shared micromobility (bikesharing and scooter sharing), transportation network companies, microtransit, and other innovative mobility modes. In *Transportation, Land Use, and Environmental Planning*, pages 237–262. Elsevier.

Shaheen, S., Cohen, A., Randolph, M., Farrar, E., Davis, R., and Nichols, A. (2019). Shared mobility policy playbook.

Shaheen, S., Cohen, A., Zohdy, I., et al. (2016). Shared mobility: current practices and guiding principles. Technical report, United States. Federal Highway Administration.

Shaheen, S., Guzman, S., and Zhang, H. (2010). Bikesharing in europe, the americas, and asia: past, present, and future. *Transportation Research Record: Journal of the Transportation Research Board*, (2143):159–167.

Shaheen, S., Martin, E., Cohen, A., and Finson, R. (2012). Public bikesharing in north america: Early operator and user understanding, mti report 11-19. Technical report, Mineta Transportation Institute.

Shaheen, S. A., Martin, E. W., Cohen, A. P., Chan, N. D., and Pogodzinski, M. (2014). Public bikesharing in north america during a period of rapid expansion: Understanding business models, industry trends & user impacts, mti report 12-29.

Shi, J.-g., Si, H., Wu, G., Su, Y., and Lan, J. (2018). Critical factors to achieve dockless bike-sharing sustainability in china: A stakeholder-oriented network perspective. *Sustainability*, 10(6):2090.

Si, H., Shi, J.-g., Wu, G., Chen, J., and Zhao, X. (2019). Mapping the bike sharing research published from 2010 to 2018: A scientometric review. *Journal of cleaner production*, 213:415–427.

Simsekoglu, Ö. and Klöckner, C. (2019). Factors related to the intention to buy an e-bike: A survey study from norway. *Transportation research part F: traffic psychology and behaviour*, 60:573–581.

Sinus Markt und Sozialforschung GmbH (2019). Fahrrad-monitor deutschland 2019. www.bmvi.de/SharedDocs. Accessed on 25.11.2019.

Small, A. (2017). The four horsemen of the bike share apocalypse.

Smith, C. S., Oh, J.-S., and Lei, C. (2015). Exploring the equity dimensions of us bicycle sharing systems. Technical report, Western Michigan University. Transportation Research Center for Livable ....

Smith, W. R. (1995). Product differentiation and market segmentation as alternative marketing strategies. *Marketing management*, 4(3):63.

Soboll, A., Elbers, M., Barthel, R., Schmude, J., Ernst, A., and Ziller, R. (2011). Integrated regional modelling and scenario development to evaluate future water demand under global change conditions. *Mitigation and Adaptation Strategies for Global Change*, 16(4):477–498.

Sociovision, S. (2018). Die sinus-milieus. https://www.sinus-institut.de/.

Soja, E. W. (2009). The city and spatial justice. *justice spatiale | spatial justice*, (1).

Soja, E. W. (2010). Seeking spatial justice university of minnesota press. *Minneapolis MN*.

Spearman, C. (1904). The proof and measurement of association between two things. *The American Journal of Psychology*, 15(1):72–101.

STATISTA (2020). Twitter Statistics & Facts.

Statistisches Bundesamt (2012). Bevölkerung und erwerbstätigkeit. bevölkerung mit migrationshintergrund. ergebnisse des mikrozensus 2011. fachserie 1, reihe 2.2. Accessed on: 31.10.2017.

Steiger, E., Westerholt, R., Resch, B., and Zipf, A. (2015). Twitter as an indicator for whereabouts of people? correlating twitter with uk census data. *Computers, environment and urban systems*, 54:255–265.

Steinbach, R., Green, J., Datta, J., and Edwards, P. (2011). Cycling and the city: a case study of how gendered, ethnic and class identities can shape healthy transport choices. *Social science & medicine*, 72(7):1123–1130.

Stobart, G. (2005). Fairness in multicultural assessment systems. *Assessment in Education: Principles, Policy & Practice*, 12(3):275–287.

Stöckle, M., Wulfhorst, I. G., Rodas, M. S. D. D., and Pfertner, M. S. M. (2020). Bike sharing systems in munich: A (non) users' behavioural, socio–demographic and psychographic analysis.

Stuart, A. L., Mudhasakul, S., and Sriwatanapongse, W. (2009). The social distribution of neighborhood-scale air pollution and monitoring protection. *Journal of the Air & Waste Management Association*, 59(5):591–602.

Sun, L., Axhausen, K. W., Lee, D.-H., and Huang, X. (2013). Understanding metropolitan patterns of daily encounters. *Proceedings of the National Academy of Sciences*, 110(34).

Sun, Y. (2018). Sharing and riding: how the dockless bike sharing scheme in china shapes the city. *Urban Science*, 2(3):68.

Sun, Z., Li, Y., and Zuo, Y. (2019). Optimizing the location of virtual stations in free-floating bike-sharing systems with the user demand during morning and evening rush hours. *Journal of Advanced Transportation*, 2019.

Swyngedouw, E. (2008). The post-political city in bavo ed urban politics now. re-imagining democracy in the neoliberal city.

Tabbone, L. (2017). *Consommations énergétiques et cadres de vie: analyses en termes de modes de vie*. PhD thesis, Ecole Polytechnique Fédérale de Lausanne.

Talen, E. (1998). Visualizing Fairness: Equity Maps for Planners. *Journal of the American Planning Association*, 64(1):22–38.

Teixeira, J. F. and Lopes, M. (2020). The link between bike sharing and subway use during the covid-19 pandemic: The case-study of new york's citi bike. *Transportation Research Interdisciplinary Perspectives*, 6:100166.

Thakkar, J. J. (2020). *Structural Equation Modelling: Application for Research and Practice (with AMOS and R)*. Springer Singapore.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1):267–288.

Tomlinson, M. (2016). Risking peace in the 'war against the poor'? social exclusion and the legacies of the northern ireland conflict. *Critical Social Policy*, 36(1):104–123.

Toole Design Group (2012). Bike Sharing in the United States: State of the practice and guide to implementation.

Töpfer, M. and Bug, P. (2015). Classical consumer lifestyle segmentation methods.

Townsend, P. (1987). Deprivation. *Journal of social policy*, 16(2):125–146.

Tran, T. D., Ovtracht, N., and d'Arcier, B. F. (2015). Modeling bike sharing system using built environment factors. *Procedia CIRP*, 30:293 – 298. 7th Industrial Product-Service Systems Conference - PSS, industry transformation for sustainability and business.

Transit.robbi5 (2019). Mvg-networkstate. https://transit.robbi5.com/mvg-networkstate-mvgrad. accessed on: 25.02.2019.

Transport for London (2011). Barriers and tipping points to cycling among low income target groups.

Tynan, A. C. and Drayton, J. (1987). Market segmentation. *Journal of Marketing Management*, 2(3):301–335.

Ursaki, J. and Aultman-Hall, L. (2015). Quantifying the Equity of Bikeshare Access in U.S. Cities. (TRC Report 15-011).

Vakulenko, Y., Shams, P., Hellström, D., and Hjort, K. (2019). Service innovation in e-commerce last mile delivery: Mapping the e-customer journey. *Journal of Business Research*, 101:461–468.

Van der Kloof, A. (2015). Lessons learned through training immigrant women in the netherlands to cycle. *Cycling Cultures*, pages 78–105.

Van Wee, B. and Geurs, K. (2011). Discussing equity and social exclusion in accessibility evaluations. *European journal of transport and infrastructure research*, 11(4).

Varian, H. (1974). Equity, envy, and efficiency. *Journal of Economic Theory*, 9(1):63–91.

Varian, H. (1975). Distributive justice, welfare economics, and the theory of fairness. *Philosophy & Public Affairs*, 4(3):223–247.

Vermessungsverwaltung, B. (2014). Amtliches topographisch-kartographisches informationssystem -digitales landschaftsmodell (atkis basis-dlm). http://vermessung.bayern.de/service/download/testdaten/atkis.html.

Villeneuve, D. (2017). *Living Without a Car: A Canada-France Comparative Outlook*. PhD, École polytechnique fédérale de Lausanne, Lausanne, Switzerland. {:DOI: https://doi.org/10.5075/epfl-thesis-7957}.

Villeneuve, D. (2020). Les méthodes mixtes de l'analyse de discours pour comprendre la mobilité des ménages non motorisés. In *Connaissance des mobilités: hybridation des méthodes, diversification des sources*, page 53-66.

Villeneuve, D., Durán-Rodas, D., Ferri, A., Kuttler, T., Magelund, J., Mögele, M., Nitschke, L., Servou, E., and Silva, C. (2020). What is interdisciplinarity in practice? critical reflections on doing mobility research in an intended interdisciplinary doctoral research group. *Sustainability*, 12(1):197.

Villeneuve, D. and Kaufmann, V. (2020). Exploring the causes of social exclusion related to mobility for non-motorized households. *Transportation research record*, 2674(8):911–920.

Vogel, P., Greiser, T., and Mattfeld, D. C. (2011). Understanding bike-sharing systems using data mining: Exploring activity patterns. *Procedia - Social and Behavioral Sciences*, 20:514 – 523.

Vogel, P., Saavedra, B. A. N., and Mattfeld, D. C. (2014). A hybrid metaheuristic to solve the resource allocation problem in bike sharing systems. In *International workshop on hybrid metaheuristics*, pages 16–29. Springer.

Von Jens, S. D. (2018). Soziale milieus in der mobilitätsforschung. In *Praxis der Sinus-Milieus®*, pages 139–153. Springer.

Voronoï, G. (1908). Nouvelles applications des paramètres continus à la théorie des formes quadratiques. deuxième mémoire. recherches sur les parallélloèdres primitifs. *Journal für die reine und angewandte Mathematik*, 134:198–287.

Walker, J. (2012). *Human transit: How clearer thinking about public transit can enrich our communities and our lives*. Island Press.

Wang, D., He, B. Y., Gao, J., Chow, J. Y., Ozbay, K., and Iyer, S. (2020). Impact of covid-19 behavioral inertia on reopening strategies for new york city transit. *arXiv preprint arXiv:2006.13368*.

Wang, K., Akar, G., and Chen, Y.-J. (2018). Bike sharing differences among millennials, gen xers, and baby boomers: Lessons learnt from new york city's bike share. *Transportation research part A: policy and practice*, 116:1–14.

Wang, X., Lindsey, G., Schoner, J., and Harrison, A. (2015). Modeling bike share station activity: Effects of nearby businesses and jobs on trips to and from stations. *Journal of Urban Planning and Development*, 142(1):04015001.

Wegener, M. and Fürst, F. (1999). Land-use transport interaction: State of the art-berichte aus dem institut für raumplanung 46. *Dortmund, Germany: Institut für Raumplanung, Universität Dortmund*.

Wegener, M. and Fürst, F. (2004). Land-use transport interaction: state of the art. *Available at SSRN 1434678*.

WHO (2018). Global status report on road safety 2018: Summary. Technical report, World Health Organization.

Willing, C., Klemmer, K., Brandt, T., and Neumann, D. (2017). Moving in time and space – location intelligence for carsharing decision support. *Decision Support Systems*, 99:75 – 85. Location Analytics and Decision Support.

Winters, M., Hosford, K., and Javaheri, S. (2019). Who are the 'super-users' of public bike share? An analysis of public bike share members in Vancouver, BC. *Preventive Medicine Reports*, 15:100946.

Wojtowicz, J. and Wallace, W. A. (2016). Use of social media by transportation agencies for traffic management. *Transportation Research Record*, 2551(1):82–89.

Wulfhorst, G. (2003). *Flächennutzung und Verkehrsverknüpfung an Personenbahnhöfen-Wirkungsabschätzung mit systemdynamischen Modellen*. Number 49.

Wulfhorst, G. (2008). Erreichbarkeit–accessibility–accessibilité. einführung in die mobil. tum 2008. In *International Conference on Mobility and Transport*.

Wüstenhagen, R., Wolsink, M., and Bürer, M. J. (2007). Social acceptance of renewable energy innovation: An introduction to the concept. *Energy policy*, 35(5):2683–2691.

Yan, A. and Howe, B. (2019). FairST: Equitable Spatial and Temporal Demand Prediction for New Mobility Systems. *arXiv:1907.03827 [cs, stat]*. arXiv: 1907.03827.

Yang, F., Jin, P., Wan, X., Li, R., and Ran, B. (2014). Dynamic origin-destination travel demand estimation using location based social networking data.

Yanocha, D., Mason, J., Patlán, M., Benicchio, T., Alfred, I., and Laksmana, U. (2018). The bike-share planning guide.

Youngblut, J. M. (1994). A consumer's guide to causal modeling: Part i. *Journal of pediatric nursing*, 9(4):268.

Zee, R. (2016). How this amsterdam inventor gave bike-sharing to the world. https://www.theguardian.com/cities/2016/apr/26/story-cities-amsterdam-bike-share-scheme. Accessed on: 05.10.2020.

Zhang, Y. and Mi, Z. (2018). Environmental benefits of bike sharing: A big data-based analysis. *Applied Energy*, 220:296–301.

Zhang, Z., He, Q., Gao, J., and Ni, M. (2018). A deep learning approach for detecting traffic accidents from social media data. *Transportation Research Part C: Emerging Technologies*, 86:580 – 596.

Zhao, F., Chow, L.-F., Li, M.-T., Ubaka, I., and Gan, A. (2003). Forecasting transit walk accessibility: Regression model alternative to buffer method. *Transportation Research Record*, 1835(1):34–41.

Zhao, J., Deng, W., and Song, Y. (2014). Ridership and effectiveness of bikesharing: The effects of urban features and system characteristics on daily use and turnover rate of public bikes in china. *Transport Policy*, 35:253 – 264.

Zuñiga, D. (2019). Chile: ¿Por que explotó el país tranquilo de Sudamérica? | DW | 20.10.2019. Library Catalog: www.dw.com.