U.PORTO
FEUP FACULDADE DE ENGENHARIA
UNIVERSIDADE DO PORTO

U.PORTO
FACULDADE DE ARQUITECTURA
UNIVERSIDADE DO PORTO

TRIALLING THE GROSS POTENTIAL FOR CYCLING

Exploring the Link with Cycling Demand in the Netherlands

ISABELLA MANN MACHADO

Dissertação submetida para satisfação parcial dos requisitos do grau de

MESTRE EM PLANEAMENTO E PROJECTO URBANO

Orientador: Professora, PhD, Cecília do Carmo Ferreira da Silva

Coorientador: Miguel Nuno Nogueira Lopes, PhD

JUNHO DE 2021

MESTRADO EM PLANEAMENTO E PROJECTO URBANO 2020/2021 - FEUP / FAUP

DEPARTAMENTO DE ENGENHARIA CIVIL

Tel. +351-22-508 1901

mppu@fe.up.pt

Editado por

FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Rua Dr. Roberto Frias

4200-465 PORTO

Portugal

Tel. +351-22-508 1400

Fax +351-22-508 1440

feup@fe.up.pt

http://www.fe.up.pt

Este documento foi escrito no idioma Inglês Americano.

To my dear parents.

"Urbanism works when it creates a journey as desirable as the destination."

Paul Goldberger

ACKNOWLEDGEMENTS

So many times, I ask myself how I got here, and most of the time, I conclude that if it was not for the support I received along the way, this dream would not have come true. So, in a brief honor, I would like to thank those who walked by my side on this journey.

To my parents, who always made me feel close to home even though an ocean separates us. Without you, I would not have learned the meaning of family, how important it is to be part of it, where I often look for examples of courage and faith. From my family, I also received support, kindness, and much love. Thank you for making my dreams the same as your dreams. Thank you for guiding my steps; without your support, none of this would be possible. To my sister, my best friend, thank you for all the kindness.

To Ronald, who serenely follows me in each decision of my life. Who, I have the joy of sharing my steps in this journey and many others. Thank you for your patience and for taking care of me tirelessly during this journey.

To my friends, those who have always walked with me and the new ones I was lucky enough to meet during this journey. Thank you for all the knowledge exchange, patience and friendship. To my friends from Porto, thank you for making me feel part of a big family.

To Professor Cecilia Silva, my supervisor, and Miguel Lopes, my cosupervisor, thank you for so many teachings; you were essential in this journey. To Miguel Lopes and Ana Dias, thanks for giving me support with the Gross Potential for Cycling. A special thank you to Miguel Lopes for always being available to solve my doubts. Thanks to the colleagues of the “Accessibility and Mobility Group” for so much knowledge exchange.

To Hans and Louise, thank you for all the patience and care that you had with me during this journey. The Data Archiving and Networked Services (DANS) team, thank you for making the Dutch mobility data available in an agile and fast way. Thank Benjamin Groenewolt and the Mobidot team, especially Marcel Bijlsma and Johan Koolwaaij, for giving their time to search, sort, and provide me with information about urban mobility in Enschede.

For the other people that I could count on during this time, thank you very much.

ABSTRACT

Active travel modes can help solve adverse problems such as pollution and congestion caused by motorized mobility in recent years. The bicycle, when compared to other modes of transportation, has a significant impact on environmental, social, and economic aspects. Due to the emerging issues faced globally by motorized modes of transportation, governments around the world are promoting initiatives that curb this. Amongst such promotions, cycling is much discussed; however, its practical application in many cities faces significant challenges. The investments made to increase cycling rates still seek a concrete place within the policies applied to a city. Therefore, various methods and tools are being developed to support and transform the built environment from a cycling perspective. The "BooST - Boosting Starter Cycling Cities" project has developed tools that provide technical and specific insights for starter cycling cities. Among these, the Gross Potential for Cycling (GPC) tool aims to evaluate the propensity to cycle in starter cities.

The objective of this thesis is to trial the validity of the conceptual model of the Gross Potential for Cycling. The research area chosen is in the eastern part of the Netherlands, close to the German border. To reach the objective, descriptive analyses are performed between the GPC and cycling demand data to have a spatial understanding of the data's performance. Then, bivariate statistical analyses are performed; these comprise correlation analysis and simple linear regressions, which are intended to identify the relationship of the GPC and its indicators individually with the cycling demand data. Multivariate statistical analysis, particularly multiple regression analysis, is performed to test the validity of the GPC conceptual model.

The research identified that among the cycling demand data, the results of the Gross Cycling Potential explain approximately 32% of the total number of bicycle trips. The number of trips per capita by bicycle, total kilometers traveled by bicycle, and kilometers traveled per capita by bicycle are explained by GPC respectively 22.8%, 10.5% and 4.5%. However, when analyzing the conceptual model from which the GPC originates, a different trend was found among some indicator' weights and their statistical significance; that is, some indicators that had more relevant weights in the conceptual model proved to be less relevant in the analyses performed, and in some cases non-significant. The conclusions drawn from this thesis support the idea that the GPC tool is relevant to evaluate the number of bicycle trips. However, it can still be improved with the combination of similar indicators and the adequacy of the weights of specific indicators.

KEYWORDS: Gross Potential for Cycling, starter cycling cities, cycling assessment method, the Netherlands, cycling demand.

RESUMO

Os modos de viagem activos podem ajudar a resolver problemas adversos como a poluição e o congestionamento provocados pela mobilidade motorizada nos últimos anos. A bicicleta, quando comparada a outros modos de transporte, tem um impacto significativo sobre os aspectos ambientais, sociais e econômicos. Devido às questões emergentes enfrentadas globalmente pelos meios de transporte motorizados, os governos de todo o mundo estão promovendo iniciativas que restringem isto. Entre tais promoções, o ciclismo é muito discutido; entretanto, sua aplicação prática em muitas cidades enfrenta desafios significativos. Os investimentos feitos para aumentar as taxas de ciclismo ainda buscam um lugar concreto dentro das políticas aplicadas a uma cidade. Portanto, vários métodos e ferramentas estão sendo desenvolvidos para apoiar e transformar o ambiente construído a partir de uma perspectiva ciclística. O projeto "BooST - Boosting Starter Cycling Cities" desenvolveu ferramentas que fornecem conhecimentos técnicos e específicos para as cidades principiantes ao ciclismo. Entre elas, a ferramenta Potencial Bruto para a Bicicleta (PBB) visa avaliar a propensão para ciclismo em cidades principiantes.

O objetivo desta tese é testar a validade do modelo conceitual do Potencial Bruto para a Bicicleta. A área de pesquisa está localizada na parte leste da Holanda, perto da fronteira com a Alemanha. Para alcançar o objetivo, são realizadas análises descritivas entre os dados PBB para a área de estudo com seus respectivos dados de demanda de ciclismo, no intuito de ter uma compreensão espacial do desempenho dos dados. Em seguida, são realizadas análises estatísticas bivariadas; estas compreendem em análises de correlações e regressão linear simples, que se destinam a identificar a relação do PBB e seus indicadores individualmente com os dados de demanda ciclística. A análise estatística multivariada, particularmente a análise de regressão múltipla, é realizada para testar a validade do modelo de cálculo do PBB.

A pesquisa identificou que entre os dados de demanda de ciclismo, o número total de viagens de bicicleta é explicado pelo resultado final do Potencial Bruto para a Bicicleta em aproximadamente 32%. O número de viagens per capita por bicicleta, o total de quilômetros percorridos por bicicleta e os quilômetros percorridos per capita por bicicleta são explicados pelo PBB respectivamente 22,8%, 10,5% e 4,5%. Entretanto, ao analisar o modelo conceitual do qual o PBB se origina, foi encontrada uma tendência diferente entre os pesos de alguns indicadores e sua significância estatística em relação ao estudo realizado nesta tese, ou seja, alguns indicadores que tinham pesos mais relevantes no modelo conceitual provaram ser menos relevantes nas análises realizadas, e em alguns casos não significativos. As conclusões extraídas desta tese apóiam a idéia de que a ferramenta PBB é uma ferramenta altamente eficiente para avaliar o número de viagens de bicicleta. No entanto, ela ainda pode ser melhorada com a combinação de indicadores similares e a adequação dos pesos de certos indicadores.

PALAVRAS-CHAVE: Potencial Bruto para a Bicicleta, cidades principiantes ao ciclismo, método de avaliação ciclística, Holanda, demanda ciclistica.

SUMMARY

FIGURES INDEX

TABLES INDEX

SYMBOLS, ACRONYMS AND ABBREVIATIONS

km_{t1} - Total kilometers traveled by bicycle

km_{t2} - Kilometers traveled per capita by bicycle

qty_{t1} - Total number of bicycle trips

qty_{t2} - Number of trips per capita by bicycle

ACP - Analysis of Cycling Potential

BCI - Bicycle Compatibility Index

BLOS - Bike Level of Service

BooST - Boosting Starter Cycling Cities

CBS - Statistics Netherlands

CMS - Cycling Measures Selector

CO_2 - Carbonic gas

DANS - Data Archiving and Networked Service

DV - Dependent variable

ESRI - Environmental Systems Research Institute

EVC - Economic Value for Cycling

FCT - Portuguese National Science and Technology Agency

FEUP - Faculty of Engineering of the University of Porto

GIS - Geographic Information Systems

GPC - Gross Potential for Cycling

HCM - Highway Capacity Manual

HEAT - World Health Organization’s Health Economic Assessment Tool

IV - Independent variable

LOS - Level of service

LTDS - Transport for London’s Travel Demand Survey

MLR - Multiple Linear Regression

MON - Mobility Research Netherlands

OD - Origin-Destination

ODiN - On the Road in the Netherlands

OSM - OpenStreetMap

OVG - Survey on Transportation Behavior

OViN - Research on Mobility in the Netherlands

PC4 - Four-digit postal zones

PC6 - Six-digit postal zones

PCT - Propensity to Cycle Tool

PSS - Planning Support Systems

RWS-WVL - Rijkswaterstaat Department of Water, Traffic and Environment

SLR - Simple Linear Regression

SPSS - Statistical Package for the Social Sciences

TFL - Transport for London

UK - United Kingdom

USA - United States of America

VIF - Variance Ignition Factor

1
INTRODUCTION

Mobility has a crucial role in the socio-economic development of cities (Ros-McDonnell et al. 2020). However, over the last 30 years, mobility has brought adverse effects to urban areas (Ros-McDonnell et al. 2020). Problems such as high levels of noise, pollution, congestion, parking problems, road trauma, and negative impacts on health are due considerably to high automobile use (Albertí et al. 2017; McLeod, Babb, and Barlow 2020; Ros-McDonnell et al. 2020). However, active modes of travel can offer solutions to these problems (McLeod et al. 2020). By comparing cycling to other modes of transportation, cycling can significantly impact environmental, social, and economic issues (Arellana et al. 2020; Cavenett 2010; Glavić, Mladenović, and Milenković 2019). Bicycle travel is low-cost and health-enhancing, as the only source of energy used is from the rider (Cavenett 2010; Handy, van Wee, and Kroesen 2014). Over the years, though, the marginalization of cycling has created a historical barrier to its use (Koglin 2015, Urry 2004, as cited in McLeod et al. 2020).

Cycling is a way to move to more sustainable transportation, making cities more livable (Koglin 2014). Due to the benefits that cycling can offer to society and the emergency issues faced globally, governments worldwide promote initiatives to improve cycling in their cities (Arellana et al. 2020). In Denmark, Germany, and the Netherlands, cycling as a transport option is already widespread (Pucher and Buehler 2008). However, the implementation of bicycling in many cities faces many challenges (Rupprecht, Urbanczyk, and Laubenheimer 2010). There is a need to change the culture regarding bicycling and its practicality, showing it is a practical, fast, and flexible mode of transport. Bringing this information to society is necessary to invest in cycling policies and provide quality infrastructure and safety for its users (Bypad 2008; Mitra and Schofield 2019). Cycling as a mode of transport has been promoted worldwide through initiatives to promote its use as well as providing infrastructure and policies (Osama et al. 2020). But investments are still searching for a concrete place within a policy package applied to a city (Glavić et al. 2019). Several methods and tools are being developed and applied to transform the built environment through a cycling perspective (Arellana et al. 2020). As a result, there is a breadth of studies focusing on identifying factors that influence bicycle (Cervero, Denman, and Jin 2019).

Studies suggest that bicycle travel is related to various factors, ranging from topographical and climate issues to the quality of the existing cycling network and pro-bicycling policies (Cervero et al. 2019). In summary, such factors are generally divided into physical, individual and social (Silva et al. 2018). The physical environment factors are significantly related to natural environmental and built environmental ones (Silva et al. 2018), as well as individual and social factors, which are strongly related to socio-demographic features (Handy et al. 2014; Xing, Volker, and Handy 2018). Several tools to support cycling development have been made available. Popular methods applied in the literature are the Bicycle Level of Service and Bikeability Index (Arellana et al. 2020). The Bikeability Index analyzes the easy access to a destination by bicycle as a mode of transportation (Arellana et al. 2020; Chevalier and Xu 2020).

Many of these tools are easily applicable in mature cycling cities, which are often called “champion” or “climbing” cities (Silva et al. 2021; Silva, Marques, et al. 2019). “Champion” cycling cities have more than 20% bicycle modal share and focus on keeping people cycling (Bypad 2008). Climber cities have, generally, between 10% and 20% bicycle modal share and aim to improve their cycling networks and promote cycling to different groups (Bypad 2008). Starting cycling cities are cities with less than 10% bicycle share, usually aiming to make bicycle commuting possible, safe and comfortable (Bypad 2008). However, there is a lack of specific tools for cycling starter cities (Silva, Marques, et al. 2019). In this context, the project “BooST - Boosting Starter Cycling Cities” developed tools that provide technical and specific knowledge for these contexts (Silva et al. 2021).

Among these tools, the Gross Potential for Cycling (GPC) aims to assess the propensity to cycle under a spatial perspective (Silva et al. 2021). Based on the literature, this tool was developed to support planners in this transition through a spatial visualization of potential cycling areas calculated via two dimensions (Silva et al. 2021). The first dimension, comprised of four indicators, is about the target population, evaluated through socio-economic factors (Silva et al. 2021). The second dimension, with six indicators, is based on the target areas, verifying issues of the natural and built environment (Silva et al. 2021). The tool has so far only been applied in starter cycling cities in Portugal and has never been applied to other contexts (Silva et al. 2021). The GPC was developed from an evolution of another tool, called the Potential for Cycling Assessment Method (Silva et al. 2018). The Potential for Cycling Assessment Method was proved helpful in the planning process during a workshop with planners (Silva, Teixeira, Proença, et al. 2019). After attending the workshop, planning professionals defined the tool as having high utility to support daily planning decisions regarding cycling (Silva, Teixeira, Proença, et al. 2019).

In summary, the GPC tool is being applied in several cities, as its usefulness among planners has already been tested in its previous version. However, the model is based on a conceptual model developed through a literature review. The literature review is focused on bicycle travel behavior, with a particular emphasis on the factors influencing bicycling in starter cycling cities. Since the GPC model is conceptual, there is a need to trial the validity of this model.

1.1. OBJECTIVE

The objective of this thesis is to trial the validity of the conceptual model of the Gross Potential for Cycling. In summary, the thesis’s primary purpose is to test the conceptual model of the GPC, the relevance and explanatory power of its indicators, and the aggregate model in generating bicycle demand. To answer the central objective of this thesis, an area in the eastern Netherlands was selected as a case study. The case study site was chosen as it is a “champion” area. The purpose of applying the tool to a “champion” area is to have a high spatial disaggregation database with a significant number of bicycle users to do statistical tests. The validation of the tool is explored using cycling demand data based on the 2018 Dutch mobility survey.

The objective is answered through descriptive analysis, bivariate, and multivariate statistical analysis based on the cycling demand. The bivariate statistical analysis is performed using correlations and simple linear regressions. The multivariate analysis is performed through multiple linear regressions. After such analysis, some model optimization tests are developed.

1.2. STRUCTURE OF THE DISSERTATION

This initial chapter includes a brief background on the research's problems, the research justification, the research question, its objective, and the organizational structure of the work. Chapter two presents the literature review, aiming to elucidate the most recent theoretical issues about (a) factors that influence bicycling measures and (b) cycling assessment methods. The first part identifies the factors that influence bicycling, whether or not it is incorporated into cycling assessment methods. It was divided into three major groups: individual, physical environment, and social environment factors. A second part reviewed methods for assessing cycling potential, revealing fourteen tools.

Chapter three presents a methodological proposal for this study. First, the (a) objective and research approach are presented, followed by (b) the study area, (c) data collection, (d) the Gross Potential for Cycling and (e) the research methods. The GPC tool is explored in this thesis, based on a case study in the eastern Netherlands. The data collection is performed through five different databases. Finally, the methods presented are based on statistical methods.

Chapter four presents (a) a descriptive analysis of the results obtained with the GPC tool linked with cycling demand. Next, (b) statistical analyses developed based on the methods presented in the methodology are shown. Finally, a (c) discussion about the obtained results is performed. Chapter five presents the final considerations relative to the research as well as recommendations for future research. Figure 1 summarizes the structure of this research.

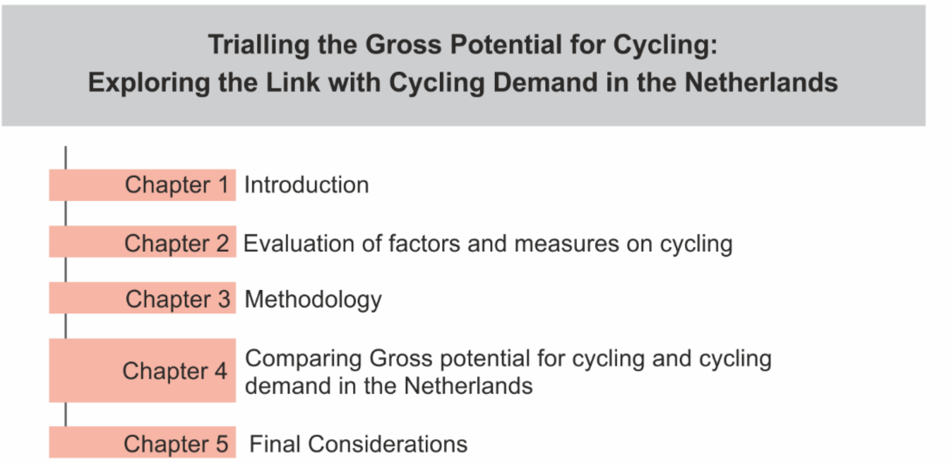


Figure 1 – Structure of the research
Source: Elaborated by the author

2
EVALUATION OF FACTORS AND MEASURES ON CYCLING

This chapter aims to elucidate the theoretical discussion about the factors that influence cycling and the tools that identify the most prone areas for cycling. The chapter is developed in two sections: the first section aims to understand the factors that influence cycling; the second section is intended to present some of the methods for assessing cycling potential available worldwide. This chapter aims to present the academic contributions to inform the discussion of this thesis.

2.1. FACTORS INFLUENCING CYCLABILITY MEASUREMENT

Bicycle commuting depends on several factors, which need to be identified to understand their influence on cycling. Several authors research the factors that influence bicycle commuting. For this study, 34 papers were reviewed, including papers of literature reviews and case studies. The factors presented by these authors were divided in this study into physical environment, individual and social factors.

2.1.1. PHYSICAL ENVIRONMENT FACTORS

In the literature review conducted by Silva et al. (2018), it is concluded that several studies relate the factors of cycling potential with the physical environment, especially with natural environmental and built environmental factors. Based on the papers studied, the cycling infrastructure, bicycle facilities, security, bike-sharing, bicycle parking, traffic calming, distance, signaling of intersections, dangerous traffic conditions, the mix of land use, pavement quality, vegetation at the intersections, population density, and presence of a university and school were analyzed as built environments factors. Topography and weather were analyzed as natural environment factors.

Regarding the built environment, this literature review revealed 16 different factors from a total of 27 papers, whether literature reviews or empirical studies. The factors are discussed below. Factors related to cycling infrastructure were found more accessible in the papers studied, so those are more detailed than the others.

Sites with a high rate of bicycle use tend to have a good cycling infrastructure (Aldred, Woodcock, and Goodman 2016; Mitra and Schofield 2019; Pucher and Buehler 2008; Pucher, Buehler, and Seinen 2011; Pucher, Dill, and Handy 2010). A paper that analyzes Welsh and English census data and bicycle commuting via surveys present that good quality infrastructure is paramount for using the bicycle

(Pucher and Buehler 2008). In England, improvements to cycle infrastructure combined with other policies increased cycling trips of 30 minutes or more once a month by 2.78% (Sloman et al. 2009 as cited in Yang et al. 2010). Other studies outside the European context also confirm that improvements in bicycle infrastructure are related to high cycling rates. The city of Portland in the United States of America (USA) has improved infrastructure and the implementation of integrated policies in various fields, which has resulted in a six-fold increase in cycling in the city since 1990 (Pucher et al. 2011). In the region of Toronto in Canada, infrastructure improvements have helped promote cycling as a fast, convenient and flexible mode of transportation (Mitra and Schofield 2019). Pucher et al. (2010), based on several authors, point out that high levels of infrastructure correlate with high travel rates.

Another strong influence in using the cycling infrastructure is segregated or off-road bicycle paths (Buehler, Pucher, and Bauman 2020; Hull and O'Holleran 2014; Titze et al. 2008 as cited in Pucher et al. 2010). Off-road bicycle paths usually have two lanes separated from motorized traffic (Pucher et al. 2010). The guidelines for cycle infrastructure in the Netherlands can be used as good examples for adopting segregated bicycle paths (Hull and O'Holleran 2014). In the Netherlands, the segregation of bicycle paths leads to a feeling of increased safety. According to the analysis conducted by Hull and O'Holleran (2014), in six cities, there is a higher number of cyclists who use segregated paths than other paths; the study presents segregation as an intervention not so expensive since bollards/vegetation are cheap and can offer enough segregation from the cyclists' point of view. In Odense, Denmark, cyclists see off-road bike paths as very safe, and these are used by women and men, old and young people (Troels Andersen - City of Odense s.d. as cited in Pucher and Buehler 2008).

A study conducted in Australia shows that off-road bicycle paths are more likely to be used (Titze et al. 2008 as cited in Pucher et al. 2010), and the same happens for studies conducted in the USA (Buehler et al. 2020). There is a greater preference in using this type of bike path than the use of painted lanes on roads, as it brings more safety to the user (Cavenett 2010; McNeil, Monsere, and Dill 2015; Mitra and Schofield 2019; Winters et al. 2013). Besides safety, in a survey conducted in Vancouver, Canada, users preferred off-road bike paths because they were closer to beautiful landscapes, without noise, traffic, or pollution (Winters et al. 2011, 2013). According to a study conducted in Melbourne, Australia, women prefer off-road bike paths, and 20% would not use the bicycle in another type of bike path (Rose 2007 as cited in Pucher et al. 2010).

Investigations highlight the importance of an infrastructure network (Buehler and Pucher 2012; Hull and O'Holleran 2014; Winters et al. 2013; Xing et al. 2018). In the Netherlands, an empirical study shows that the improvement and the increase of the extension of bicycle networks increased the use of this type of transport. During the three-year follow-up, there was an 8% increase in the distance cycled per person and 4% in the bicycle use frequency per person (Wilmink e Hartman 1987, as cited in Yang et al., 2010). An investigation conducted in the cities of Edinburgh located in Scotland, Cambridge located in England, Amsterdam, Den Haag, Rotterdam and Utrecht located in the Netherlands, concluded that cycling infrastructure design is essential to encourage cycling, specifically with a vast network to connect all land uses (Hull and O'Holleran 2014).

It is essential to connect the cycling network with bicycle facilities (Winters et al. 2013). These may be described as lockers, changing rooms, locker rooms, bicycle maintenance equipment, showers, among others (Pucher and Buehler 2008). Bicycle facilities encourage women to use this type of transport (Buehler et al. 2020). Denmark, Germany, and the Netherlands have been planning and building bicycle facilities since the 1970s; each municipality is responsible for developing plans that fit their local needs (Pucher and Buehler 2008). There is a need for bike facilities between three and six blocks from anywhere in the city (Pucher et al. 2011).

The most mentioned bicycle facilities are showers at workplaces (Hull and O'Holleran 2014; Lee and Pojani 2019; Pucher et al. 2010), which significantly impact the bicycle use to go to work (Wardman et al. 2007, as cited in Pucher et al. 2010). In surveys conducted in Singapore, sweating was one of the most significant barriers for workers to go to work by bicycle; also, for women, there is a need for a changing room to change clothes and redo their makeup (Lee and Pojani 2019). Other factors mentioned are bicycle repair facilities, lockers near public transportation, bicycle rental, bike wash, and elevators. Hartanto (2017) presents the need for bicycle hubs with existing bicycle repair stations. Based on an application of a Western Bikeability Index in the Chinese context, Chevalier and Xu (2020) opine that bicycle repair stores impact bicycle ownership. The use of lockers has significant impacts on cyclists at transportation stations (Taylor and Mahmassani 1996 as cited in Pucher et al. 2010). In the Netherlands, rental bicycles in train stations resulted in a slight reduction of car use and increased train travel (Martens 2007; Pucher and Buehler 2008). Moreover, the review conducted by Pucher et al. (2010) emphasizes the importance of bicycle washing in stations. In Washington, the Metrorail system has elevators to facilitate the access of bicycles (Pucher et al. 2011).

The word safety is strictly related to cycling, as this is one of the main reasons that the Netherlands, Germany, and Denmark have higher levels of bicycle use than countries as the United Kingdom (UK) and USA, among the elderly, children, and women (Pucher and Buehler 2008). These authors (2008) show that cycling in Germany and Denmark is twice as safe as cycling in the UK and that in the Netherlands, it is three times as safe as cycling in the UK. The authors also point out that the three countries have started to improve cycling safety since 1970. Winters et al. (2011) conclude from surveys applied in Metro Vancouver that one of the essential factors in the probability of riding a bicycle is safety. Mitra and Schofield (2019) applied surveys in Toronto at three train stations, and their literature review suggests that women are encouraged to ride a bicycle to train stations in the suburbs if they feel safe.

Bicycle theft, lack of lighting, and traffic safety are significant concerns of cyclists. In the research conducted by Cavenett (2010), one of the biggest concerns of cyclists in Amsterdam in 2006 was bicycle theft. In interviews conducted in Cambridge, England, most respondents had hostile relationships with owning a bike due to the high risk of theft and vandalism (Aldred 2010). In the literature review by Pucher et al. (2010), in northern European countries, such as the Netherlands, Germany, and Denmark, specific facilities such as guarded parking are proposed to reduce theft and increase safety. Lee and Pojani (2019) also show that the most important safety concerns are bike theft and better lighting in their literature review. The cities of Amsterdam, Den Haag, Rotterdam, and Utrecht in the study conducted by Hull and O'Holleran (2014) are scored as the highest in terms of attractiveness due to the high perception of safety. One of the best points analyzed was that the suburban cycling routes had high-quality lighting even at night.

Bicycle parking and traffic calming; distance and population density; intersections signalization and dangerous traffic conditions; the mix of land use, pavement quality, vegetation, and presence of the university and school had a similar incidence in the papers studied. These are described in a decreasing way, being the bicycle parking and traffic calming with more mentions and mix of land use among others with fewer mentions.

Table 1 – Influence on the use of the bicycle on built environment factors I
Source: Elaborated by the author

Factor	Definition	Influence	References
Cycling infrastructure	Good infrastructure for cycling	+	Aldred et al. (2016); Pucher and Buehler (2008); Pucher at al. (2011, 2010); Sloman et al. (2009), as cited in Yang et al. (2010); Mitra and Schofield (2019)
Cycling infrastructure	Segregated bicycle paths or off-road bicycle paths	+	Buehler et al. (2020); Cavenett (2010); Hull and O'Holleran (2014); McNeil et al. (2015); Mitra and Schofield (2019); Rose (2007), as cited in Pucher et al. (2010); Titze et al. (2008), as cited in Pucher et al. (2010); Troels Andersen - City of Odense s.d., as cited in Pucher and Buehler (2008); Winters et al. (2013)
Cycling infrastructure	Existence and increase of networks	+	Buehler and Pucher (2012); Hull and O'Holleran (2014); Wilmink e Hartman (1987), as cited in Yang et al. (2010); Winters et al. (2013); Xing et al. (2018)
Bicycle facilities	Bicycle facilities at workplaces	+	Hull and O'Holleran (2014); Lee and Pojani (2019); Wardman et al. 2007, as cited in Pucher et al. (2010)
Bicycle facilities	Different bicycle facilities	+	Chevalier and Xu (2020); Martens (2007); Pucher and Buehler (2008); Taylor and Mahmassani (1996), as cited in Pucher et al. (2010)
Safety	Safety	+	Mitra and Schofield (2019); Pucher and Buehler (2008); Winters et al. (2011)
Safety	Bicycle theft	-	Aldred (2010); Cavenett (2010); Pucher et al. (2010)
Safety	Lack of lighting	-	Hull and O'Holleran (2014)

Several authors present the importance of good and secure bicycle parking infrastructure in the physical environment to positively influence bicycle commuting (Hull and O'Holleran 2014; Martens 2007; Mitra and Schofield 2019). The literature review by Pucher et al. (2010) shows that bicycle parking lots in European, North American and Australian cities have grown almost threefold in the recent decades. Parking increases the perception of convenience when using the bicycle (Pucher et al. 2011) since the lack of secure parking areas negatively influences the use of the bicycle (Cavenett 2010). Hull and O'Holleran (2014) studied the three Dutch cities with high-quality bicycle parking; Martens (2007) study states that cyclist satisfaction has increased after a program to upgrade bicycle parking near Dutch train stations was applied. In Cambridge, some car parking was converted into bicycle parking and had positive results (Hull and O'Holleran 2014). In surveys applied in Toronto, bicycle parking lots are established as necessary at the end of trips to the recreational cyclist (Mitra and Schofield 2019). Also, it is recommended in some empirical studies that cycling infrastructure, such as bicycle parking, should be strongly related to public transport use so that users can cycle to public transportation stations or stops (Cavenett 2010; Martens 2007; Mitra and Schofield 2019).

Another facilitator of cycling are bicycle-sharing systems, according to the literature review of McLeod et al. (2020) and Xing et al. (2018). As reported, bicycle rental at public transportation stations or stops and other strategic places positively influences bicycle commuting (Martens 2007; Mitra and Schofield 2019). According to a literature review by Pucher et al. (2010), the city of Amsterdam started bike-sharing programs in 1960, promoting access to bicycles for the entire community, whether short-term or annual sharing. As another example, China offers a very accessible bicycle sharing system for cyclists (Yang et al. 2019); after the implementation of the program, more than 19 million Chinese started using the system (Tsing Hua University Planning and Design Institution and Mobike 2017, as cited in Yang et al. 2019). In Washington, in the USA, the expansion of bicycle sharing tripled bicycle trips to work between 1990 and 2008 (Handy et al. 2014).

Traffic calming increases the perception of safety (Hull and O’Holleran 2014; Pucher and Buehler 2008). It limits cars’ speed in residential neighborhoods, imposing restricted traffic rules (Pucher and Buehler 2008). Among the central policies and measures to promote bicycle use, Dutch, German and Danish cities promote traffic calming for all neighborhoods, streets where the bicycle has priority over cars (Pucher and Buehler 2008). The European experience shows that traffic calming encourages cyclists to pedal (Clarke and Dornfeld 1994, as cited in Pucher et al. 2010). Cambridge promotes comfort to cyclists due to the traffic calming measures (Hull and O’Holleran 2014). The city of Vancouver, Canada, is a leader in traffic calming (Pucher et al. 2011), and the streets with traffic calming are the most used by cyclists (Winters et al. 2011).

The use of the bicycle as a mode of transportation is more common among small distances (Carse et al. 2013; Cavenett 2010). A study conducted in Vancouver, Canada, states that cyclists are willing to ride a maximum of half an hour (Winters et al. 2013). The study conducted in Cambridge indicated distance as the key to success in using the bike (Carse et al. 2013); in the city, the distances to points of interest are mainly short, facilitating the use of the bicycle (Aldred 2015). The literature review by Handy et al. (2014) and Lee and Pojani (2019) shows that in short distances, cycling is positive, and longer distances generate a negative impact on each increment of distance, which favors the use of another type of transport, such as the car.

According to studies conducted in the United States applied in the form of a survey, people living in high-density neighborhoods are more likely to use the bicycle (Buehler et al. 2020; Schneider and Stefanich 2015, as cited in Kamel, Sayed, and Bigazzi 2020; Pucher and Buehler 2006). Land use planning in northern European countries promotes mixed and compact development in cities to drive high-density neighborhoods, consequently generating more healing travel distances and encouraging bicycle use (Schmidt and Buehler 2007 as cited in Pucher et al. 2010).

Priority in the intersection is a concern of cyclists. In 2006, research conducted by Cavenett (2010) in Amsterdam showed that one of the biggest concerns between cyclists was the long wait at intersections. Bicycle lanes should become colorful at intersections, which should feature synchronized signals and signaling along the road to indicate the correct speeds (Pucher and Buehler 2008). It is becoming more and more apparent that roads designed for cars can negatively affect bicycle use (Aldred 2010; Buehler et al. 2020). As proof of this need, one author brings the information that people are willing to make longer journeys if it is related to less traffic (Aldred 2015).

Other relevant factors that are included in the choice of this type of transport are a mix of land use (McLeod et al. 2020), which aims to keep trips short, reducing the need for the car (Pucher and Buehler 2008); quality of the pavement (Landis et al. 1998 as cited in Pucher et al. 2010), and vegetation at the intersections. Regarding this last factor, cited during interviews conducted in Singapore, interviewees stated that they prefer shading provided by vegetation to human-made shelters (Lee and Pojani 2019). Also, the presence of student environment, such as schools and universities, is more likely to promote the use of the bicycle (Sisson et al. 2006 as cited in Pucher et al. 2010).

Table 2 – Influence on the use of the bicycle on built environment factors II
Source: Elaborated by the author

Factor	Definition	Influence	References
Bicycle parking	Bicycle parking	+	Cavenett (2010); Hull and O'Holleran (2014); Martens (2007); Mitra and Schofield (2019)
Bicycle sharing	Bicycle sharing in strategic points	+	Handy et al. (2014); Martens (2007); Mitra and Schofield (2019); Yang et al. (2019)
Traffic calming	Traffic calming	+	Clarke and Dornfeld (1994), as cited in Pucher et al. (2010); Hull and O'Holleran (2014); Pucher and Buehler (2008); Winters et al. (2011)
Distances	Small distances	+	Carse et al. (2013); Cavenett (2010); Winters et al. (2013)
Population density	High population density	+	Buehler et al. (2020); Schmidt and Buehler (2007), as cited in Pucher et al. (2010); Schneider and Stefanich 2015, as cited in Kamel, Sayed, and Bigazzi (2020)
Intersections signalization	Intersections signalization	+	Cavenett (2010)
Intersections signalization	Shortcuts	+	Pucher and Buehler (2008)
Dangerous traffic conditions	Roads designed for cars	-	Aldred (2010); Buehler et al. (2020)
The mix of land use	The mix of land use	+	McLeod et al. (2020); Pucher and Buehler (2008)
Pavement quality	Pavement quality	+	Landis et al. 1998, as cited in Pucher et al. (2010)
Vegetation	Vegetation	+	Lee and Pojani (2019)
Presence of university and school	Presence of university and school	+	Sisson et al. 2006, as cited in Pucher et al. (2010)

Regarding the natural environmental factors, attention is drawn to topography and climate (Pucher et al. 2011). These are referred to equally among the papers studied.

Table 3 – Influence on the use of the bicycle on natural environment factors
Source: Elaborated by the author

Factor	Definition	Influence	References
Topography	Flat topographies	+	Cavenett (2010)
Topography	Steep topographies	-	Hartanto (2017); Winters et al. (2013)
Weather	Rainy climate	-	Winters et al. (2013)
Weather	High temperatures	-	Lee and Pojani (2019)

Flat topographies are more convenient for cyclists. This is why the Amsterdam topography is ideal for cycling (Cavenett 2010). The literature review by Lee and Pojani (2019) shows that steep topography is not very suitable for cyclists. Steep topographies are usually avoided, according to a study conducted at 21 train stations in the Arnhem-Nijmegen region of the Netherlands (Hartanto 2017). Hilliness is negatively associated with cycling in the study conducted in Metro Vancouver (Winters et al. 2013). Slopes between 0% and 3% are considered flat and with total fitness for cycling, stretches with 3% to 5% slope are considered somewhat satisfactory for cycling up to medium distances, while slopes above

5% are unsuitable for cycling (Instituto da Mobilidade e dos Transportes Terrestres 2011). However, slopes of 5% to 6% are acceptable for up to 240 meters, 7% routes up to 120 meters, 8% routes up to 90 meters, 9% routes up to 60 meters, 10% routes up to 30 meters and greater than 11% routes up to 15 meters (Instituto da Mobilidade e dos Transportes Terrestres 2011).

Rainy climates are not convenient for cyclists (Winters et al. 2011), but the climate is also a barrier in high temperature environments. For example, in Singapore, cycling rates fall during the afternoon due to high temperatures (Lee and Pojani 2019). A mild climate is best suited for cycling (Heinen, van Wee, and Maat 2010).

2.1.2. Individual and Social Factors

Individual and social factors are strongly related to socio-demographic factors (Handy et al. 2014; Xing et al. 2018). The influence of gender, age, income, car ownership, presence of students, level of education, and ethnicity are analyzed as individual factors. The support to the social environment is analyzed at the end. A total of 19 papers were analyzed, being literature reviews or empirical studies.

Gender is among the preferred individual factors, then age, income, and car ownership were detailed similarly, as they were found in similar empirical studies. Education level, ethnicity and the social environment support were the less detailed factors since they were less common in the literature studied.

The influence of gender on bicycle use is a subject frequently discussed among authors. Gender influence on bicycle commuting is seen differently among countries. Investigations in English-speaking countries such as Australia, Canada, the USA, and the UK, shows that these are more likely to have more men using the bicycle than women, revealing a significant gender difference (Aldred 2010; Buehler et al. 2020; Mitra and Schofield 2019; Pucher and Buehler 2008; Pucher et al. 2011; Garrard 2003, as cited in Steinbach et al. 2011; Winters et al. 2011), and up to three times as likely in countries as the USA (Buehler et al. 2020). In countries like Australia, Canada, the USA, and the UK, just 30% or less of women use the bicycle as a mode of transportation (Pucher and Buehler 2008; Pucher et al. 2011).

Table 4 – Influence on the use of the bicycle on individual factors

Source: Elaborated by the author

Factor	Definition	Influence	References
Gender	Female	-	Aldred (2010); Buehler et al. (2020); Garrard (2003), as cited in Steinbach et al. (2011); Mitra and Schofield (2019); Pucher and Buehler (2008); Pucher et al. (2011); Winters et al. (2011)
Age	Adults and youth	+	Aldred et al. (2016); Buehler et al. (2020)
Age	Elderly and children	-	Buehler et al. (2020); Dill and McNeil (2013); Transport for London (2017)
Income	High income	-	Aldred (2010); Cavenett (2010); Lee and Pojani (2019); Pucher and Buehler (2006)
Car ownership	Car ownership	-	Aldred (2015); Buehler et al. (2020); Pucher and Buehler (2008); Winters et al. (2011)
Students	Students	+	Cavenett (2010); Yang et al. (2010)
Education Level	Graduates	+	Buehler et al. (2020)
Ethnicity	White ethnicity	+	Steinbach et al. (2011)

In countries with high cycling rates, such as the Netherlands and Denmark, women are more likely to use this type of transport (Lovelace et al. 2017; Pucher and Buehler 2008). In the Netherlands, most of the trips made by women are shopping, leisure and educational trips (Harms, Bertolini, and te Brömmelstroet 2014, as cited in Aldred et al. 2016) while women's travel in London accounts for only a third and face barriers with shopping and educational trips (Garrard 2003 as cited in Steinbach et al. 2011). This gender difference between countries may be because women are more concerned about their safety when using their bicycles (Aldred et al. 2016; Mitra and Schofield 2019).

Pucher and Buehler (2008) conclude that older people in the Netherlands do 24% of their trips by bicycle. The literature review of Aldred et al. (2016) shows that this percentage is higher than the reported perception in any other Dutch age group over 26 years. In Amsterdam, from children to the elderly, everyone uses the bicycle for at least 20% of their trips (City of Amsterdam 2003b as cited in Cavenett 2010). The Dutch law protects young cyclists and states that drivers have redoubled care with elderly and children's cyclists. The same happens in German law (Cavenett 2010). In the USA, bicycle use is predominant among people between 16 and 44 years old (Buehler et al. 2020), and a study in Portland, USA, revealed that people over 55 years of age were in the non-cyclist category but had an interest in cycling (Dill and McNeil 2013). In England and Wales, cycling is also dominated by adults and youth (Aldred et al. 2016). In London, a study proved that children and older people are less likely to ride bicycles over long distances (Transport for London 2017). Still, in countries with low bicycle use, it is necessary to take more measures that impact the use of the bicycle by the elderly, adolescents, and children since their use rates are the smallest (Buehler et al. 2020). Some authors present the need to build a more favorable environment for cycling by the elderly and the change of stereotype that only young people use this type of transportation (Aldred et al. 2016).

Based on the literature review carried out by Silva et al. (2018) on studies focused on income, it is concluded that the relationship between income and the use of the bicycle is not very clear. A significant impact of high income is related to the probability of car ownership (Pucher and Buehler 2006). Some authors cite the prejudice of users who think the bicycle is for the poor and prefer to drive a car (Aldred 2010; Cavenett 2010; Lee and Pojani 2019). Thus, car ownership is directly related to the low use of the bicycle (Aldred 2015; Buehler et al. 2020). Regular cyclists are less likely to own cars in a study performed in Vancouver, Canada (Winters et al. 2011). People who ride a bicycle often use this type of transport because it is cheap (Aldred 2015), since the purchase of a car in countries such as the Netherlands, Denmark and Germany is significantly related to high parking fees and fees for obtaining a driver's license (Pucher and Buehler 2008).

The literature reviews by Lee and Pojani (2019), Pucher et al. (2011), and Silva et al. (2018) regarding the relationship between students and cycling concluded that students are more likely to use the bicycle, and they are the principal target of the population to promote cycling. There are several policies related to encouraging students to use the bicycle. In Amsterdam, the Netherlands, the government provides bicycles for those who cannot afford them (Cavenett 2010). Some schools in several countries promote promotional activities related to using this type of transportation (Yang et al. 2010).

A study shows that the relationship between people who use bicycles and the level of schooling has varied over the years, as in 2001, graduates had similar rates of ridership than undergraduates, whereas, in 2017, graduates had rates twice as high (Buehler et al. 2020). Another factor identified is ethnicity, as verified in London, the UK, where 94% of the cyclists identified themselves as white (Steinbach et al. 2011).

Table 5 – Influence on the use of the bicycle on social environment factors
Source: Elaborated by the author

Factor	Definition	Influence	References
Social environment	Family and friends	+	Bartle, Avineri, and Chatterjee (2013), as cited in Handy et al. (2014)
Social environment	Sharing information	+	Aldred (2010)

As social environment support, family and friends are essential in encouraging the use of the bicycle (Bartle, Avineri, and Chatterjee 2013, as cited in Handy et al. 2014), and it can happen in the suggestion of equipment and cycling information sharing (Aldred 2010).

2.2. CYCLING ASSESSMENT METHODS

A review of the assessment methods on cycling potential revealed fourteen tools summarized in Table 6. Methods were applied at the global level or for specific contexts, such as the Chinese and global south, as well as at the local level. When evaluating these tools, it was recognized that almost all studies bring mapping information as final data presentation, and most studies have limitations on data extracting and analyzing data, as well as the use of open data platforms. Most of the presented methods are GIS-based, and a few of them are presented in ranking and statistics. All tools are indicated to support planners; some are presented as user-friendly tools, such as those presented by Copenhagenize Index (2019), Winters et al. (2013), Krenn, Oja, and Titze (2015). Other tools can be easily used by inhabitants, like the one presented by Walk Score (2020). These tools are intended to support the planning and development of policies, mainly focused on cycling.

Planning Support Systems (PSS) are a particular field of supporting tools for planning and development of policies (Klosterman, 1997 as cited in Lovelace et al. 2017), introducing spatial information to support planning actions (Brömmelstroet 2013). Lovelace (2017) also explains that a PSS generally presents an interactive map of the needs of the areas studied, thus facilitating the visualization of change scenarios and the possibility of changes. Among the PSS, Silva et al. (2021) highlights in the literature review the PSS focused on cycling, being these tools based on the evaluation of cycling in the city by broad measures, indicators of evaluation of streets for cycling, bikeability index, among others. The Propensity to Cycle Tool is an example of PSS (Lovelace et al. 2017).

Most of the methods studied are based on the concept of bikeability. This is defined as the review of the literature of Kellstedt et al. (2020) as the analysis of the perception of the safety of the real environment in the use of the bicycle, but the author adds that there is no universal definition of the word. The evaluations made according to the concept of bikeability evaluate the bike facilities and the areas that are less suitable for bicycle use (McNeil 2011). Some examples may be related to bike route density, bike route separation, connectivity, topography, destination density (Winters et al. 2012). The analysis of bikeability can be carried out from surveys, discussions, interviews to analyze perceptions and geospatial methods to analyze physical characteristics (Kellstedt et al. 2020).

The Bike Score (Walk Score 2020), the Bikeability Index (Winters et al. 2013), the Potential Bikeability (Greenstein 2015), and the Index of City Readiness for Cycling applied to Egyptian cities (Zayed 2016) are grouped by similarity, as these authors only consider slightly different factors in their evaluations, such as bicycle network, bicycle infrastructure and topography.

Table 6 – Cycling assessment methods summary
Source: Elaborated by the author

Methods	Application	Shape	Strength
The Bike Score (Walk Score 2020)	Canada and USA	Ranking/ Map-based	This tool can be used by planners or by inhabitants, for example, to search for bikeability zones to live
The Bikeability Index (Winters et al. 2013)	Metro Vancouver region (Canada)	GIS-based	This tool intended to be flexible by using standard data
Potential Bikeability (Greenstein 2015)	Austin (USA)	GIS-based	It reveals the most critical factors related to bikeability in Austin and guides planners to make investments in strategic points to have a more significant impact on cyclists
The Bikeability Index for a Mid-sized European Cities (Krenn et al. 2015)	Mid-European cities, Graz (Austria)	GIS-based	The index tends to be a simple tool to be applied in the European territory
The Index of City Readiness for Cycling (Zayed 2016)	Egyptian cities	Statistic	The study serves as a basis for the development of frameworks for bicycle-friendly cities.
The Bikeability Index (Motta 2017)	Curitiba (Brazil)	GIS-based	It was the first study to apply the bike-ability method in a Brazilian city
The Copenhagenize Index 2019 (Copenhagenize Index 2019)	Global	Ranking	Cities can easily compare their efforts to be bicycle-friendly cities with other cities around the world
The Street Score Framework for Walkability and Bikeability (Gu et al. 2018)	Chinese context	Statistic/ Map-based	The tool intended to be directly connected to China's urban transportation planning and uses open-source data
The Bikeability Framework (Grigore et al. 2019)	Basel (Switzerland)	GIS-based	Method to model cyclability, it is suitable as a collaborative tool in urban planning
The Urban Bikeability Index (Arellana et al. 2020)	Global South, Barranquilla (Colombia)	GIS-based	The methodology is focused on different types of cyclists, distinguishing them socio-economically, by perceptions of the built environment and by preferences
The Bicycle Level of Service (Landis, Vattikuti, and Brannick 1997)	America	Statistic/ Ranking	A popular method to calculate the safety and comfort score of roadway segments
The Bicycle Compatibility Index (Federal Highway Administration 1998)	America	Statistic/ Ranking	A popular method to calculate the quality of bicycles facilities
Analysis of Cycling Potential Tool (Transport for London 2010)	London	Statistic	The tool help plan interventions that attend the cycling needs and that bring an excellent cost-benefit to the city
The Propensity to Cycle Tool (Lovelace et al. 2017)	The United Kingdom and Wales	Map-based	It is open source to map the cycling potential; it is possible to view the results at different geographical levels

The Bike Score (Walk Score 2020) defines whether a site is suitable for cycling on a scale of 0-100, analyzing destinations and road connectivity. The method is based on bike lane infrastructure data taken from the OpenStreetMap (OSM), topography data taken from the National Elevation Data set from the United States Geological Survey's, connectivity and destination data calculated based on the calculations presented in the Walk Score. Similarly, Greenstein (2015) analyzes road network connectivity, while others analyze network-related issues slightly differently, such as bike network density and bike-friendly streets connectivity analyzed by Winters et al. (2013), as well as road network length analyzed by Zayed (2016). These tools can be used by planners or by inhabitants, for example, to search for bikeability zones to live in.

The Bikeability Index (Winters et al. 2013), applied across the Metro Vancouver region in Canada, is one of the pioneering methods that analyze cycling potential by zones. The purpose of the tool is to show the areas that are most likely to be used by cyclists and the less likely ones. To develop the study, a GIS tool, travel behavior studies, and opinion surveys were applied. Focus groups were identified to help define the main factors of the index, and these groups were divided into prospective cyclists, regular cyclists, cycling activists, and occasional cyclists. Among the established factors, the topography factor is the one that is most repeated when correlating with other studies. Krenn et al. (2015), Motta (2017) and Winters et al. (2013) have a factor called topography in their analysis, whereas Greenstein (2015) and Walk Score (2020) present slightly different factors but related to the topography as slope and hills, respectively. To summarize the results of the Bikeability Index, a map is generated with a score for more and less cycling-friendly zones. This tool is intended to be flexible by using standard data. The authors present the definition of latent demand for cycling as a limitation of this study, as it does not foresee any changes in cycling rates.

The Potential Bikeability (Greenstein 2015) was developed based on the city's 2014 Bicycle Master Plan Update for the city of Austin in the USA. The plan aims to improve bicycle conditions in central Texas, which is related to ensuring infrastructure for 8 to 80 years old to relate short trips with bike trips, while another goal of the plan is to reduce network barriers. Each factor has a weight, being bicycling facilities the most important factor since. Among the five factors analyzed, two are correlated by similarity with other authors, being land-use, a slightly similar factor considered in Motta (2017) as a mix of land-use, and another is topography. The author (Greenstein 2015) maps current bikeability and potential bikeability in Austin, Texas; the second map brings an idea of how the implementation of the 2014 Bicycle Master Plan Update impact bicycle use in the city, i.e., the map transmits recommendations of locations to increase the bicycle network and locations to implement security components for cyclists. The spatial analysis used in the maps was based on GIS. A positive point of the study is that it reveals the most critical factors related to bikeability in Austin and guides planners to make investments in strategic points to have a more significant impact on cyclists.

The Bikeability index for mid-sized European cities (Krenn et al. 2015), applied in Graz, Austria, aims to map the bicycle-friendliness of the city. The data was based on studies conducted with inhabitants who drew their most frequent bicycle routes on a map and with inhabitants who proposed to use GPS data to identify the paths they took. The final mapping was based on GIS and aimed to show bicycle-friendliness in urban areas of the city through different colors. Three factors out of five correlates to infrastructure, being these bicycle infrastructure, main roads without any parallel bicycle infrastructure, and presence of separated bicycle pathways. Other authors correlate to infrastructure, such as the cases of the Walk Score (2020), Arellana et al. (2020) and Copenhagenize Index (2019). However, thesewere not grouped in this item because they do not correlate with many other factors in this grouping. Motta (2017) correlates to bicycle infrastructure in a slightly different way, by differentitating infrastructure by types (those where it is possible to ride bicycles, being bicycle paths, roads in general or exclusive lines for buses). The index tends to be a simple tool to be applied in the European territory. This research indicates that regular cyclists tend to live in bicycle-friendly neighborhoods, which differs from non-cyclists. They present as a negative point the dependence on the database containing maps, particularly when not updated after a change in the built environment. As a positive point, cycling maps can be of great value for the development of bicycle-friendly transportation, especially in the European context.

The Index of City Readiness for Cycling, applied to Egyptian cities (Zayed 2016), aims to analyze city readiness for cycling and classify cities with high, neutral, and low readiness levels. The factors related to this study were based on the main variables of 20 case study cities, which were present in the Copenhagenize Index. The author suggests that the most important indicator of this study is the city population and that this study serves as a basis for the development of frameworks for bicycle-friendly cities. *The Bikeability Index* (Motta, 2017), applied in Curitiba, Brazil, analyzes five different variables. This Index is related to the study of Krenn et al. (2015) and Winters et al. (2013) due to the similarity of variables. GIS, government data, and surveys were used to better understand the motivators and barriers to bicycle use to analyze the variables. In the surveys, inhabitants were divided by transport behavior and by income level, and at the end, a binary logistic regression was performed to correlate these. There was a higher value description between topography, climate, distance, and integration with public transport for non-users, and cyclists were more concerned with accessibility improvements for bicycle and speed reduction measures. A weight was assigned to each index variable to present a bikeability map, demonstrating areas more prone to bicycle use and areas that need improvement. This was the first study to apply a bikeability method in a Brazilian city. The study's weakness is the low amount of survey results, which may not have been ideal for factor analysis.

The methodologies of the Copenhagenize Index 2019 (Copenhagenize Index 2019), the Street Score Framework for Walkability and Bikeability (Gu et al. 2018), the Bikeability Framework (Grigore et al. 2019), and the Urban bikeability Index (Arellana et al. 2020), were, moreover, grouped by similarity, according to the relation of their factors with attractiveness, comfort, and safety.

The Copenhagenize Index 2019 (Copenhagenize Index 2019) is an international index that analyzes three groups: physical environment, social environment, and individual. This index is one of the most holistic and established globally, is updated every year since 2011, and aims to create a ranking of the cities with more than 600,000 inhabitants that are more bicycle-friendly. The Top 20 is published on the index website. In the 2019 edition, a section called "Success Stories" was added on the website, bringing stories of cities that are not in the Top 20 of the ranking but serve as inspiration as how to create initiatives to make bicycle-friendly. Every year the number of cities is expanded by increasing the data set to hundreds represented worldwide. The first place in the ranking is given to the city that makes the most efforts to use the bicycle as an accessible and viable type of transport. These efforts are measured in thirteen factors. One of those is the image of the bicycle, attributing points to the cities where the bicycle is respected, attractive, and accepted as a standard type of transport. This factor has slight differences from those presented by Grigore et al. (2019) and Arellana et al. (2020) as attractiveness. The authors bring the competitiveness between cities as a positive point of the tool, as cities can easily compare their efforts with other cities worldwide. A failure of the index is that the factors are focused on cities that already have bicycle infrastructure, which makes it difficult for beginner cities to use the tool. There is also a barrier to small cities since the application is for cities with over 600,000 inhabitants. Moreover, some authors show that this tool is suitable only for the western context (Chevalier and Xu 2020).

The Copenhagenize Index has been adapted for creating other indexes, such as the Western Bikeability Index in the Chinese Context (Chevalier and Xu 2020). This study has the city as a scale of application and was applied in Shanghai to verify the level of relevance of each factor of the Copenhagenize Index. During the study, Shanghai is presented as a unique city because of the urban environment, economy, demography and exemplify that the factors can be attenuating between the city and the whole country. Thus, some factors used in the Copenhagenize Bikeability Index had their objectives reformulated to be used in the Western Bikeability Index in the Chinese Context, and three new parameters have been added: parallel economies, urban forms, and bicycle ownership. Even if this tool tries to adapt to the

Western context, it presents limitations in several factors, being one of most critical the higher propensity of the Chinese to use the bicycle than the other inhabitants of Western countries.

The Street Score Framework for Walkability and Bikeability (Gu et al. 2018) was applied in the Chinese context directly in four cities: Tianjin, Shijiazhuang, Kunming, and Chongqing. The tool is intended to be directly connected to China's urban transportation planning and uses open-source data. This tool evaluates walkability and bikeability in the form of scores considering safety, comfort, and convenience. One of the study's results was that there is a bad influence on bicycle use from the illegal car parking on bike lanes and sidewalks and a relationship between comfort and safety when riding a bike. The study shows that flat cities tend to have a preliminary cycling network, but this network is drastically shorter than sidewalks. The four cities had high scores related to safety, which shows that the government prioritizes this factor. One limitation of the study is that it depends on open-source data, and the authors recommend that the results are tested in other contexts.

The bikeability framework (Grigore et al. 2019), applied in Basel, Switzerland, intended to be a method to model bikeability and suitable as a collaborative tool in urban planning, i.e. this tool can help identify places that need improvement the cyclability. Initially, it analyzed the quality factors of cycling; among them is the comfort that is also analyzed in the methodologies of Copenhagenize Index (2019), Gu et al. (2018) and Arellana et al. (2020). After identifying the trips' main destinations and calculating the cycling quality, the mapping of cycling quality was performed on GIS. A map of bikeability to Basel was developed, representing places with high and low bikeability divided by colors. As a result of the study, the authors state that in Basel city center the values found were better than in other neighborhoods, because the distances to workplaces were shorter. A weak point of the study is that a deeper analysis of the influence of factors on cycling quality is needed to have more concrete results.

The Urban bikeability Index (Arellana et al. 2020) is a global south index applied in Latin America in Barranquilla, Colombia. First, the factors for the construction of the cycling index were selected based on surveys and expert reviews. Then weights for each factor were estimated based on surveys applied to frequent cyclists and non-cyclists. Among the factors analyzed, those related to safety and traffic safety are slightly different from those considered as safety indicators by the Copenhagenize Index (2019) that scores cities that place the responsibility for safety on drivers. However, other authors such as Motta (2017), Gu et al. (2018), and Grigore et al. (2019) consider safety in their analysis. At the end of the analysis, a mapping using GIS represents where investments in infrastructure for cyclists should be prioritized, and cartographic data was also obtained by traffic counting and OD (origin-destination) surveys. The positive point of the methodology is that it focuses on different types of cyclists, distinguishing them socio-economically, by perceptions of the built environment and by preferences. This research has positive results in terms of choosing the type of transportation and available infrastructure among sports users, while the biggest concern of workers is safety. The problem with safety is also documented in other studies conducted in Latin America. The authors suggest that investments in infrastructure could close the gap between rich and poor people in these Latin American cities and improve safety.

The Bicycle Level of Service (Landis et al. 1997) and the Bicycle Compatibility Index (Federal Highway Administration 1998) were developed based on the concept of level of service and thus are similar. What differs in their analysis, according to a detailed study conducted by Liu, Homma, and Iki (2019), are some factors referent to pavement condition, lane number, which are present only in the study of Federal Highway Administration (1998), as well as roadside development and right turns, which are present only in the study of Landis et al. (1997). The Analysis of Cycling Potential tool (Transport for London 2010) is an analytical tool that estimates the impact of cycling policies as well as infrastructure interventions on the level of cycling service and demand. The Propensity to Cycle Tool (Lovelace et al.

2017) has a theoretical relation with the Analysis of Cycling Potential tool (Transport for London 2010); both use Origin-Destination surveys.

The Bicycle Level of Service (Landis et al. 1997) is based on the level of service (LOS) presented by the Highway Capacity Manual (HCM). It was developed in 1960 to measure safety in bicycle facilities on roads in America. The development of the Index had the help of 150 participants who filled out a form with general questions, recognized the profile of the participants, and then participated in a course to evaluate the quality of road links, excluding intersections. Participants had to assess on a scale of A-F (6 points) how comfortable and safe they felt with their right-of-way, so that level A was the least dangerous and level F the most dangerous. With the results obtained, the most relevant variables were identified and the best configuration of each variable. After the evaluation, it is possible to use GIS to demonstrate the results in a color-coded map, which presents streets and their classifications. This study considers the Bike Level of Service (BLOS) model 2.0.

The Bicycle Compatibility Index (Federal Highway Administration 1998) is a tool that also has a Level of Service concept. Created in 1998 to measure cycling in road segments in America, especially for urban and suburban areas, it was based on the perspective of 200 participants from three different locations who classified on a six-point scale (A-F) videos from 67 sites; the scale varied from highly comfortable to highly uncomfortable to cycling. Based on this analysis, the most important variables were identified, and a regression model formula for the analysis of Bicycle Compatibility Index (BCI) was defined. The result is inserted in a six-point table to identify the compatibility level, and this is classified from highly high (A) to shallow (F). After the score analysis, it is possible to develop a color-coded map in GIS that identifies the streets and their capability level. Mapping can help planners to easily identify areas that need intervention.

The Analysis of Cycling Potential (Transport for London 2010, 2017) was developed by Transport for London (TFL) in 2010. It presents heat maps to identify the cycling potential in the city of London, UK. The tool's purpose is to help plan interventions that meet the inhabitants' cycling needs and bring an excellent cost-benefit to the city. The Analysis of Cycling Potential (ACP) uses data from travel demand research based on TFL's Travel Demand Survey (LTDS). This seeks to analyze which of the motorized trips conducted in the survey could be transformed into cycling trips based on travel and individual criteria. Two layers are evaluated; the first is the cycling potential achieved by providing a suitable cycling environment, and the second is the cycling potential of existing behavior. However, one weakness of the tool is that it does not analyze the cycling potential of visitors and tourists in London.

The Propensity to Cycle Tool (Lovelace et al. 2017) was founded by the UK's Department for Transport. Developed after the ACP, the Propensity to Cycle Tool (PCT) also uses OD surveys in the methodology. The creation of the tool responds to a generalizable and scalable tool deficit based on PSS. With an open-source nature, it maps cycling potential and estimate the health and carbonic gas (CO_2) data at the street level. The tool brings the possibility to visualize results at different geographical levels, for example, at a local or regional level. The tool's primary approach is to use OD data grouped in pairs which, combined with geographic population data, represent "desire lines" for the transportation network. For the development of the tool, the 2011 census data on cycling in Wales and England were used and modeled according to the slope of routes and distances. Four bicycle usage scenarios were developed: Government goal, gender equality, GoDutch, E-bikes. It was evaluated how each scenario can impact users' health, for which the World Health Organization's Health Economic Assessment Tool (HEAT) data were used. As well, it measures the CO_2 reduction that each group can generate. As a result of the analysis, an interactive online map is presented with the "desire lines" defined through aggregate pairs OD in two directions and a "flow" centroid. The map has different layers according to the pre-established scenarios. The online map can be downloaded in GIS software. A strength of the tool is that it has an open-source code to be studied and modified as needed by users for future research. For the current case, the data is limited to the 2011 Census because this is the only one that presents OD data regarding cycling levels and with high geographic resolution nationwide; this limitation is, therefore, one of the weaknesses of this tool.

Table 7 – Cycling assessment methods and factors
Source: Elaborated by the author

Cycling Assessment Methods	**Factors**
The Bike Score (Walk Score 2020)	Bike lanes, hills, destinations and road connectivity, bike commuting mode share
The Bikeability Index (Winters et al. 2013)	Bike network density, route separation, bike-friendly streets connectivity, bike-friendly destination density, and topography
Potential Bikeability (Greenstein 2015)	Bicycle facilities, network connectivity, land-use, slope, and barriers
The Bikeability Index for a Mid-sized European cities (Krenn et al. 2015)	Cycling infrastructure, presence of separated bicycle pathways, main roads without any parallel bicycle infrastructure, aesthetic areas, and topography
The Index of City Readiness for Cycling (Zayed 2016)	City population, city area, city form, road network length and motorized transport modal split as the fundamentals of cycling commuting
The Bikeability Index (Motta 2017)	Residential density, mixed land-use, topography, safety and types of infrastructure
The Copenhagenize Index 2019 (Copenhagenize Index 2019)	Bicycle infrastructure, bicycle facilities, traffic calming, gender split, modal share for bicycles, modal share increase over the last 10 years, indicators of safety, image of the bicycle, cargo bikes, advocacy, politics, bike share, urban planning
The Street Score Framework for Walkability and Bikeability (Gu et al. 2018)	Safety, comfort, convenience
The bikeability framework (Grigore et al. 2019)	Comfort, safety, attractiveness for cycling, distance for cycling routes, perceived distance to the destinations of interest
The Urban bikeability Index (Arellana et al. 2020)	Directness and coherence, comfort and attractiveness, traffic safety, security, climate, presence of bicycle infrastructure, and cost of the trip
The Bicycle Level of Service (Landis et al. 1997)	Volume of directional traffic in 15-minute time period, total number of through lanes, effective speed limit, percentage of heavy vehicles, average effective width of outside through lane, total width of outside lane and shoulder/parking pavement, width of paving from outside lane stripe to pavement edge, width reduction due to encroachments in outside lane, and Federal Highway Administration in America 5-point surface condition rating
The Bicycle Compatibility Index (Federal Highway Administration 1998)	Presence of a bicycle lane or paved shoulder, bicycle lane width, curb lane width, curb lane volume, other lanes volume, legal speed limit, presence of a parking lane with more than 30% occupancy, and type of roadside development
Analysis of Cycling Potential tool (Transport for London 2010)	Trip distance, time of day and commuters characteristics like age and profession
The Propensity to Cycle Tool (Lovelace et al. 2017)	Origin-destination data set

Among these tools, high utilization of factors enhances the existing bicycle infrastructure, which is a barrier for beginning cities to start using such tools. The factors with the highest repetition among all studies are within the group of physical environments are the presence and network of cycling infrastructure, safety perception, and topography. Factors related to the presence and network of cycling infrastructure include all the bike lanes inside and outside the streets, i.e., from lane sharing cyclists to off-road bike lanes (Chevalier and Xu 2020; Copenhagenize Index 2019; Walk Score 2020). This factor is given as one of the most critical that influence the choice of the bicycle as a mode of transportation (Arellana et al. 2020). The perception of safety is considered through installations with basic security for cyclists, whether on footpaths, intersections, or bicycle paths (Gu et al. 2018). One of the biggest problems with safety is related to illegal parking of cars on footpaths (Gu et al. 2018), the number of lanes (Grigore et al. 2019), legislation (Chevalier and Xu 2020; Copenhagenize Index 2019; Gu et al. 2018). This factor is seen as one of the most important for those travelling to work by bicycle (Arellana et al. 2020). Finally, the topography factor is positive if inversely related to the hills (Grigore et al., 2019; Krenn et al., 2015; Winters et al., 2013).

3
METHODOLOGY

The theoretical contributions presented in the previous chapter allow for an understanding of the measurement factors that influence bikeability and of some tools that exist worldwide to measure it. To answer the research objective, the approach of this research is based on a case study in the eastern Netherlands. This section presents the objective and research approach, followed by presenting the study area, the database, and Gross Potential for Cycling tool. Finally, the method is presented, explaining the statistical analysis process used.

3.1. OBJECTIVE AND RESEARCH APPROACH

The objective of this thesis is to trial the validity of the conceptual model of the Gross Potential for Cycling. The objective is achieved through descriptive analysis, bivariate and multivariate statistical analysis; these compare the GPC and its indicators with cycling demand data. A "champion" area was chosen as a case study because it has a significant amount of cycling demand data than starter cycling cities. However, the author was aware of the limitations of the analysis concerning exploring a tool created for the starter context in a "champion" area; these were explored later in this chapter and the results. The cycling demand data for this thesis is defined in four concepts based on the Dutch mobility survey, On the road in the Netherlands[1] (CBS and RWS 2018).

The first cycling demand concept refers to the total bicycle kilometers traveled (km_{t1}). km_{t1} is a multiplication of the area's inhabitants by the per capita bicycle kilometers traveled. The second is the kilometers traveled per capita by bicycle (km_{t2}). To obtain the km_{t2} value the total distance traveled by bicycle is divided by the total number of mobility survey respondents. The third concept refers to the total number of bicycle trips (qty_{t1}). This formula is similar to km_{t1}'s, however, using data of the number of bicycle trips. The last formula refers to the number of trips per capita by bicycle (qty_{t2}).

$$km_{t1} = \frac{Ihabitants_{total}\ x\ Km_{bike}}{Respondents_{total}} \tag{1}$$

[1] Translated from Dutch, *Onderweg in Nederland.*

$$km_{t2} = \frac{Km_{bike}}{Respondents_{total}} \quad (2)$$

$$qty_{t1} = \frac{Ihabitants_{total} \ x \ Trips_{bike}}{Respondents_{total}} \quad (3)$$

$$qty_{t2} = \frac{Trips_{bike}}{Respondents_{total}} \quad (4)$$

The ODIN 2018 is an origin-destination survey, this was provided in the form of microdata. For this thesis, all trips that start and end in the study area were considered. The trip chain[2] concept (Li et al. 2013; Transport for London 2017) supports the decision to consider all trips that begin and end in the study area. Among cycling demand data collection, the ODiN 2018 differentiates between electric and non-electric bicycle trips, but the GPC tool does not distinguish between both modes. Thus, both trips, whether made by electric bicycle or not, were considered bicycle trips.

Table 8 – Gross Potential for Cycling: Cycling indicators and weight

Source: Adapted from BooST (2020)

Group	***Code***	***Indicators***	***Weight***	***Description***
Target area	A1	Accessibility to education facilities	3	Identifies the areas prone to cycling to access education facilities
	A2	Accessibility to centralities	2	Identifies the areas prone to cycling to perform day-to-day trips (shopping, leisure, among others)
	A3	Accessibility to transport interfaces	2	Identifies the areas prone to cycling as extending the coverage of public transport (first and last kilometres)
	A4	Relative accessibility	3	Classifies the municipalities' urban area according to the average distance a bicycle can circulate in 5 minutes in comparison to a car's average distance in the same period
	A5	Connectivity	1	Identifies the areas with more blocks with adequate cycling dimensions
	A6	Occupation diversity	1	Identifies the areas with a greater diversity of commerce and services
Target population	P1	Age	3	Identifies the areas where more people with ages prone to cycling reside
	P2	Population density	3	Identifies the areas with a greater density
	P3	Employment density	3	Identifies the areas with more workers
	P4	Motorization rate	2	Identifies the areas with more residents who own a car, this value is compared with the national average

[2] A trip chain correlates with travel mode choice due to the location or nature of the trip initiation (Transport for London 2017). A person who commutes from home to work by bicycle is likely to make the subsequent trips by bicycle. The chain concept assumes that the trips made by an individual are linked together until the person returns to his home (Transport for London 2017).

The GPC is a tool that analyzes the gross potential for bicycle use in starting cycling cities through four indicators referring to the target population and six indicators referring to the target areas (Table 8). The target population group, through its indicators, verifies information identifying the location of the population segment most prone to cycling (Silva et al. 2021). The target areas indicators evaluate the cycling potential of the built environment and the natural environment (Silva et al. 2021). Each of the ten indicators has a weight (Table 8) relative to the impact in promoting bicycle use (BooST 2020). The aggregated value, called the GPC score, is calculated based on a weighted average of the indicator weights and their final values.

$$GPC = \frac{\sum_i s_i \ x \ w_i}{\sum_i w_i} \tag{5}$$

Where:

$s = score\ for\ indicator\ i$

$w = weight\ of\ indicator\ i$

Thus, the conceptual model to be trialled is the one represented in formula 5. For this thesis, variable P3 was not considered due to a lack of data; this is discussed further. Furthermore, the GPC methodology needed to be adapted for this research due to the scale of disaggregation of cycling demand data. All analyses are performed at the smallest disaggregation scale and weighted by the population at the same disaggregation scale for cycling demand. The only indicator calculated directly at the same disaggregation scale as cycling demand is the motorization rate indicator (P4). The methodology applied to some indicators also needed to be adapted. The adaptations are explored more effectively in the following sections, where the application of the tool to the Dutch context is discussed.

3.2. Study Area

The Netherlands is a remarkable case concerning cycling as transport (Pucher and Buehler 2008), as the bicycle is an important way to move around the country (Cavenett 2010). The Netherlands is among the countries that make cycling safe, attractive, and comfortable for users (Pucher and Buehler 2008). In 2019 the country had 273,417 km of bike routes (CBS 2019a). Within the proportion of passenger kilometers in the Dutch modal split, 9% of daily trips were made by bicycle in 2018 (CBS 2019b). This commuting mode grew by 1% from 2017 to 2018 (CBS 2019b). In 2019, 4.8 billion bicycle trips were made (CBS 2020b), and 17.6 billion bicycle kilometers were traveled (CBS 2020b). In 2019, 28% of all trips were made by bicycle (CBS 2019b), similar to the 27% recorded in 2018 (CBS 2020b). The study area of this thesis is located in two provinces in the Netherlands, namely Gelderland and Overijssel (Figure 2).

The province of Overijssel in 2019 had 28,128 km of bike routes, the fourth largest among the provinces (CBS 2019a). In Overijssel, the study area partly covers 17 municipalities, 1,712 km², with 729,605 inhabitants (CBS 2016). The province of Gelderland in 2019 had the most extensive bike routes among the provinces, totaling 42,067 km (CBS 2019a). In Overijssel, the study area partly covers 17 municipalities with 459,220 inhabitants and 1,377 km² (CBS 2016). The population of the province of Overijssel and Gelderland commutes on average 38.91 km per day per person (CBS 2020a). The average cycled in Overijssel is 3.17 km and in Gelderland is 3.53 km (CBS 2020a).

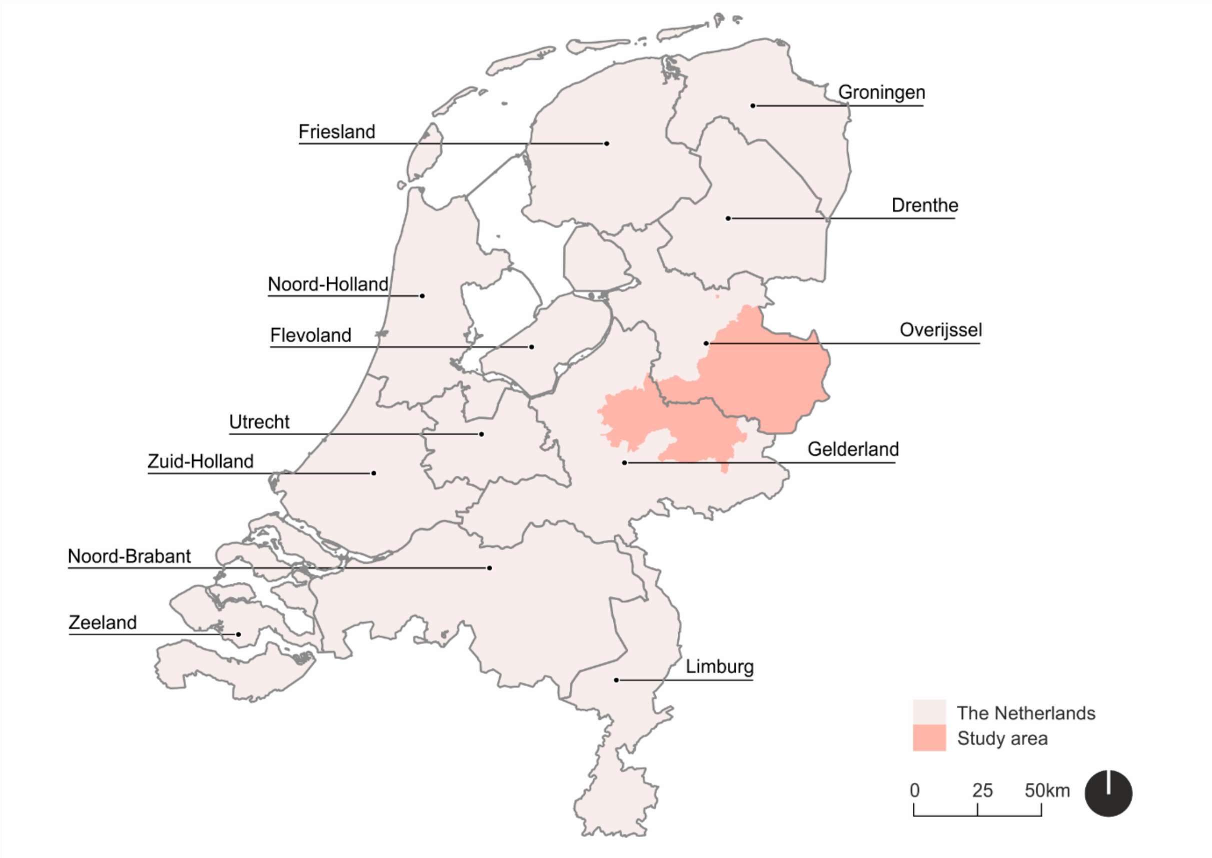


Figure 2 – Map of the study area location
Source: Elaborated by the author from the data provided by CBS (2016)

The municipalities with the most significant territorial extensions are Apeldoorn, Ede, and Hardenberg (CBS 2016). The smallest municipalities in territorial extension are Westervoort, Doesburg and Oldenzaal (CBS 2016). Some municipalities in the study area border Germany, namely Hardenberg, Twenterand, Tubbergen, Dinkelland, Losser, Enschede, Haaksbergen, Zevenaar and Rijnwaarden. Among the municipalities covered by the study area, Apeldoorn, Enschede, and Ede are the most populated (CBS 2016). The lowest populated were in 2016, Rozendaal, Rijnvaarden and Doesburg (CBS 2016). Westervoort, Oldenzaal and Hengelo have the highest population density (CBS 2016). Among the cities with the lowest population density are Rozendaal, Ommen and Bronckhorst (CBS 2016).

Apeldoorn and Enschede are defined as metropolitan agglomerations (CBS 2015); these are areas of urban development in which most human activities occur, where most business and public facilities are located (CBS 2015). Both metropolitan agglomerations are surrounded by smaller municipalities (CBS 2015). According to CBS (2015), (A) Enschede is connected to Borne, Oldenzaal, Losser, Hengelo, while (B) Apeldoorn is connected to Voorst, Rozendaal, Rheden, Westervoort, Duiven.

In addition to these two urban agglomerations identified by CBS (2015), the analysis of population density (Figure 4) and road network (Figure 5) highlights four clusters with potential for urban agglomeration. These are located among the municipalities of (C) Twenterand, Wierden, and Almelo; (D) Deventer; (E) Zutphen; (F) Montferland and Zevenaar. The six centers in this thesis are referred to as densely populated centers (Figure 6).

Table 9 – Main characteristics of the study area
Source: Elaborated by the author from the data provided by CBS (2016)

	Municipality	Population	Total area (km^2)	Population density ($inhab/km^2$)	Urbanity(1)
Overijssel	Almelo	72,425	69.41	1043.44	Highly urban
	Borne	22,343	26.16	854.09	Moderately Urban
	Deventer	98,869	134.30	736.18	Highly urban
	Dinkelland	26,120	176.80	147.74	Non-urban
	Enschede	158,351	142.70	1109.68	Highly urban
	Haaksbergen	24,332	105.50	230.64	Moderately Urban
	Hardenberg	59,687	317.10	188.23	Suburban
	Hellendoorn	35,651	139.00	256.48	Suburban
	Hengelo	81,075	61.83	1311.26	Highly urban
	Hof van Twente	34,881	215.40	161.94	Suburban
	Losser	22,444	99.62	225.30	Suburban
	Oldenzaal	32,110	21.95	1462.87	Moderately Urban
	Ommen	17,696	182.00	97.23	Suburban
	Rijssen-Holten	37,875	94.38	401.30	Moderately Urban
	Tubbergen	21,120	147.40	143.28	Non-urban
	Twenterand	33,846	108.10	313.10	Suburban
	Wierden	23,952	95.39	251.10	Suburban
Gelderland	Apeldoorn	159,025	341.20	466.08	Highly urban
	Berkelland	44,437	260.50	170.58	Suburban
	Bronckhorst	36,510	286.40	127.48	Non-urban
	Brummen	20,938	85.01	246.30	Suburban
	Doesburg	11,336	12.96	874.69	Suburban
	Duiven	25,433	35.19	722.73	Moderately Urban
	Ede	112,427	318.60	352.88	Highly urban
	Lochem	33,333	215.90	154.39	Suburban
	Montferland	35,173	106.60	329.95	Suburban
	Oost Gelre	29,537	83.34	354.42	Suburban
	Rheden	43,824	84.35	519.55	Moderately Urban
	Rijnwaarden	10,866	48.08	226.00	Moderately Urban
	Rozendaal	1,498	27.92	53.65	Highly urban
	Voorst	23,984	126.50	189.60	Suburban
	Westervoort	15,001	7.84	1913.39	Moderately Urban
	Zevenaar	32,269	58.00	556.36	Moderately Urban
	Zutphen	46,997	42.93	1094.74	Highly urban

(1) Determined by the address density of an area with a radius of 1 km around that address is determined. The perimeter address density of a municipality is the average value of this for all addresses within that municipality. Urbanity terms according to CBS (2016): Highly urban (surrounding address density of 1,500 or more); moderately urban (surrounding address density of 1,000 to 1,500); suburban (local address density of 500 to 1,000); non-urban (surrounding address density of less than 500).

For the wider study area, in 2018, cycling accounts for 29.70% of all trips made; of all trips, 53.83% are made by private motor vehicle, 8.31% by public transport, 8.03% walking and 0.12% by other types of transportation (CBS and RWS 2018). An aggregation of travel data between 2004 and 2016 shows that among the cities studied, cycling mode share rates are between 32% and 38% (Goudappel Coffeng 2016). In most central municipalities, cycling mode share data tends to be higher than 20%. Some municipalities have high rates for their entire territory, such as the municipality of Berkelland, which has a population density below 250 inhabitants per km^2, has in most of the study area between 30% and 40% cycling mode share. Berkelland, with an average cycling mode share of 31% (Goudappel Coffeng 2016), is ranked among the top 100 cycling cities of 2020 by Cycling City[3] (Fietsersbond 2020b). The municipality of Borne, which has a population density close to 900 inhabitants per km^2, has cycling mode share rates mostly above 30%, which is reflected in the final average cycling mode share of the municipality, which is approximately 38% (Goudappel Coffeng 2016). Borne is one of the cities studied that were among the top 100 cycling cities in 2018 and 2020, according to Cycling City (Fietsersbond 2018, 2020a). Rijssen-Holten stands out among the best cycling cities in the Netherlands; it is among the Cycling City top 10 in 2018 and 2020 (Fietsersbond 2018, 2020a). The municipality has an average population size of fewer than 500 inhabitants per km^2. When looking at a smaller disaggregation scale, most of the municipality area with a population density higher than 500 inhabitants per km^2 has cycling rates of 30% to 40%; the municipality average is around 35% (Goudappel Coffeng 2016).

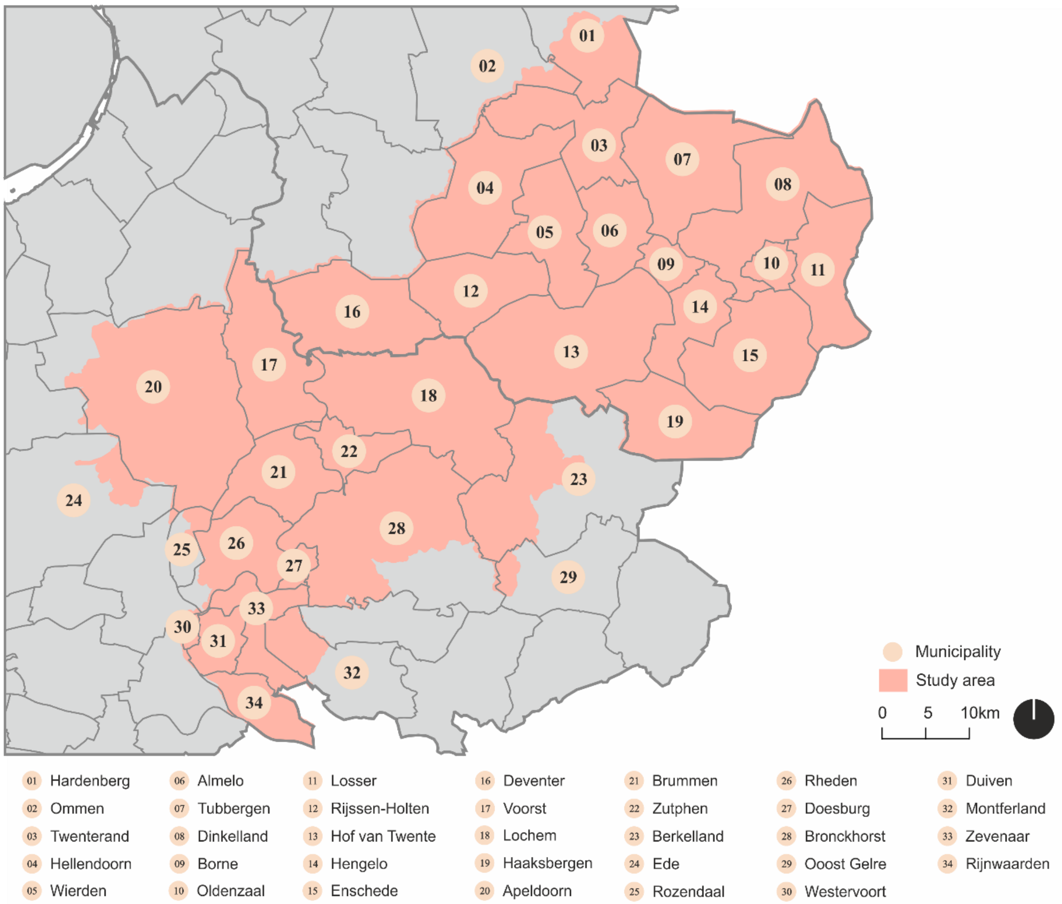


Figure 3 – Map of the study area's location divided by municipalities

Source: Elaborated by the author from the data provided by CBS (2016)

[3] Translated from Dutch, *Fietsstad*. It is a national election to encourage municipalities in the Netherlands to promote cycling (Fietsersbond 2020b). The election takes place once every two years. This is developed by Fietsersbond.

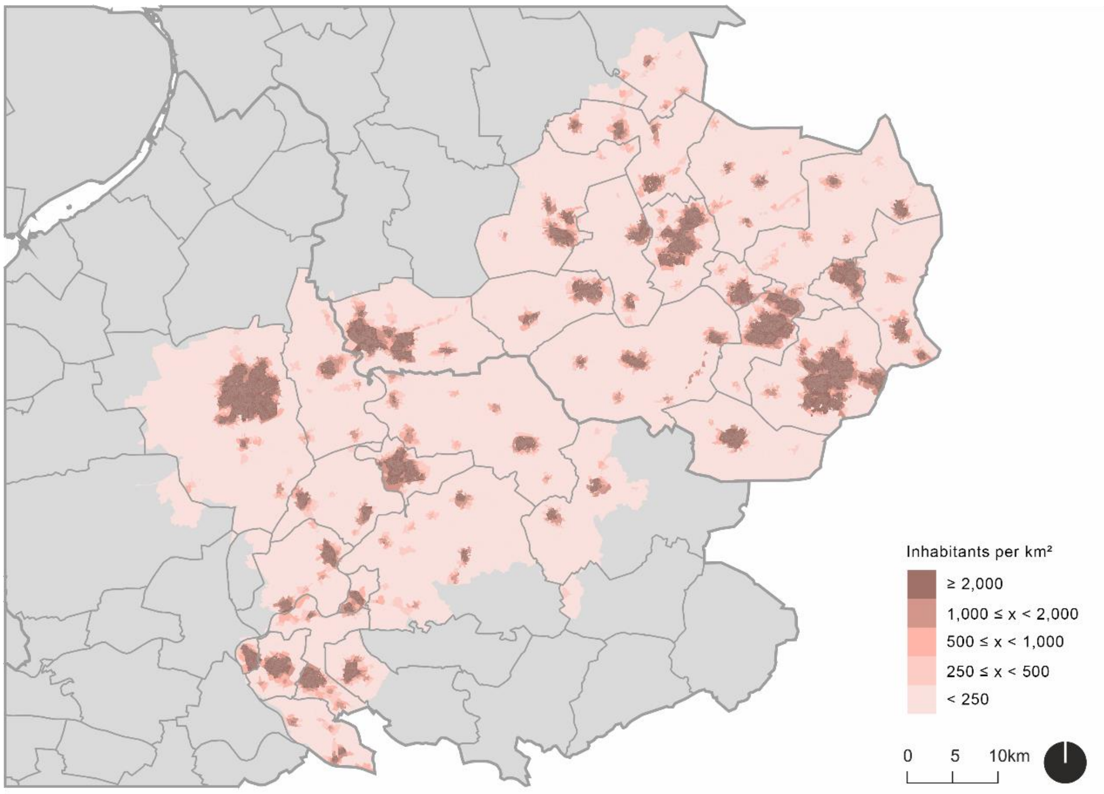


Figure 4 – Map of population density of the study area
Source: Elaborated by the author from the data provided by CBS (2016)

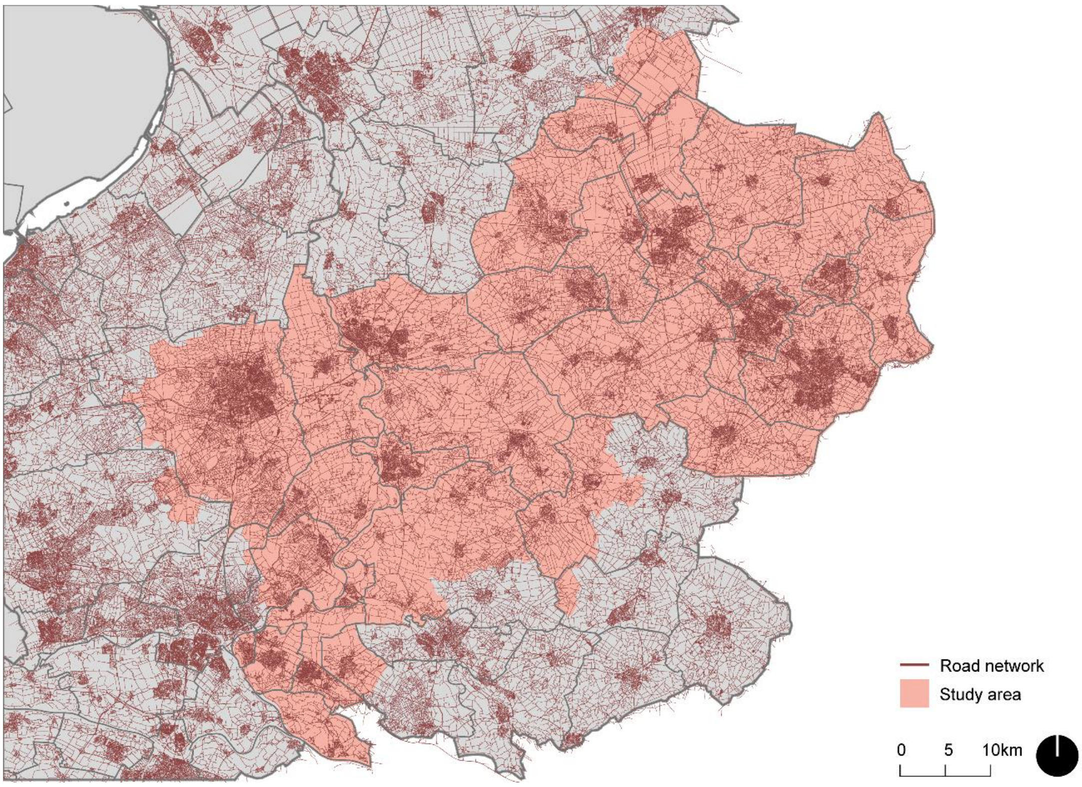


Figure 5 – Map of the road network of the study area
Source: Elaborated by the author from the data provided by CBS (2016)

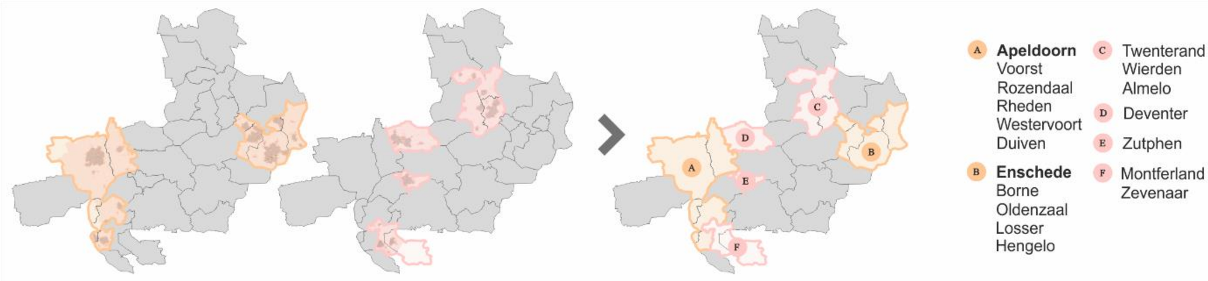


Figure 6 – Urban agglomeration scheme
Source: Elaborated by the author from the data provided by CBS (2015, 2016)

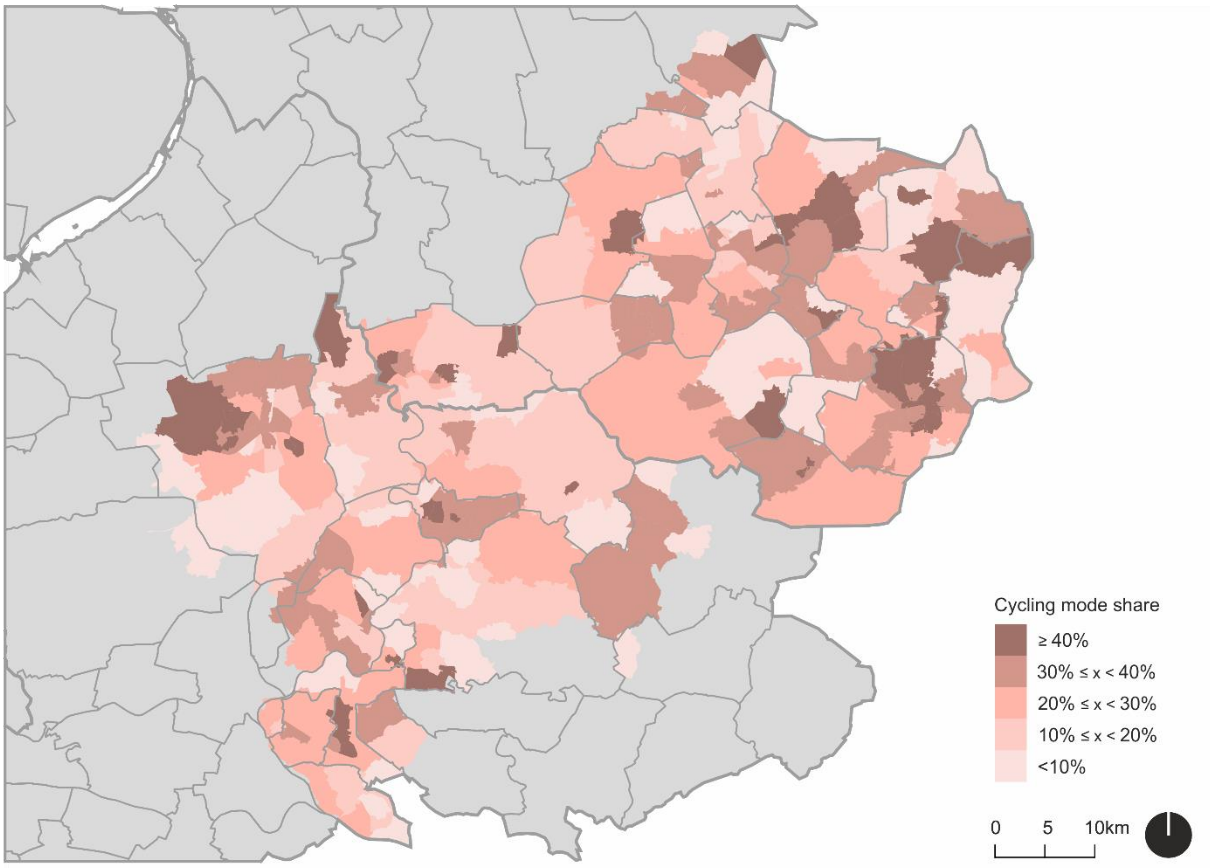


Figure 7 – Cycling mode share map of the study area
Source: Elaborated by the author from the data provided by CBS and RWS (2018).

Also, among the municipalities studied, Enschede, the largest city in Overijssel, has the highest Cycling City title; it is among the top 5 cities in 2020 and the top 10 in 2018. For the most part, Enschede has cycling rates higher than 20%, but in areas that appear to be more densely populated, the cycling rate is higher than 30%. The final average cycling share in the city of Enschede is close to 35% (Goudappel Coffeng 2016). For years, Enschede is an ambitious city for cyclists to implement measures and invest in innovation to make cycling more attractive (Gemeente Enschede 2021). The city was a pioneer in the 1990s in implementing roundabouts with priority for cyclists (Keypoint Consultancy 2011) and developed the first traffic signals that turn green in all directions when the motor vehicle traffic signal is closed (Wagenbuur 2014). Enschede has policies that pay attention to cycling since 1996 (Keypoint

Consultancy 2011). The city made several investments in bicycle bridges and off-road cycling paths (Fietsersbond 2020c) and uses its demographics effectively in bicycle policies to improve cycling (Kuiper 2012).

The municipality with the highest bicycle use among those studied is Borne. However, among the municipalities studied, all have a cycling modal share rate above 24% in 2018 (CBS and RWS 2018). Among the two agglomerations identified by CBS (2015) and among the four clusters identified by the author are the locations with the most cycling modal share rates above 30% (CBS and RWS 2018). Of the 34 municipalities, 14 were selected in 2018 among the 100 best cities for cycling, and 11 of these remained in the next edition of the ranking in 2020. Enschede and Rijssen-Holten were among the 10 best cycling cities in the Netherlands in 2018 and 2020.

3.3. DATA COLLECTION

Five databases supported the data collection process. Population information and area limits were taken from Statistics Netherlands[4] (CBS), the national statistical office of the Netherlands. This study use data from 2016, one of the most recent years for which CBS provides free information at the six-digit postal zones (PC6) level. This database was chosen because, for some GPC indicators, the values at the PC6 level can be used to calculate averages at the four-digit postal zones (PC4) level.

Table 10 – Data collection

Source: Elaborated by the author

Source	Year	Collected Information	Usefulness
CBS	2016	Age distribution	Age (P1)
		Population distribution	All GPC indicators, aggregated GPC value; km_{t1}, km_{t2}, qty_{t1} and qty_{t2}
		Borders of postal areas	All GPC indicators, aggregated GPC value, km_{t1}, km_{t2}, qty_{t1} and qty_{t2}
Copernicus	2021	Topography	Calibration
ODiN	2018	Cycling demand	km_{t1}, km_{t2}, qty_{t1} and qty_{t2}
		Car ownership	Motorization rate (P4)
OSM	2021	Road infrastructure	Accessibility to education facilities (A1), accessibility to centralities (A2), accessibility to transport interfaces (A3), relative accessibility (A4), and calibration
		Urban grid	Connectivity (A5)
		Areas of interest	Accessibility to centralities (A2) and occupation diversity (A6)
		Transportation interface	Accessibility to transport interfaces (A3)
Schools on the Map	2021	Schools and Universities	Accessibility to education facilities (A1)

Topographic data, from 2021, were downloaded from the Copernicus Land Monitoring Service. The data referring to the 2021 road infrastructure were based on the OpenStreetMap[5] (OSM) platform. Also, through OSM, information such as the location of the areas of interest and transportation interfaces were

[4] Translated from Dutch, *Centraal Bureau voor de Statistiek*. Available on: https://www.cbs.nl/.

[5] Available on: https://www.openstreetmap.org/.

downloaded, with Google Maps[6] being used for occasional validation. The address of the educational establishments was collected based on Schools on Map[7] (Scholen op de kaart 2021).

Information about the car ownership and bicycle commuting was obtained from the ODiN database. The ODiN compiles statistical information about the daily mobility of the Dutch (CBS 2018). The ODiN results are available as microdata, so it is possible to access the individual answers. Among the answers, it is only possible to access information at the PC4 level due to privacy concerns (CBS and RWS 2018). The author had access to the 2018 version of this survey through the Data Archiving and Networked Service[8] (DANS) in January 2021. The ODiN is a continuation of other mobility surveys from previous years, such as Research on Mobility in the Netherlands[9] (OViN), Mobility Research Netherlands[10] (MON), Survey on Transportation Behavior[11] (OVG).

3.4. THE GROSS POTENTIAL FOR CYCLING

The Gross Potential for Cycling is one of the tools developed by the project "BooST - Boosting Starter Cycling Cities"12 (Silva et al. 2021). The first version of the tool was developed by Silva et al. (2018); later refined in the BooST research project. The GPC tool was developed to identify the spatial disaggregation of cycling potential; the tool's results can be easily used to evaluate scenarios, comparing the current condition of the city and the potential gains that could happen by building a new cycling infrastructure (Silva et al. 2019). The GPC does not evaluate the existing cycling infrastructure, a common factor used to evaluate "champion" cycling cities (BooST 2020). This PSS been developed for starter cycling cities and has only been applied in such contexts (Silva et al. 2021).

The factors investigated in this method were established based on an extensive literature review (Silva et al. 2018), summarizing the international practices regarding indicators that influence bicycle use. The GPC evaluates ten indicators, divided into two groups, target area and target population. Each indicator is rated on a scale of 1 (lowest potential) to 5 (highest potential). The model is also calibrated by the conditions of circulation, which comprise cycling infrastructure, road hierarchy, road network speed, accidents, and topography (BooST 2020). The calibration is necessary since these factors can influence the average speed of the bicycle, and hence the behavior of the territory. Detailed maps are developed per indicator and an aggregate map to provide a unique overview of the cyclists' potential (Silva 2019).

Among the target area indicators, six indicators are considered. The accessibility to education facilities (A1) is considered based on the time it takes to reach an education facility by bicycle. The A1 is included in the tool due to positive empirical evidence of the impact of cycling in areas with more significant

[6] Free tool for searching, viewing maps and satellite images of the earth provide by Google. Available on: https://www.google.com/maps.

[7] Translated from Dutch, Scholen op Kaart. Available on: https://scholenopdekaart.nl/.

[8] Dutch national center of expertise and research data repository. Available on: https://dans.knaw.nl/.

[9] Translated from Dutch, *Onderzoek Verplaatsingen in Nederland.*

[10] Translated from Dutch, *Mobiliteitsonderzoek Nederland.*

[11] Translated from Dutch, *Onderzoek Verplaatsingsgedrag.*

[12] Available on: https://boost.up.pt/.

numbers of young people, such as educational establishments (Silva et al. 2021). The highest level (5) refers to areas where the time to reach a basic education or secondary education facility is a maximum of five minutes, or a university facility a maximum of ten minutes (BooST 2020). The lowest level (1) is a bicycle ride of at least 20 minutes to a primary school, at least 25 minutes to a secondary school, or at least 30 minutes to a university (BooST 2020). The indicator accessibility to centralities (A2) refers to the time needed to reach the closest centrality by bicycle, intending to measure the compactness of a city (BooST 2020). The A2 is based on studies developed by several authors who argue that bicycle use is mainly carried out over shorter travel distances, which are made possible through denser urban areas (Silva et al. 2021). The highest score (5) equals less than 10 minutes to reach the primary center (often represented by the city council building) and less than 5 minutes to reach the secondary center (BooST 2020). The lowest score (1) represents more than 30 minutes to reach the primary center and more than 15 minutes to reach the secondary center (BooST 2020). The accessibility to transport interfaces (A3) is defined by the time to reach a transport interface by bicycle (BooST 2020). A transport interface is defined as an element of a transport network featuring a high capacity service, namely a train, tram or major bus station. The A3 is based on the fact that accessibility to interfaces, when integrated with cycling, extends the travel distance and becomes competitive with car use (Silva et al. 2021). The highest level (5) equals areas with an average maximum time to reach bicycle transport interfaces of 2.5 minutes. The lowest level (1) equals a time of at least 10 minutes.

Relative accessibility (A4) compares average distances by car and bicycle (Silva et al. 2021). It identifies competitiveness between these two modes (Silva, Teixeira, and Proença 2019). The highest (5) score level indicates that the average distance traveled by bicycle is higher than the distance traveled by car. The lowest (1) score level indicates that the average distance cycled is less than 25% of the distance driven by car. The indicator connectivity (A5) identifies average block areas according to their cycling capacity. The A5 refers to the effectiveness of the road network to reach destinations, highlighting the concern discussed by several authors about minimizing travel time as of utmost importance for active mobility (Silva et al. 2021). It is considered that smaller blocks improve physical connectivity (Silva et al. 2021). The indicator defines average block sizes based on a manual of good urban design practices (Barton, Grant, and Guise 2003, as cited in Silva et al. 2021). The most suitable areas, characterized by level 5, have, on average, blocks with areas smaller than 8,000 m^2. The average of blocks larger than 200,000 m^2 is considered as a weaker connectivity; these are identified as level 1.

Table 11 – Target area indicators score scale

Source: Elaborated by the author from the data provided by BooST (2020)

		5	**4**	**3**	**2**	**1**
A1	Basic Education	< 5 min	$5 - 10$ min	$10 - 15$ min	$15 - 20$ min	> 20 min
	Secondary Education	< 5 min	$5 - 10$ min	$10 - 15$ min	$15 - 20$ min	> 20 min
	Superior Education	< 10 min	$10 - 15$ min	$15 - 20$ min	$20 - 30$ min	> 30 min
A2	Primary Centre	< 10 min	$10 - 15$ min	$15 - 20$ min	$20 - 30$ min	> 30 min
	Secondary Centre	< 5 min	$5 - 7.5$ min	$7.5 - 10$ min	$10 - 15$ min	> 15 min
A3		$< 2{,}5$ min	$2.5 - 5$ min	$5 - 7.5$ min	$7.5 - 10$ min	> 10 min
A4		Bike $>$ Car	Bike $\in [75\% - 100\%]$Car	Bike $\in [50\% - 75\%[$ Car	Bike $\in [25\% - 50\%[$ Car	Bike $< 25\%$ Car
A5		$< 8{,}000$ m^2	$8{,}000 - 20{,}000$ m^2	$20{,}000 - 80{,}000$ m^2	$80{,}000 - 200{,}000$ m^2	$> 200{,}000$ m^2
A6		9 types of activities	$8 - 9$ types of activities	$6 - 4$ types of activities	$3 - 1$ types of activities	0 types of activities

The occupation diversity indicator (A6) analyses nine types of businesses and services within a radius of 500 meters. It is based on the idea that the active mobility environment has high densities and diversity of uses, while the car commuting environment is the opposite (Silva et al. 2021). The facilities comprise primary and secondary education institutions, restaurants, food service facilities, shopping facilities, pharmacies, health centers, general interest services, culture, and leisure. Level 5 is the highest score, in which there is a variety of these nine facilities. On the other levels, this variety of establishments gradually decreases. Level 1 identifies areas that are not close to any of these facilities.

Among the target population indicators, four indicators are considered. The age indicator (P1) measures the distribution of age profiles (BooST 2020). The indicator is based on several authors who claim that the most cycling-friendly ages are younger ages and is based on the understanding that students and younger adults are crucial elements in changing travel behavior in starter cycling cities. Among the authors on which this indicator was based is cited Goldsmith (1992, as cited in Silva et al. 2018), who analyze census data from major USA cities and conclude that bicycling rates are highest in the twenties and that the decline is steady until age 45, the age at which the reduction is significant. Other American studies on which the indicator was based identifies a low cycling rate among ages over 55 (Plaut 2005, as cited in Silva et al. 2018), Dill and McNeil (2013) classify this group as non-cyclists. The indicator defines the age group most likely to travel (level 5) by bicycle as those between the ages of 15 and 29. The group least prone to cycling (level 1) is younger than 10 or older than 50. Usually, the GPC age scale is divided into five different age groups; however, the indicator score must be adapted for this thesis due to the unavailability of data at this age group level. The CBS open data only has age information divided into five broad groups (Van Leeuwen 2019): up to 14 years, 15 year to 25 years, 26 years to 44 years, 45 years to 64 years, 65 years and older. The indicator was adapted as directed by the BooST team. The age group with the highest propensity (level 5) to cycle was changed to 15 to 25 years old. The age group with the lowest propensity (level 2) became 65 and older.

Table 12 – Comparison of the scoring scale of the age indicator (P1)
Source: Elaborated by the author from the data provided by BooST (2021)

Score	Usual	Adapted
5	15-29 years	15-25 years
4	10-14 or 30-39 years	0-14 or 26-44 years
3	40-44 years	45-64 years
2	45-49 years	> 65 years
1	< 10 or > 50 years	

The potential demand density (P2) refers to the density of people who travel within distances with a propensity for cycling (BooST 2020). A filter is used to check the people who use any mode of transport which could start using the bicycle; this filter is applied on an 8 km threshold (Silva et al. 2021). This indicator is based on several authors who claim that longer travel distances have a negative impact on cycling (Silva et al. 2021). In this thesis, due to the lack of detailed data on modal share for commuting, this indicator was replaced by population density. The highest value (5) of the scale refers to the population density of the specific study area greater than or equal to the cities' average plus its standard deviation. The lowest value of the scale (1) identifies that the density potential demand is less than the mean minus the standard deviation. Employment density (P3) identifies the most likely areas to offer employment opportunities; this follows the same scale of levels as the potential demand density indicator (P2) (Silva et al. 2021). The P3 indicator is not considered in this thesis due to a lack of access to such data. The decision to remove indicators due to lack of data has already been made in other cities where the GPC was previously calculated (BooST 2020).

The motorization rate (P4) indicator refers to the number of drivers per thousand residents (Silva et al. 2021). The indicator uses for the calculation a variable present in the Portuguese census, which is the primary mode of transportation used for the trips, compared to the national average (Silva et al. 2021). Indicator P4 is based on research that identifies car ownership as a negative influence on cycling rates (Silva et al. 2021). For this thesis, the indicator was adapted. The ODiN response of car ownership in the study region was considered a proxy for census data. The highest level (5) of the score is equivalent to a rate of fewer than 120 drivers per 1000 residents. The lowest level (1) of motorization rate equals higher 484 (the Dutch national average) drivers per 1000 residents. At the end of the analysis of the indicators, an aggregate value of these is calculated based on the weighted average of the indicators' weights and their final scores.

Table 13 – Target population indicators score scale

Source: Elaborated by the author from the data provided by BooST (2021)

	1	2	3	4	5
P2	$\text{Dens.} \geq \bar{x} + \sigma$	$\bar{x} + \sigma > \text{Dens.} \geq \bar{x} + \frac{1}{2}\sigma$	$\bar{x} + \frac{1}{2}\sigma > \text{Dens.} \geq \bar{x} - \frac{1}{2}\sigma$	$\bar{x} + \frac{1}{2}\sigma > \text{Dens.} \geq \bar{x} - \sigma$	$\text{Dens.} < \bar{x} - \sigma$
P3	$\text{Dens.} \geq \bar{x} + \sigma$	$\bar{x} + \sigma > \text{Dens.} \geq \bar{x} + \frac{1}{2}\sigma$	$\bar{x} + \frac{1}{2}\sigma > \text{Dens.} \geq \bar{x} - \frac{1}{2}\sigma$	$\bar{x} + \frac{1}{2}\sigma > \text{Dens.} \geq \bar{x} - \sigma$	$\text{Dens.} < \bar{x} - \sigma$
P4	≥ 484	$363 - 483$	$242 - 362$	$121 - 241$	≤ 120

For this thesis, the BooST team calculated the GPC indicators and aggregate value. The data collection for these calculations was done by the author and the BooST team (Table 14), as well as the development of the maps.

Table 14 – Summary of the average values of the indicators and the final GPC score

Source: Elaborated by the author from the data provided by BooST (2021)

Group	***Code***	***Indicators***	***Score***
Target area	A1	Accessibility to education facilities	4.882
	A2	Accessibility to centralities	4.602
	A3	Accessibility to transport interfaces	2.088
	A4	Relative accessibility	2.637
	A5	Connectivity	3.298
	A6	Occupation diversity	2.741
Target population	P1	Age	4.086
	P2	Population density	3.159
	P4	Motorization rate	1.349
Gross Potential for Cycling			3.320

Within the target area group, the indicator with the highest score is the accessibility to education facilities (A1), also classified as the indicator with the highest value between the two groups. The indicator with the lowest score is the accessibility to transport facilities (A3). In the target population group, the indicator with the highest score is age (P1), and the indicator with the lowest score is the motorization rate (P4), classified as the indicator with the lowest value of the two groups. The aggregate indicator representing the value of the Gross Potential for Cycling refers to a score of 3.320. An overall GPC map is presented in Figure 8; these are presented in a larger size in Appendix I.

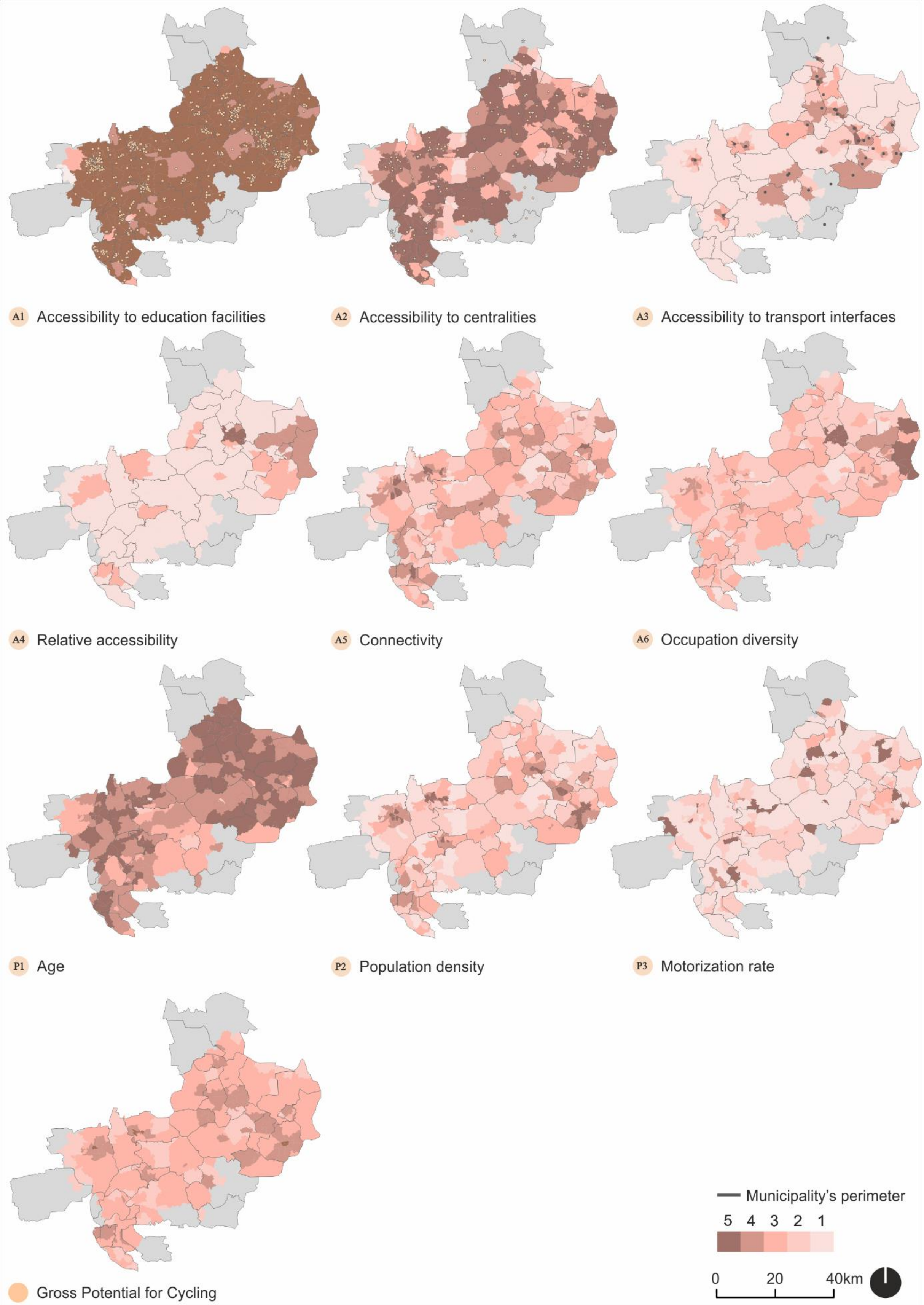


Figure 8 – Overall Gross Potential for Cycling

Source: Elaborated by the author from the data provided by BooST (2021)

3.5. METHOD

In this thesis, three analyses are performed, descriptive analysis, bivariate and multivariate statistical analysis. The descriptive analysis refers to a side-by-side analysis of the maps developed by the GPC indicator and the maps with the cycling demand data. In the bivariate statistical method (Figure 9), correlation tests identify the association level between two variables, as Motulsky (2018) indicated. Furthermore, within the bivariate statistical method, simple linear regression (SLR) tests were performed. Among the multivariate statistical methods (Figure 9), multivariate linear regression (MLR) is used. The linear regression analysis aims to verify the predictive relationship between the variables (Field and Viali 2000; Motulsky 2018; Seltman 2018; Weisberg 2014). In the end, extra tests were performed to optimize the model applied in the multivariate analysis through backward stepwise MLR, as Field and Viali (2000) indicated.

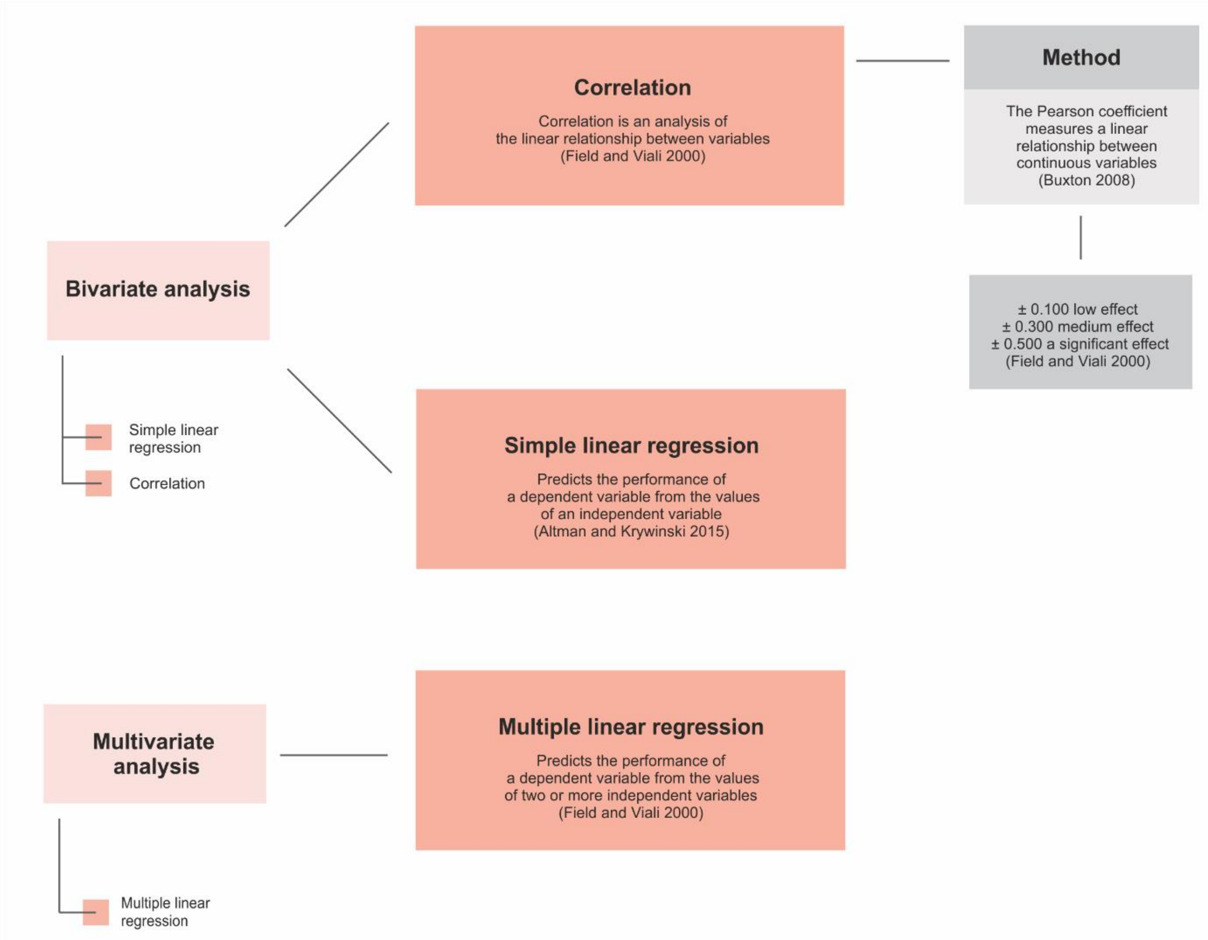


Figure 9 – Method overview

Source: Elaborated by the author

In summary, to achieve the objective, 11 models are developed for each variable of cycling demand, 10 of these referring to bivariate analysis and one referring to multivariate analysis (Figure 10). The data that comes from the GPC calculation, whether its indicators or aggregated value, are defined as independent variables[13] (IV), while the dependent variable[14] (DV) is evaluated through the cycling demand data. In the case of bivariate analysis, there is only one dependent and one independent variable. In the multivariate analysis, there is one dependent variable and two or more independent variables, in this case, nine independent variables, i.e., all the GPC indicators. In total, 52 models were tested, including 44 statistical analysis models (Figure 10) and 7 additional model optimization tests (Figure 11). Before performing the established statistical tests, a treatment was performed on all the data, including the dependent and independent variables, such as a normalization process (Eesa and Arabo 2017; Al Shalabi and Shaaban 2006). The normalization transformed the data on a scale from 0 (minimum value) to 1 (maximum value).

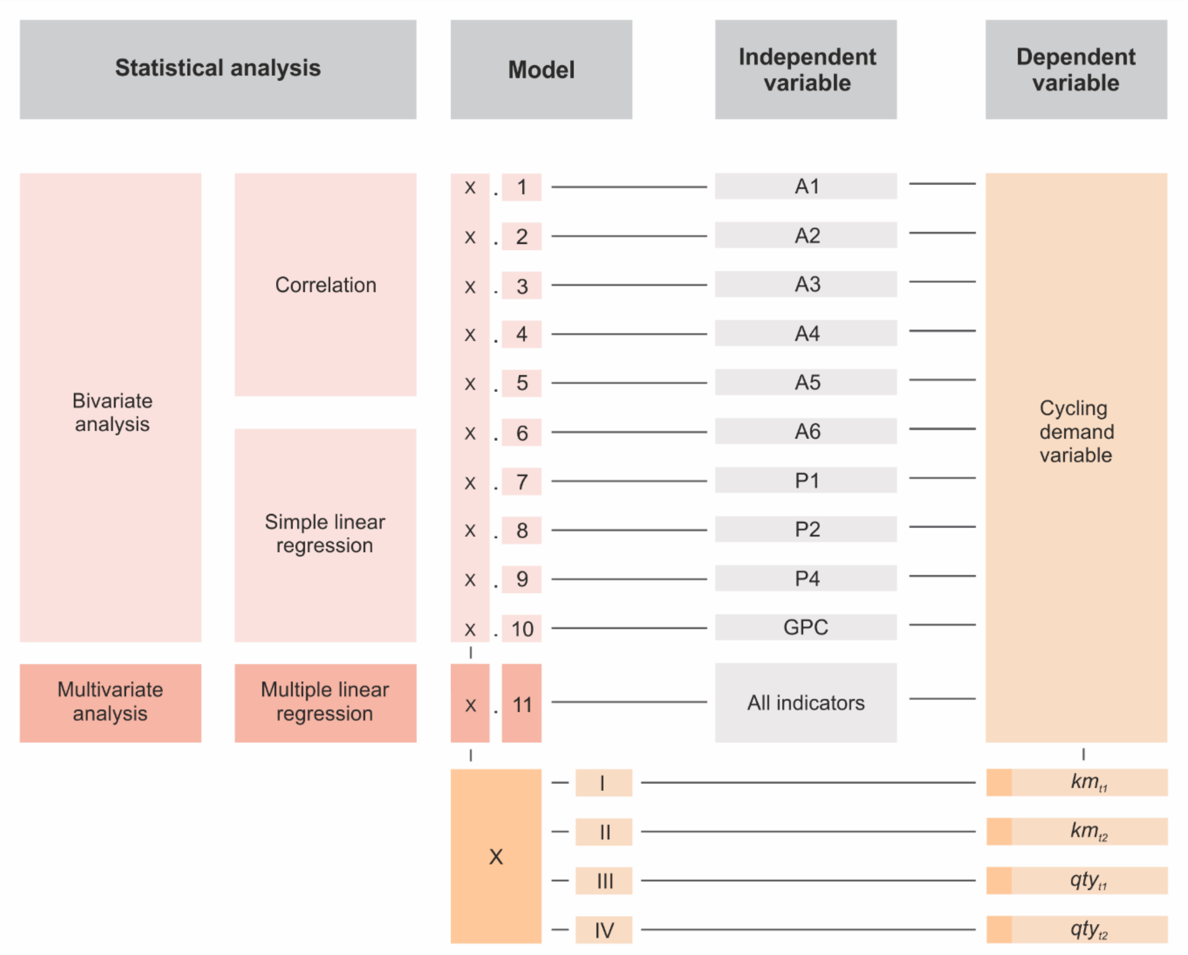


Figure 10 – Schematic of the models
Source: Elaborated by the author

[13] The independent variable, also called the predictor variable, is the variable that is used to explain the variation in the dependent variable of a model (Field and Viali 2000).

[14] The dependent variable is the variable that is being explained by the independent variable in a model (Field and Viali 2000).

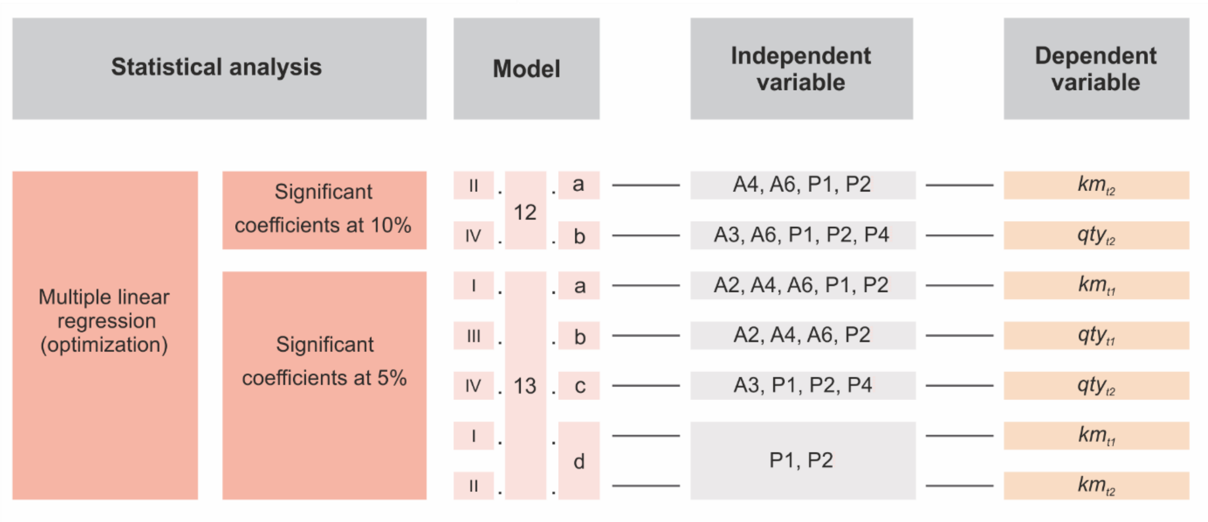


Figure 11 – Schematic of the additional models' optimization
Source: Elaborated by the Author

Moreover, some of the variables were submitted to outlier elimination (Chagas 2017; Cook and Weisberg 1999; Field and Viali 2000). This elimination was performed on each model separately. Outliers were identified using Cook Distance (D_i) (Cook and Weisberg 1999), the D_i values that obtained a result higher than $^4/_n$ were checked, results above such value are mainly detrimental to the model (Belsley et al. 1980 as cited in Meer and Grotenhuis 2010). Each outlier was analyzed separately; when the model was significantly improved by eliminating such an outlier, it was eventually eliminated for the model analysis, as indicated by Chagas (2017), Rousseeuw and van Zomeren (1990).

Due to the several requirements for performing linear regression, which is discussed below, some of the models also have suffered logarithmic transformation of both the dependent and independent variables to pass the linear regression requirements; this transformation was based on Benoit (2011), Field and Viali (2000).

For all statistical analyses, all cycling demand samples with fewer than nine respondents or a response rate of less than 0.19% were not considered for analysis. The choice to remove such data from the sample was based on the tendency to misinterpret the statistical tests due to having too few respondents. After exclusion, the response rate is defined in the range of 0.19% to 0.55%. Of the 276 spatial units for which statistical data was collected, 136 remained (Figure 12). Besides bringing more consistency to the research data, the choice of excluding this data set was defined as not leaving the sample smaller than the minimum acceptable, according to Green (1991, as cited in Field and Viali 2000). The minimum number of samples was defined as 122.

The Statistical Package for the Social Sciences (IBM SPSS) 27[15] was used to perform the statistical analyses. A normality check through the Shapiro-Wilk test was also performed in the software before proceeding to the statistical tests. The data is non-normal ($p < 0.001$), except for the GPC, as in the Shapiro-Wilk test, the GPC present normality ($p = 0.102$).

[15] Available on: https://www.ibm.com/analytics/spss-statistics-software.

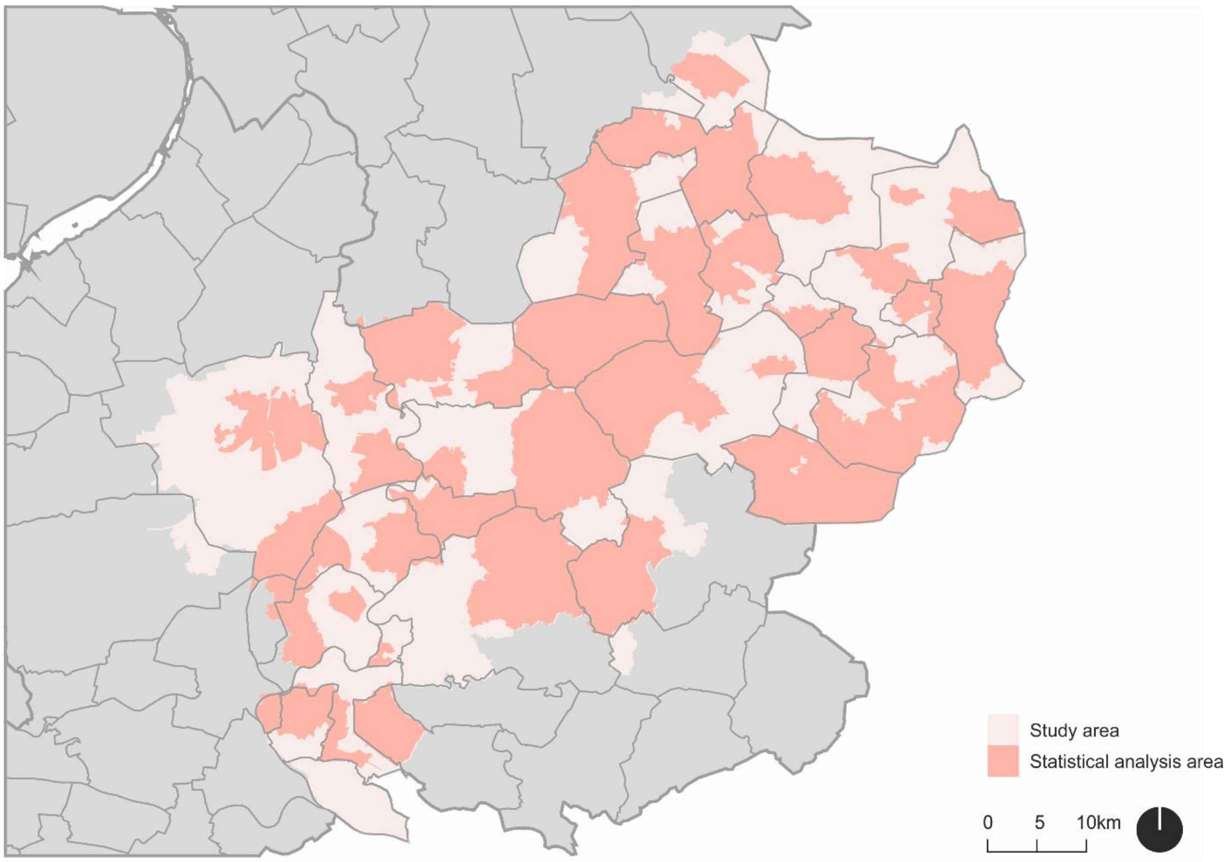


Figure 12 – Study area related to statistical analysis
Source: Elaborated by the author from the data provided by CBS (2016)

Correlation is an analysis of the linear relationship between variables (Field and Viali 2000). It brings a numerical value corresponding to the magnitude of association between two variables (Buxton 2008). In this thesis, the Pearson correlation coefficient (r) was used for the calculation, which uses a two-sided test. The models submitted to the correlation test are continuous, linear, and mainly with a non-normal distribution, except for the variable referring to the aggregate value of the GPC. However, the person correlation test continued to be used because it is a robust coefficient to non-normality, so the assumption of normality can be disputed (Havlicek and Peterson 1977).

The effect of Pearson's r is verified through Field and Viali's (2000) concept. Values of ± 0.100 represent a weak correlation effect, values of ± 0.300 represent a medium effect, and ± 0.500 a highly effect. The positive sign of Pearson's r indicates that the variables are positively correlated and the negative sign negatively correlated (Buxton 2008; Field and Viali 2000; Schober, Boer, and Schwarte 2018). When the variables are negatively correlated, the higher the value of one variable, the lower the value of the other variable.

Correlation helps check the intensity of the relationship between variables but does not provide information about the power of the relationship of variables (Altman and Krzywinski 2015; Field and Viali 2000). Regression makes it possible to check the power of relationships between variables by exploring the dependent variable as a function of one or more independent variables (Field and Viali 2000).

A simple linear regression (SLR) model predicts an output variable through only one independent variable (Field and Viali 2000). Several simple linear regression models were developed, always with the cycling demand data as the dependent variable and the GPC indicators and their aggregated value as independent variables analyzed separately. The multiple linear regression (MLR) model, on the other hand, predicts the output variable through two or more independent variables (Field and Viali 2000). In the multiple linear regression models adopted, data referring to cycling demand analyzed separately were used as dependent variables, and as independent variables, all the GPC indicators were inserted in the model in a forced manner.

Table 15 – Summary of bivariate models
Source: Elaborated by the author

Model			**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	(DV)	(IV)	A1	A2	A3	A4	A5	A6	P1	P2	P4	GPC
I	km_{t1}	Transformation	Log									
		Outliers			2		2	3		3	0	3
II	km_{t2}	Transformation										
		Outliers						1		2	1	2
III	qty_{t1}	Transformation	Log									Log
		Outliers	5	2	2	1	8	5		8	2	6
IV	qty_{t2}	Transformation	Log	Log								Log
		Outliers	1	4	5		2	8		1	1	7

(1) The "Log" symbolizes logarithmic transformation in both the dependent and independent variables.

Table 16 – Summary of multivariate models
Source: Elaborated by the author

Model			**11**	**12**		**13**			
				a	b	a	b	c	d
	(DV)	(IV)	A1, A2, A3, A4, A5, A6, P1, P2, P3	A4, A6, P1, P2	A3, A6, P1, P2, P4	A2, A4, A6, P1, P2	A2, A4, A6, P2	A3, P1, P2, P4	P1, P2
I	km_{t1}	Transformation							
		Outliers	9			9			9
II	km_{t2}	Transformation							
		Outliers	6	6					6
III	qty_{t1}	Transformation					2		
		Outliers	2				**		
IV	qty_{t2}	Transformation	Log		Log			Log	
		Outliers	4		4			4	

(1) The "Log" symbolizes logarithmic transformation in both the dependent and independent variables.

The linear regression models applied to this thesis did not violate the assumptions defined by Field and Viali (2000) for the method. The linear regression method is robust to non-normality (Chagas 2017;

Seltman 2018), so this does not affect the proposed analysis. Each model was tested using a t-test[16] considering a standard error to check if an output value is significant (Field and Viali 2000); models that were considered non-significant ($p > 0.05$) were not considered for this analysis. To check if the established models could predict the outcome of a sample, the principle of cross-validation called adjusted r^2[17], was used. At last, to obtain an optimized model, a MLR analysis through the backward stepwise method was used; this was calculated step-by-step by the author. The backward stepwise method initially incorporates all variables into the model, and then, in stages, variables that do not have significant coefficients are excluded from the model (Chagas 2017). The initial models of the stepwise backward analysis, which incorporate all variables, are the same models applied in the multivariate analysis performed (model I.11, II.11, III.11, IV.11). For this thesis, in the model optimization tests, only the models that obtained significant coefficients at 10% and 5% are presented.

[16] The t-test compares a model with no predictor to the specified model (Field and Viali 2000). A model with no significance means that the fit of the intercept-only model is significantly reduced compared to the specified model (Field and Viali 2000).

[17] The adjusted r^2 is the percentage of variation in the response that is explained by the model (Field and Viali 2000). The adjusted r^2 is calculated as one minus the ratio of the mean square of the error to the total mean square (Field and Viali 2000).

4
COMPARING GROSS POTENTIAL FOR CYCLING AND CYCLING DEMAND IN THE NETHERLANDS

This chapter presents a descriptive analysis of the comparison of the results obtained through applying the Gross Potential for Cycling in the study area with the cycling demand data extracted from the ODiN 2018. After that, different statistical analyses are performed, these divided into bivariate and multivariate analyzes. The bivariate analyses comprise the individual evaluation of each GPC indicator and its aggregate value with the cycling demand data. The multivariate analysis comprises a joint evaluation of the GPC indicators with the cycling demand data. Following the analysis, model optimization tests are performed. In the end, a discussion of the results verified through the analyses is conducted.

4.1. A DESCRIPTIVE ANALYSIS OF THE GROSS POTENTIAL FOR CYCLING

The spatial analysis of the Gross Potential for Cycling shows the highest potential among Enschede and Apeldoorn, which are known as municipal agglomerations, being employment and facility access hubs. These municipalities center areas have a population density higher than 2000 inhabitants per km^2.

When relating the total kilometers traveled by bicycle (km_{t1}) to the aggregated value of the GPC, there is an ascending trend, which means wherever there are fewer kilometers traveled, the GPC score is also lower and so on. Where the GPC score is below level two, the total bicycle kilometers traveled is less than 20,000 km, except for two locations, south of the municipality of Almelo and southwest of Lochem. The areas have approximately 21,000 km and 23,000 km traveled by bicycle, respectively; both have low population density, are located not so far from primary centralities and close to secondary centralities.

The area corresponding to the aggregated value of level three has 90% of its extension with a total amount of travel distance below 60,000 km (Table 17). The data are more dispersed when comparing the total bicycle travel distance and the GPC scores corresponding to four and five. Level four has a lower value of locations with travel distances over 100,000 km than locations with travel distances under 20,000 km; however, there are more locations with travel distances between 20,000 and 60,000 km. Within level five, the higher number of travel distance areas is between 60,000 km and 100,000 km. The areas corresponding to scores four and five mostly have easy access to primary and secondary centralities.

Some areas within municipalities tend to contain few similarities to the GPC (Figure 13); for example, some locations within the highly dense municipality center of Apeldoorn have bicycle travel distances of less than 20,000 km and a score of three according to the GPC. In the case of Apeldoorn, this region has high accessibility to educational facilities and transportation interface. Among the municipalities defined as densely populated centers, their limits tend to have lower cycling demand. Voorst and Losser, suburban municipalities, on the other hand, do not follow this trend and have lower cycling demand in the whole territory. However, in most municipal centers, where population density is high and access to facilities is easy, the total travel distance tends to increase more than in other regions. Most of the GPC aggregate areas with scores equivalent to levels two and three have more significant similarity to the total kilometers traveled by bicycle data (Figure 13); in these areas, the tendency to have shorter trip distances is similar to the tendency to obtain lower GPC scores. The areas with low score have lower population densities, on average less than 250 inhabitants per km^2 and do not have a diversity of educational establishments; most of the establishments in these localities are primary schools. Moreover, the relative accessibility in these areas is also low; that is, the distance traveled by car is relatively higher than the distance traveled by bicycle. For the most part, accessibility to transport interfaces is low. All these causes tend to contribute to this similarity for shorter bicycle distances to have lower GPC score values.

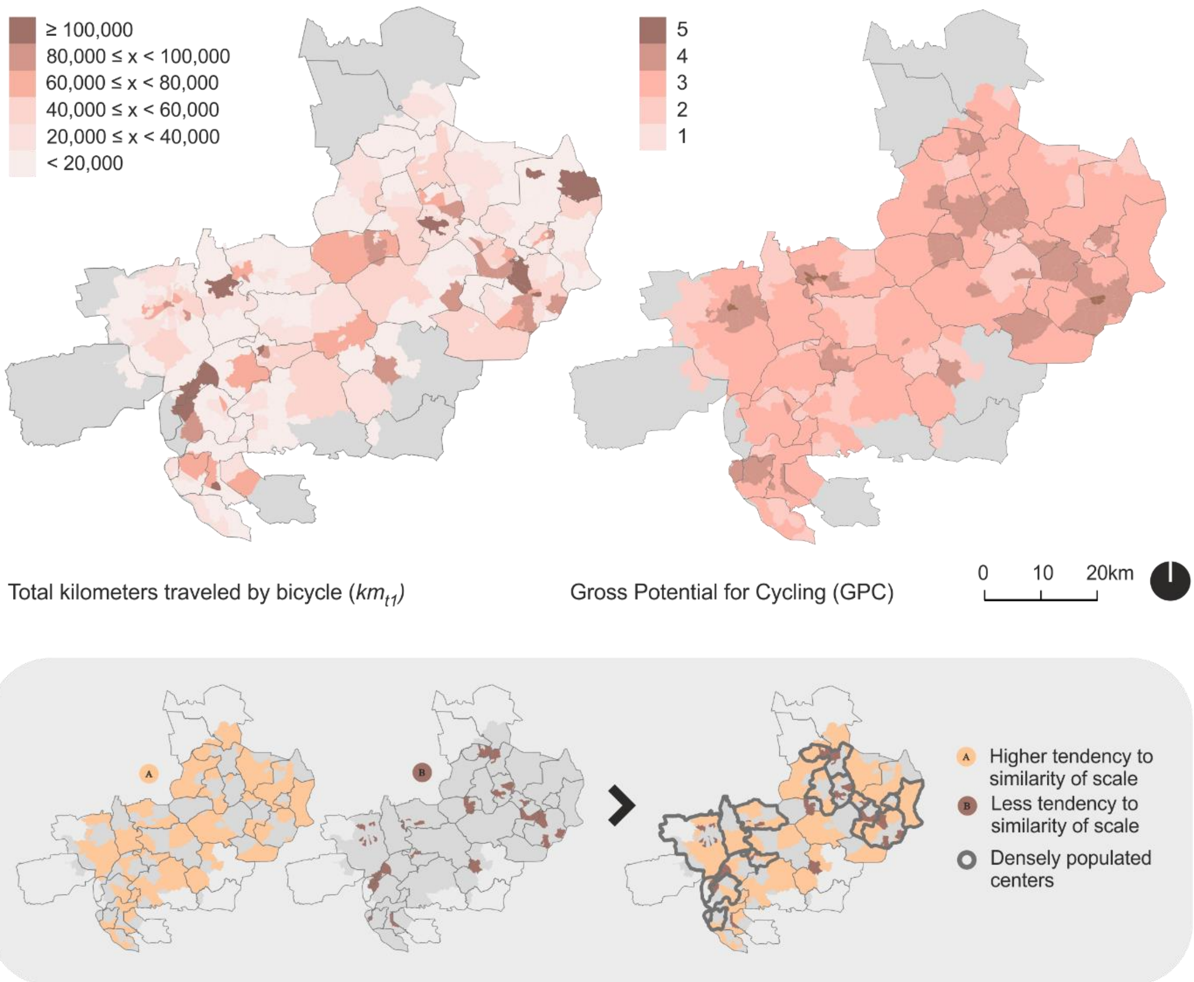


Figure 13 – Total kilometers traveled by bicycle (km_{t1}) compared to GPC
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

Table 17 – Total kilometers traveled by bicycle (km_{t1}) compared to GPC by area and inhabitants
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

		Area [%]				Inhabitants [%]			
km_{t1}	GPC	2	3	4	5	2	3	4	5
≥ 100,000			2.42	9.72	9.59		9.49	8.95	18.41
80,000 ≤ x < 100,000			1.43	14.46	31.42		3.30	24.71	45.31
60,000 ≤ x < 80,000							10.51	21.89	24.72
40,000 ≤ x < 60,000			18.60	29.71	23.85		0.13	0.03	0.01
20,000 ≤ x < 40,000		6.14	25.07	16.63	18.20	8.97	32.14	34.21	11.55
< 20,000		93.86	46.69	9.51		91.03	44.43	10.21	

Considering the kilometers traveled per capita by bicycle (km_{t2}) map compared to the aggregated GPC map, there is an increasing tendency between the data again on a macro scale. However, the analysis on a micro scale does not tend to be so precise as on a macro scale. The localities with a score of level two, in more than half of its extension, has average users making trips up to 2 km. These locations tend to be closer to the borders between the municipality, where population density is below 250 inhabitants per km^2, and access to facilities is limited. There is a dispersion of travel distance at levels three and four of the GPC, but there is a tendency to have a more significant travel distance per capita near densely populated centers. At level five, the travel distance per capita is always more than 4 km. Those living on half of the territorial extension of the area, classified as level five, make on average a travel distance per capita of more than 10 km per trip; these areas are between the densely populated centers of Apeldoorn and Enschede.

Table 18 – Kilometers traveled per capita by bicycle (km_{t2}) compared to GPC by area and inhabitants
Source: Elaborated by the author from the data provided by BooST (2021)

		Area [%]				Inhabitants [%]			
km_{t2}	GPC	2	3	4	5	2	3	4	5
≥ 10		20.53	16.00	16.69	50.51	14.51	15.81	9.88	45.39
8 ≤ x < 10		1.89	10.31	16.46	12.56	18.49	43.48	52.16	39.44
6 ≤ x < 8		3.61	19.61	19.84	20.25				
4 ≤ x < 6		7.08	24.02	34.23	16.68	13.13	21.43	25.46	15.17
2 ≤ x < 4		11.78	13.02	6.92		12.98	10.65	9.88	
< 2		55.11	17.04	5.85		40.89	8.62	2.62	

The lowest similarities of travel distance per capita with the GPC are in localities with a GPC score of two and three with total travel distance per capita of more than 10 km, such values exceeding the average (Figure 14). However, these localities are close to densely populated centers and have relatively close access to facilities. In most of these areas, the population tends to be young and adult on average. The most significant similarities are the places that obtain level two classification in half of their territorial extension (Figure 14). These have inhabitants who travel less than 2 km on average. Such locations tend to be close to municipal borders, places with no diversity of schools, far from public transportation interfaces, and lack a range of facilities around them. The places with a level five classification have inhabitants who make on average trips of more than 10 km in half of their territorial extension. However, these areas are among the densely populated centers with more than 2000 inhabitants per km^2 and easy access to public transportation, jobs, and educational establishments. These trends show that residents who have easy access to a diversity of activities tend to cycle longer distances than those who are more distant from these facilities.

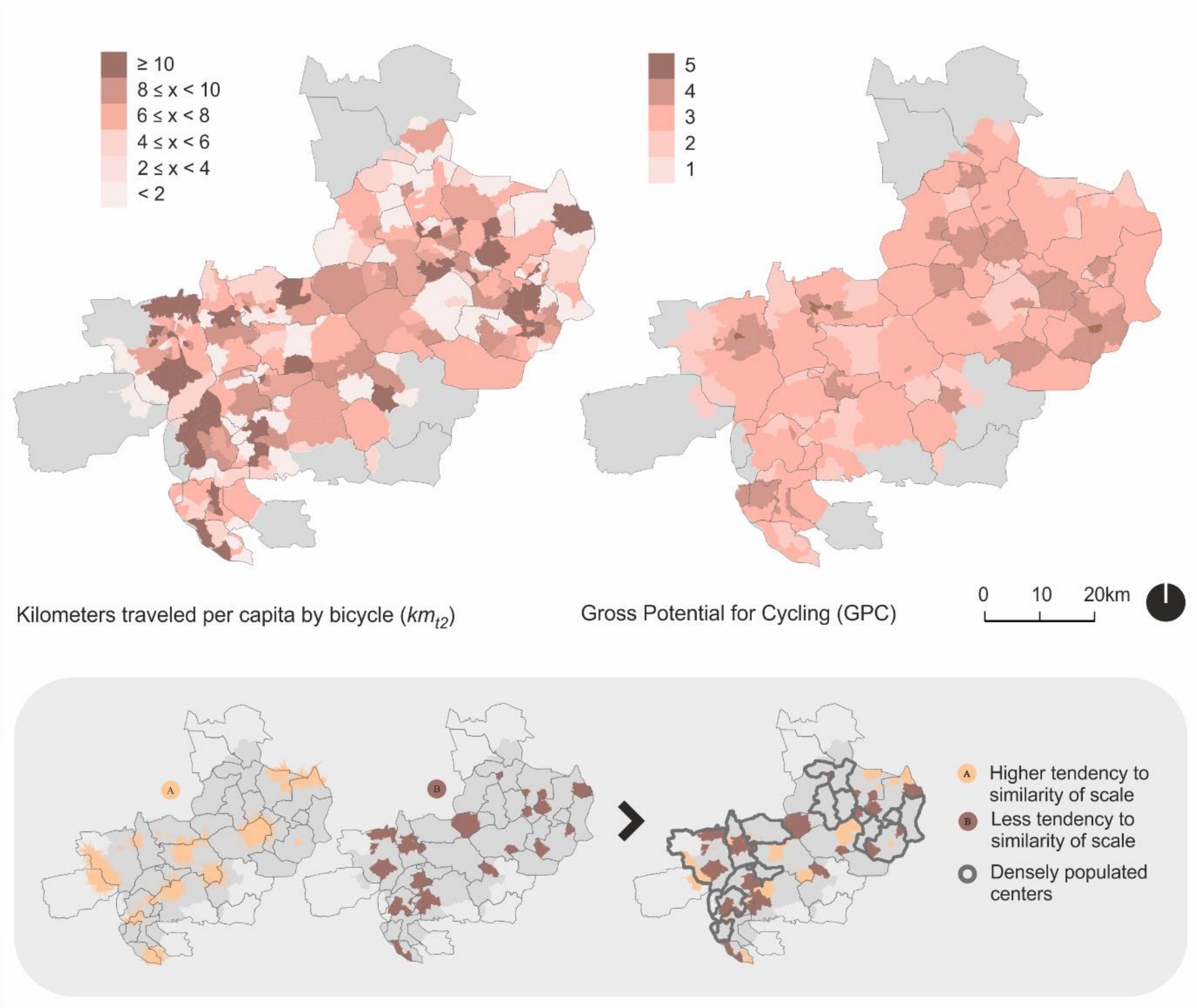


Figure 14 – Kilometers traveled per capita by bicycle (km_{t2}) compared to GPC
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

The total amount of trips (qty_{t1}) compared to the aggregate value of the GPC on a macro scale has an increasing scale; the more trips, the higher the GPC score. At the micro scale, this tendency tends to remain clear. Level two areas have trip quantity almost entirely below 4,000 trips except for one locality south of Almelo, which has 4,600 trips made by bicycle. Level three areas have an average of less than 16,000 bicycle trips except for just under one-fifth of the areas with an average number of bicycle trips higher than 16,000. These exception areas have lower inhabitants' numbers and lower territorial distribution than all the areas scored at level three. As for the level four areas, there is a tendency for the average number of trips to exceed 12,000. There are some exceptions, like some areas located in the center of Apeldoorn and Twenterand, but these have a lower amount of inhabitants compared to the other areas at level four. More than half of the areas at level five have a trip number higher than 20,000; these tend to have more inhabitants and have easy access to centralities. The areas that have low similarity are few compared to those that have high similarity (Figure 15). Among the areas with low similarity are those identified at level three. Among such areas, the population is lower than the whole area, which may cause an unexpected trend in such zones. The localities farthest from the population centers have lower GPC values, as well as a lower total number of trips, and those closer to the population centers have a higher number.

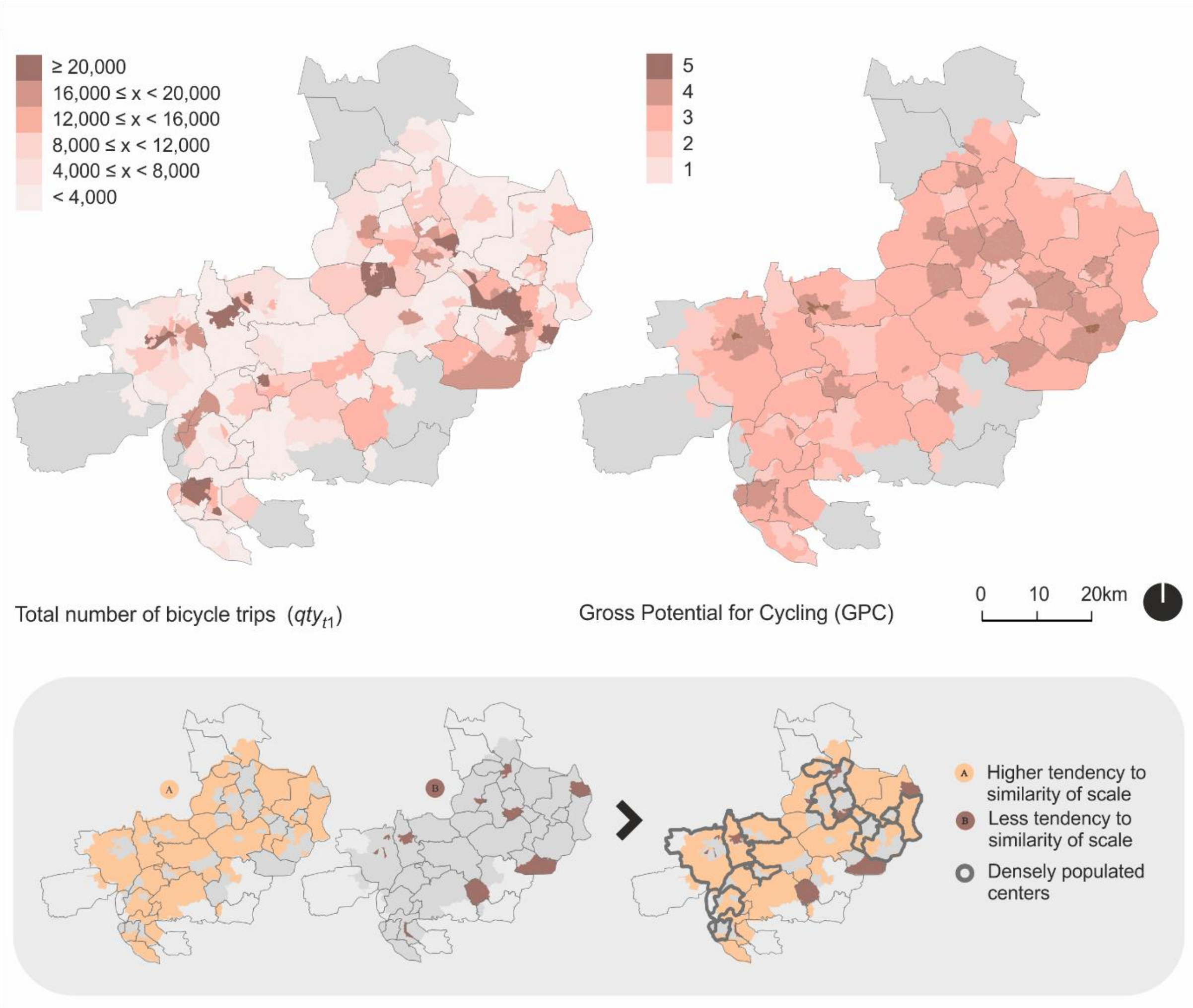


Figure 15 – Total number of bicycle trips (qty_{t1}) compared to GPC
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

Table 19 – Total number of bicycle trips (qty_{t1}) compared to GPC by area and inhabitants
Source: Elaborated by the author from the data provided by BooST (2021)

	Area [%]				Inhabitants [%]			
qty_{t1} GPC	2	3	4	5	2	3	4	5
≥ 20,000		0.71	19.12	67.19		3.56	24.49	71.39
16,000 ≤ x < 20,000		3.42	16.10	7.17		3.10	17.85	9.47
12,000 ≤ x < 16,000		5.45	27.78	7.44		9.21	20.27	10.75
8,000 ≤ x < 12,000		14.92	24.24	5.12		22.57	23.39	3.56
4,000 ≤ x < 8,000	3.23	24.95	8.14	13.08	5.43	29.06	12.21	4.84
< 4,000	96.77	50.55	4.62		94.57	32.49	1.80	

The number of trips per capita by bicycle (qty_{t2}) has an increasing trend at the macro scale of analysis compared to the GPC, similar to the other cycling demand coefficients. However, in a micro analysis, this trend is not as clear as the one observed in the qty_{t1} analysis. Score two areas have in more than half of their extension less than one trip per capita (Table 20). Some level two areas have average per capita trips above three; these have fewer inhabitants than the rest of the level two area. The exception areas are located south of Almelo and northwest of Apeldoorn. The south of Almelo location has already been highlighted in the other comparisons made. The locations with a score of three have, within a large part, an average of per capita travel amounts below three; however, there are some localities among Enschede, Apeldoorn, and Deventer with per capita travel amounts above four. Among the areas classified at level four on GPC, the number of trips tends to be below three; there are some areas with over five trips per capita, these have a relatively low number of inhabitants when compared to the rest of the area at level four, they are among localities with a population density above 500 inhabitants per km^2 and in centralities, with easy access to educational establishments and facilities. Among the areas classified at level five, there is a difficulty in verifying a trend in the data; however, such areas have a per capita number of trips above one.

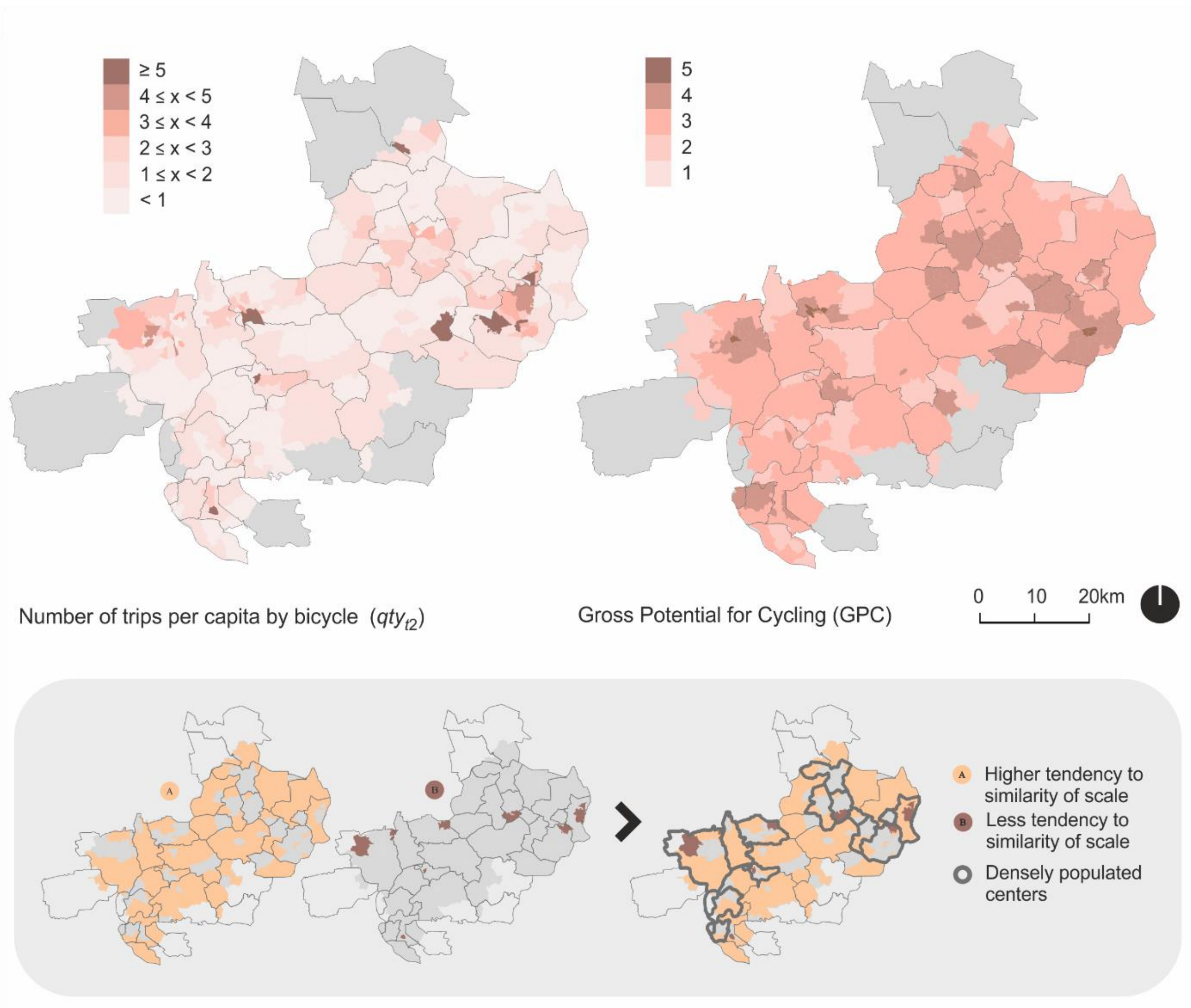


Figure 16 – Number of trips per capita by bicycle (qty_{t2}) compared to GPC
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

Table 20 – Number of trips per capita by bicycle (qty_{t2}) compared to GPC by area and inhabitants
Source: Elaborated by the author from the data provided by BooST (2021)

		Area [%]				Inhabitants [%]			
qty_{t2}	GPC	2	3	4	5	2	3	4	5
≥ 5			1.89	1.09	18.46		0.84	1.73	15.13
4 ≤ x < 5		7.59	1.16			0.74	1.50		
3 ≤ x < 4		1.08		5.67	37.18	1.29		5.98	41.93
2 ≤ x < 3		12.28	6.86	16.66	23.85	13.21	11.77	22.05	27.35
1 ≤ x < 2		11.58	50.83	61.45	20.52	12.52	56.63	60.31	15.59
< 1		67.48	39.26	15.13		72.24	29.26	9.94	

Similarly, to the comparison made with qty_{t1}, the areas that present low similarities are areas that have few inhabitants on average (Figure 16). Such locations are classified with scores two and three on GPC and with a per capita number of trips higher than three. The areas with the highest similarities are those that have fewer trips below level two. As well as the number of trips per capita below two, which represent more than half of all areas at level three. In summary, the areas with the highest rates of cycling demand tend to be among the densely populated centers. However, the data for the total amount of trips and per capita number of trips seem to have more similarity between scaled values of the aggregated GPC value than those for total trip distance and per capita trip distance.

Considering the target area indicators used to calculate the aggregate value of the GPC, the accessibility to education facilities indicator (A1) and the relative accessibility indicator (A4) have the highest weight from the calculation of the aggregate value of the GPC. However, performing a spatial analysis of the indicator of accessibility to education facilities shows a distribution of educational facilities throughout the study area, but this distribution is greater in densely populated centers. The areas identified as having the best accessibility to education facilities do not appear to be strongly correlated with cycling demand data. The relative accessibility indicator (A4), on the other hand, has higher accessibility levels among densely populated centers, specifically among Apeldoorn and Enschede, metropolitan agglomerations, as well as Almelo, Deventer, Duiven, Hengelo, Losser Zevenaar, and Zutphen. These densely populated center areas tend to have higher cycling demand. Within the indicator for accessibility to centralities (A2), areas on average within reach of the primary center in less than 10 minutes are in parts with higher values of cycling demand. Such areas, have on average per capita bicycle trip distances (km_{t2}) higher than 2 km. When analyzing accessibility to transport interfaces (A3), measured by the time to reach a transport interface by bicycle, it is one of the indicators with the lowest value; its final average value is 2.08. A large part of the map of accessibility to transport interfaces is indicated as having lower potential, i.e. time to reach a transport interface by bicycle more than 10 minutes. The connectivity indicator (A5) has weight one among the GPC aggregate value, the areas with the highest connectivity have block sizes below 20,000 m^2, these are mostly between densely populated centers, places in which tend to have higher cycling demand rates; this means that blocks are more permeable between densely populated centers, and people make in part more trips than other areas. It is noticeable that in the areas farther away from these centers, people tend to make fewer trips, but longer trips; this can partly be associated with the level of connectivity in which these areas are located. The level of connectivity indicates that the blocks in areas farther away from the centers are less permeable. Therefore, people need to travel long distances to reach their destination. This leads to the idea that more permeable blocks encourage more travel due to the ease of getting from point A to point B. The occupation diversity indicator (A6) has weight one among the aggregated GPC value. This shows that there is great diversification in the number of activities present in the study area. A large portion of the study area has access to one to six types of activities within a 500 meter ratio. Sites with fewer than six different activities tend to have longer per capita travel distances but fewer trips per capita; this suggests that places that do not have a range of activities within a 500 meter radius force people to travel longer distances and tend to discourage cycling.

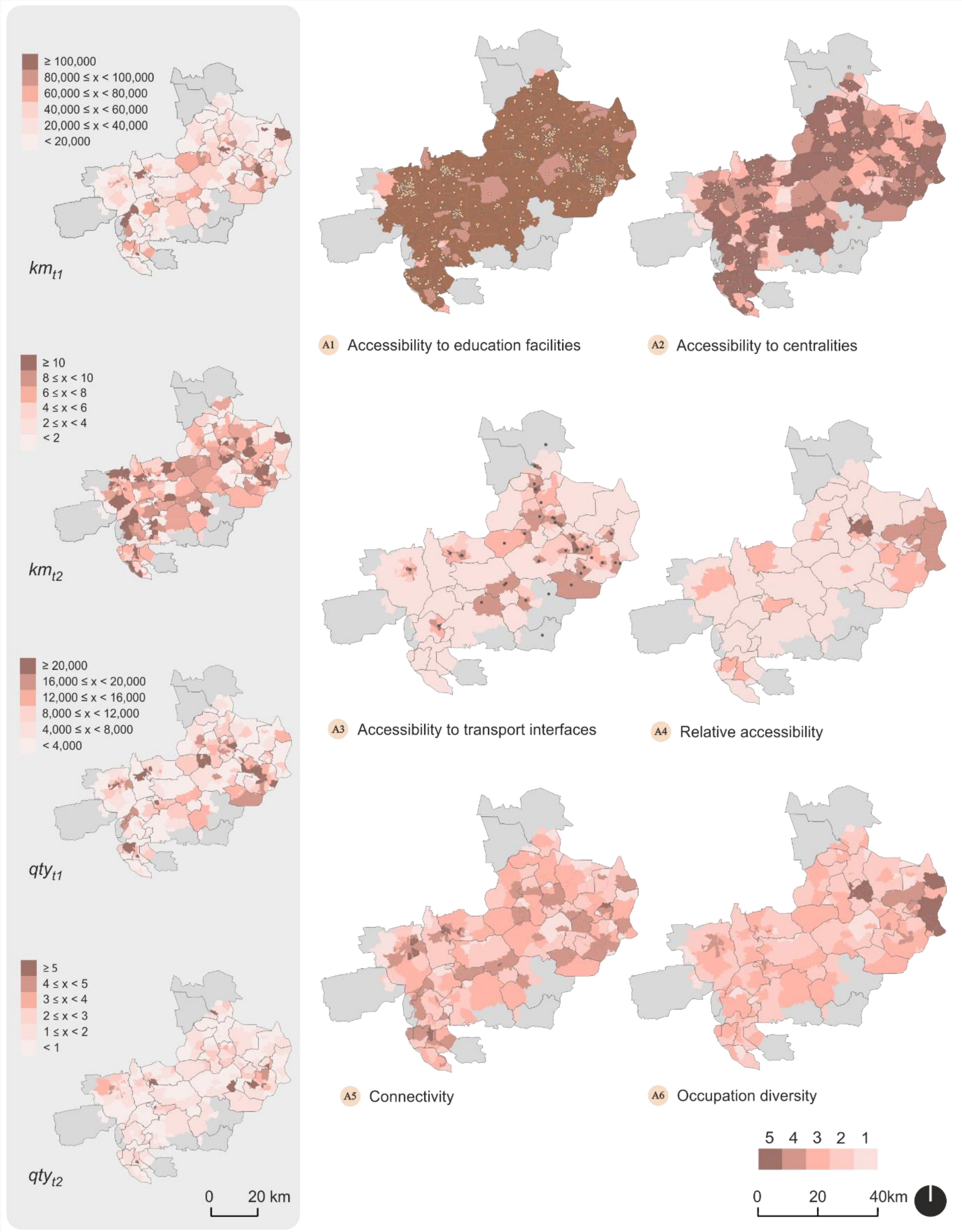


Figure 17 – Cycling demand data and Gross Potential for Cycling indicators referring to the target area
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

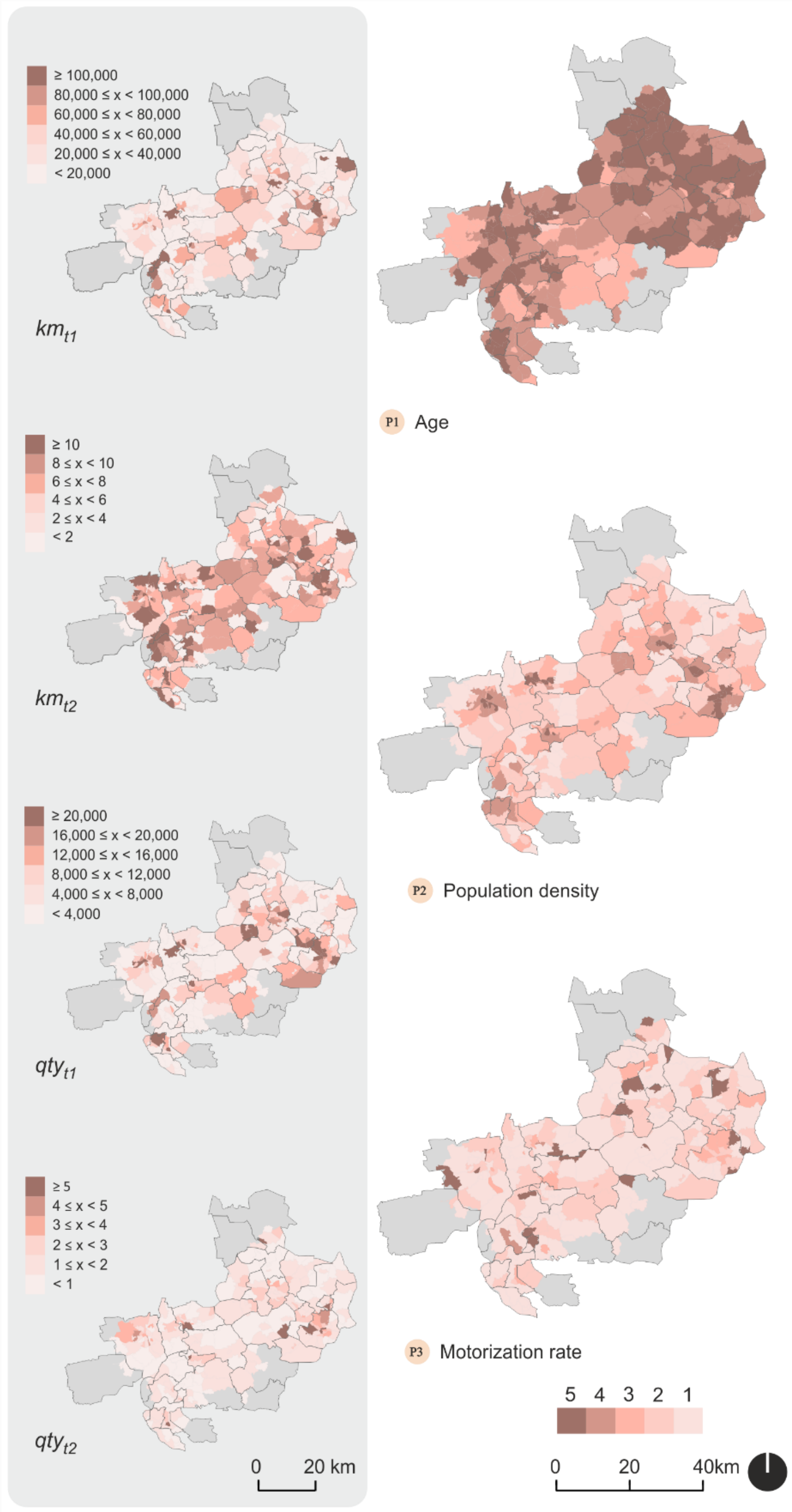


Figure 18 – Cycling demand data and Gross Potential for Cycling indicators referring to the target population
Source: Elaborated by the author from the data provided by CBS (2016) and BooST (2021)

Looking at the age indicator (P1), half of the areas refer to localities with an age range of 15 to 25 years (level five). After the 15 to 25 age group, the 0 to 14 and 26 to 44 age group are adapted as the most cycling prone group (level four). The area indicated as level four in this research is equivalent to a little more than a quarter of the mapped areas. Next, the 45 to 64 age group (cycling propensity level equivalent to three) is represented on the map by a little more than a tenth of the entire study area. Finally, the over 65 age group is presented as having the least potential for cycling (level two), represented in only a few areas on the map. However, when comparing each value for km_{t2} and qty_{t2}, separated by the CBS age group, each age group follows similar commuting trends (Figure 19). However, the 45 to 64 age group has slightly higher rates than the average. With little difference to the 45 to 64 age group, the group aged up to 15 years has more trips but fewer kilometers. Results tend to show that the age context seems to be not so relevant when applied in the "champion" context than in starter cycling cities.

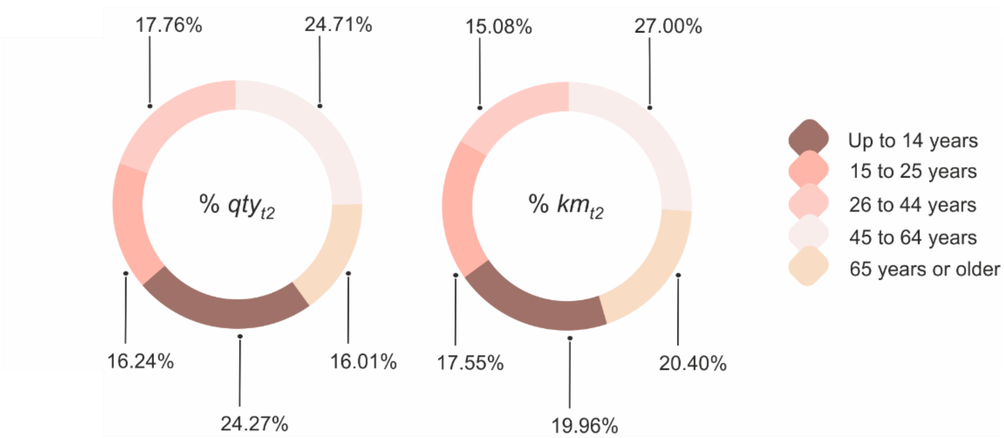


Figure 19 – Difference between age groups, kilometers traveled per capita by bicycle (km_{t2}) and number of trips per capita by bicycle (qty_{t2})

Source: Elaborated by the author from the data provided by BooST (2021)

Though, when combined with the data on the distance traveled per person (km_{t2}) and the number of trips traveled per person (qty_{t2}) according to the groups indicated by the BooST team, there is a change in the classification of the groups. The group with the highest number of bicycle trips per person and the highest bicycle distance traveled per person is the group indicated at level two of the GPC, 0 to 14 years, and 26 to 44 years. The next group with the most significant variation is 45 to 64 years. The last two groups are reversed according to the distance per capita and the number of trips per capita. The per capita distance shows the 15 to 25 age as the group that makes the shortest trips. On the other hand, the per capita number of trips indicates that the group over 65 years old is the one that makes the fewest trips on average; the difference is almost null with the 14 to 25 age group, but it exists. In summary, the analysis of age showed a similar trend among the age groups regarding cycling demand. This may be directly correlated with the fact that the analysis was performed in a "champion" area. The assumption established by the GPC that the highest cycling potential is among the 15-29 age group is broken, showing that the behavior in this case study is different than in a starter city. Regarding the other indicators related to the target population, it is possible to verify a trend that locations with high population density (P2) tend to have higher cycling demand values than locations with low population density. Also, most of the population owns motor vehicles when compared to the national average.

In summary, a significant portion of the territory has high accessibility to educational facilities (A1). A significant part of the indicators based on target areas highlight the presence of centers with a high population density, places in which there is a wide range of access to facilities. Such centers are easily noticed when it comes to access to centralities (A2) and diversity of occupation (A6). Accessibility to public transportation (A5) follows the transportation interfaces, mostly train stations located within the centralities. The connectivity (A5) identifies that the most permeable areas are located within the centralities, where have designs more prone to human scale. Age (P1) seems to have a different behavior between the champion and starter cities contexts. In the areas evaluated in this study, the age groups seem to have similarity in bicycle use. Population density (P2) is higher in the centers of the municipalities. Such densely populated centers tend to have higher potential bicycle use, as well as higher cycling demand. The opposite happens in areas with low population density.

4.2. Statistical Analysis

The statistical analyses are divided into three steps: bivariate, multivariate, and additional model optimization tests. All models represented in this article related to bivariate statistical analysis are in Appendix II. The multivariate statistical analysis models are in Appendix III. The optimization models are presented in Appendix IV. Models that did not show significance in the t-test for overall significance are not considered in the appendices, as the statistical tests are non-relevant.

4.2.1. Bivariate Statistical Analysis

The analysis between the coefficients of cycling demand as dependent variables and Gross Potential for Cycling as an independent variable shows that GPC better explains the coefficients related to the number of bicycle trips (qty_{t1}). However, both the coefficient of the total number of bicycle trips (qty_{t1}) (model III.10) and the number of trips per capita by bicycle (qty_{t2}) (model IV.10) have a high correlation effect. The model (I.10) with the coefficient referring to the total kilometers traveled by bicycle (km_{t1}) has a medium correlation. The model (II.10) with the coefficient of kilometers traveled per capita by bicycle (km_{t2}) has the lowest correlation among the cycling demand coefficients, being a weak-medium correlation. Such levels of correlation reflect the explanatory power among the variables; 32.4% of the indicator qty_{t1} is explained by GPC (model III.10), while GPC explains only 4.5% of the indicator km_{t2} (model II.10).

Other analyses are performed, with the cycling demand coefficient as the dependent variable and the GPC indicators as independent variables. Among the analysis performed with the total kilometers traveled by bicycle (km_{t1}), the indicators related to accessibility to centralities (A2), relative accessibility (A4), age (P1) and motorization rate (P4) do not show a significant relationship with km_{t1} when analyzed separately. The population density (P2) is the coefficient with the highest explanatory power among the bivariate analysis with km_{t1} as the dependent variable; 13.3% of km_{t1} is explained by population density (model I.8). Within the GPC conceptual model, this indicator weights three, the highest value of all the weights. Occupation diversity (A6) has the lowest explanatory power; 4.0% of km_{t1} is explained by occupation diversity (model I.6). This indicator, among the GPC conceptual model, has one of the lowest weights. However, all correlations between the dependent and independent variables are weak to medium.

Using kilometers traveled per capita by bicycle (km_{t2}) as the dependent variable, the accessibility to education facilities (A1), accessibility to centralities (A2), accessibility to transport interfaces (A3), relative accessibility (A4), and connectivity (A5) have no significant relationship. The other indicators are significant, but the correlation is weak. Among the bivariate analysis, the strongest explanatory power indicator is within indicator age (P1), which explains 3.3% of km_{t2} (model II.7), while population density (P2) explains 3.2% of km_{t2} (model II.8). On the other hand, the motorization rate (P4) explains even less than km_{t2}, comprising 2.2% (model II.9). This indicator weighs two among the weights in the GPC conceptual model. Among the analyses, the model with the age indicator (P1) as an independent variable (model II.7) presents an inversely proportional correlation, meaning that the higher the km_{t2} value, the lower the age indicator's level.

Table 21 – Summary of bivariate model results

Source: Elaborated by the Author

Model			1	2	3	4	5	6	7	8	9	10
	(DV)	(IV)	A1	A2	A3	A4	A5	A6	P1	P2	P4	GPC
I	km_{t1}	r	0.241		0.222		0.308	0.218		0.374		0.334
		Adj r^2	0.051		0.042		0.088	0.040		0.133		0.105
			**		**		**	*		**		**
II	km_{t2}	r						0.192	-0.200	0.197	0.170	0.228
		Adj r^2						0.030	0.033	0.032	0.022	0.045
								*	*	*	*	**
III	qty_{t1}	r	0.428	0.327	0.325	0.205	0.424	0.394		0.496	0.230	0.574
		Adj r^2	0.177	0.100	0.099	0.035	0.173	0.149		0.240	0.046	0.324
			**	**	**	*	**	**		**	**	**
IV	qty_{t2}	r	0.393	0.338	0.415	0.227	0.390	0.463		0.426	0.320	0.483
		Adj r^2	0.148	0.108	0.166	0.045	0.145	0.209		0.176	0.092	0.228
			**	**	**	**	*	**		*	**	**

(1) The r corresponds to the value of the Pearson correlation. Values of ± 0.100 represent a weak correlation effect, values of ± 0.300 represent a medium effect, and ± 0.500 a high effect. The "Adj r^2" represents the adjusted r^2. The "*" symbolizes significance at 0.05. The "**" symbolizes significance at 0.01.

When the total number of bicycle trips (qty_{t1}) is entered as the dependent variable, the correlations between the indicators and the dependent variable become, in most models, are significant correlations. Age (P1) has no significance with qty_{t1}. The population density (P2) is the one that has the most significant explanatory indicator over qty_{t1} in the bivariate analysis, comprising 24.0% (model III.8). The relative accessibility (A4) explains 3.5% of qty_{t1} (model III.4); the smallest value of explanation among the analyses. The same trend that occurs in the total number of bicycle trips (qty_{t1}), occurs in the models that contain the number of trips per capita by bicycle (qty_{t2}) as the dependent variable. These models have significant correlations. The indicator with the lowest explanatory indicator power is also the same; relative accessibility (A4) explains 4.5% of qty_{t2} (model IV.4). However, the occupation diversity (A6) indicator has the most significant value; it explains 20.9% of the qty_{t2} (model IV.6). This differs sharply from the GPC conceptual model, which has the occupation diversity indicator as one of the lowest weights in the model. Age (P1) remains non-significant.

In all analyses, the coefficients of the indicators remain positive, except for the age (P1) indicator. The indicator P1, referring to the age profile of residents, in its only significant relation, has an inversely proportional relation; this being with km_{t2} as the dependent variable. However, in the GPC conceptual model, it has one of the highest weights. The population density (P2) is the one that best explains the cycling demand data among all the GPC indicators; there is an exception only in the model with qty_{t2}. The population density (P2) indicator weights three in the GPC conceptual model, one of the indicators with the highest weight. The accessibility to centralities (A2) and accessibility to transport interfaces

(A3), when among significant models, have median coefficients, the weights of the conceptual models are equivalent to two. Occupation diversity (A6) among the models with $km_{t1}$and km_{t2} have the lowest coefficient values, as happens in the GPC conceptual model, which presents a weight of one. However, occupation diversity (A6) among the models with qty_{t1} and qty_{t2} already seems to have coefficients with more significant weights. When significant, relative accessibility (A4) has the lowest coefficient values, contrary to the GPC conceptual model in which it weights three. The accessibility to education facilities (A1) weighs three in the GPC conceptual model, but it appears to have medium coefficients in the models tested in this thesis. Connectivity (A5) weights one in the GPC conceptual model, and in the tested models, it seems to have average coefficients. The significant models between the analyses in qty_{t1} and qty_{t2} are similar. The analysis with km_{t2} is the one that presents the least amount (four out of nine) of significant models. The variable km_{t2} showed to be the one with the lowest correlation level between the indicators of the GPC and the aggregated value. On the other hand, the variable $qty_{t1}$is the variable that is best explained by the GPC indicators and aggregated value.

4.2.2. Multivariate Statistical Analysis

The GPC indicators are classified as independent variables in the multivariate analysis, whereas the cycling demand data are classified as dependent. These models are called forced models since all indicators are entered at the same time. These models follow the hierarchy of explanatory power presented in the bivariate analysis with the GPC as the dependent variable. Thus, the model that has the total number of bicycle trips (qty_{t1}) as the dependent variable has the highest explanatory value, being this 33.3% (model III.11). All GPC indicators explain 32.8% of qty_{t2} (model IV.11), 26.0% of km_{t1} (model I.11), and 11.6% of km_{t2} (model II.11).

Table 22 – Summary of multivariate model results
Source: Elaborated by the author

Model			**11**								
	(DV)	(IV)	A1	A2	A3	A4	A5	A6	P1	P2	P4
I	km_{t1}	Coefficients	-0.386	-0.394 .	0.021	-0.413 **	0.012	0.341 *	-0.197 .	0.616 **	-0.200
		Adj r^2	0.260 **								
II	km_{t2}	Coefficients	-0.206	-0.106	0.020	-0.160 *	0.070	0.203 *	-0.116 .	0.127	0.112
		Adj r^2	0.116 **								
III	qty_{t1}	Coefficients	0.396	-0.537	0.087	-0.247	-0.086	0.322 .	-0.066	0.745 **	-0.210
		Adj r^2	0.333 **								
IV	qty_{t2}	Coefficients	0.257	-0.057	0.083 *	-0.109	0.097	0.198 .	-0.160 *	0.190 .	0.211 *
		Adj r^2	0.328 **								

(1) The "Adj r^2" represents the adjusted r^2. The "*" symbolizes significance at 0.05. The "**" symbolizes significance at 0.01. The "." symbolizes significance at 0.10.

The analysis with the total kilometers traveled by bicycle (km_{t1}) as dependent variable (model I.11), comprises only five indicators with significance below 10%, i.e., four indicators present in the model do not tend to add to the explanatory power of the set of variables in relation to km_{t1}. These four indicators are accessibility to education facilities (A1), accessibility to transport interfaces (A3), connectivity (A5), and motorization rate (P4), which have weights of three, two, one and two, respectively, in the GPC conceptual model. Among the five remaining indicators, population density (P2) is the indicator with the highest coefficient, which is also one of the indicators with the highest weight in the GPC conceptual model. For the age (P1) indicator, it has to tend the lowest coefficient and is inversely proportional. The age weight differs sharply from the GPC conceptual model, which presents this indicator with one of the highest weights, and in this case, it is the coefficient with the lowest value among the significant ones. Among the other three indicators that are in the middle of the extreme values presented, these have increasing coefficients, respectively occupation diversity (A6), accessibility to centralities (A2) and relative accessibility (A4). Such indicators also have increasing weights within the GPC conceptual model, respectively one, two, and three. However, the indicators of accessibility to centralities (A2) and relative accessibility (A4) are inversely proportional in the model.

The analysis with kilometers traveled per capita by bicycle (km_{t2}) as dependent variable (model II.11), which has the lowest explanatory power among the cycling demand variables, has six indicators as non-significant out of nine. Among the three significant indicators, the one with the highest coefficient is occupation diversity (A6), which has the lowest weight in the GPC conceptual model. The model with the lowest coefficient, among the significant coefficients, age (P1), is the indicator that has one of the highest weights in the GPC conceptual model. Relative accessibility (A4), which has one of the lowest coefficients after occupation diversity (A6), is identified as one of the indicators of the greatest weight in the GPC and has inversely proportional variation in the model developed.

The model (III.11) with the total number of bicycle trips (qty_{t1}) has the best explanatory power among the models developed with all GPC indicators as the independent variable and cycling demand data as the dependent variable. However, it has only two indicators significant at 10%, being Occupation diversity (A6) and population density (P2). The population density indicator (P2) has the highest coefficient explanation, similar to the GPC conceptual model. However, occupation diversity (A6) has the lowest coefficient among the significant coefficients, inversely to the GPC conceptual model.

The model (IV.11) that presents the number of trips per capita by bicycle (qty_{t2}) as the dependent variable has the second best explanatory power among the forced models. Among the indicators, relative accessibility (A4), accessibility to centralities (A2), connectivity (A5), and accessibility to educational facilities do not have significant coefficients. Motorization rate (P4) has the highest coefficient among the significant ones and has medium weight in the GPC conceptual model. The indicators potential demand (P2) and occupation diversity (A6) have coefficients that tend to be more similar than the motorization rate (P4). Accessibility to transport interfaces (A3) has the lowest coefficient among the significant ones, which in the GPC conceptual model has a medium value. Age (P1) seems to be a medium weight coefficient and is inversely proportional.

Occupancy diversity (A6) is the only indicator that is present among the four models as significant. It has coefficients of different weights among the models, from the indicator with the highest coefficient among the significant ones to the lowest. This indicator only has the lowest weight among the significant coefficients in the model measuring qty_{t1}, however, the model only has two significant variables. The weight of the occupancy diversity coefficient in the qty_{t1} model is similar to that of the km_{t1} model, as both, evaluate cycling demand coefficients relative to total values. The occupation diversity coefficient also tends to have similar coefficient values among the cycling demand data per capita, however in the case of the km_{t2} model this has the highest coefficient among all indicators. In the GPC conceptual model, it has the lowest weight, which differs from the trend observed in the application of these models.

The indicator of population density (P2) is the one with the highest significant coefficient among the models that contain total quantities, being km_{t1} and qty_{t1}, which is in line with what is established by the conceptual model of the GPC. In the analysis of travel distance, both total and per capita, the age indicator (P1) shows the lowest significant coefficient and an inversely proportional coefficient. This differs from the conceptual model established for the GPC which identifies age as having weight three. The age indicator is more relevant in the number of trips made than in the number of kilometers traveled. The relative accessibility indicator, determined by the GPC conceptual model as weight three, has significant coefficients only within the travel distance model and is inversely proportional. Its coefficients in the travel distance models tend to be above average.

4.2.3. Additional Optimization Tests

In order to optimize the four models presented in a multivariate analysis, the concept of stepwise regression in the models was performed manually by the author. Several other models were developed through the concept of linear regression until a statistically and theoretically significant model was reached. With this, it was possible to verify that the explanatory power of the indicators related to cycling demand tends to increase.

Using the variable total kilometers traveled by bicycle (km_{t1}) as the dependent variable, a model (I.13.a) with significance at 5% was obtained with the variables accessibility to centralities (A2), relative accessibility (A4) and age (P1) with inversely proportional coefficients, as well as with occupation diversity (A6) and population density (P2) with proportional coefficients. In this model (I.13.a), the independent variables explain 26.7 % of the value of km_{t1}. However, by further refining this model, the explanatory power of age (P1) and population density (P2) in km_{t1} turns out to be 21.7% (model I.13.d). Only two indicators have an explanatory power almost similar to that of the five indicators together. When using kilometers traveled per capita by bicycle (km_{t2}) as a dependent variable, the optimized model that best shows explanatory power is the one that contains relative accessibility (A4), connectivity (A5), age (P1) and population density (P2). These indicators explain 11.7% of km_{t2} (model II.12.a). However, in the same way, as in km_{t1}, the indicators age (P1) and population density (P2) together explain most of the model. The two indicators together explain 9.3% of km_{t2} (model II.13.d).

Optimizing the model that has the total number of bicycle trips (qty_{t1}) as the dependent variable achieves an explanatory value of 34.9% (model IV.12.b), a value in which km_{t1} is explained by accessibility to transport interfaces (A3), occupation diversity (A6), age (P1), population density (P2) and motorization rate (P4). By removing the indicator related to occupation diversity (A6) from the model, the explanatory power of the model is 33.2% (model III.13.b), a value very similar to the model with all nine indicators (model III.11). The optimized model of the number of trips per capita bicycle (qty_{t2}) reaches similar explanatory power as the model with qty_{t1}. The indicators accessibility to transport interfaces (A3), age (P1), population density (P2) and motorization rate (P4) explain 33.9 of qty_{t2}.

Even though the modes do not present multicollinearity when checked through the Variance Ignition Factor (VIF)[18], one of the prerequisites of linear regression analysis, some indicators when correlated among themselves tend to have high similarity, as is the case of the indicators of relative accessibility

[18] For this thesis, none of the models have VIF values above five; values equal to or above five are indicated by Daoud (2018) as biased towards multicollinearity.

(A4) and occupation diversity (A6), as well as the indicator of population density (P2) and connectivity (A5). Among the factor analysis, the indicators of relative accessibility (A4) and occupation diversity (A6) tend to be also clustered; the clustering has an acceptable Cronbach's alpha of 0.895.

4.3. DISCUSSION

The Gross Potential for Cycling, when compared with cycling demand data, in the descriptive analysis, presented greater similarities with the total number of bicycle trips model (qty_{t1}), a greater similarity that was confirmed among the statistical analyses. The analysis using the number of trips per capita by bicycle (qty_{t2}) also showed significant values. Thus, it appears that the GPC tends to have greater validity with trip quantity data than with trip length. The GPC conceptual model appears to have significant explanatory power; up to 32.4% in the case of qty_{t1}. However, when analyzing the conceptual model from which the GPC originates, a different trend was found among the weights of some indicators as well as their significance concerning the models developed in this thesis.

The accessibility to education facilities (A1), tends to be a more relevant indicator when evaluated individually in the analysis regarding the amount of travel, whether total or per capita (model III.1 and model IV.1). This tends to suggest that as more schools exist, more bicycle trips are made. However, this indicator, when evaluated along with the other GPC indicators, does not seem to have a statistically significant coefficient in any of the cycling demand models evaluated (model I.11, II.11, III.11 and IV.11). This tends to indicate that such indicator is not relevant when analyzed with other indicators and that it has a behavior inversely proportional to the distance (km_{t1} and km_{t2}) when evaluated as multivariate analysis (model I.11 and model II.11). Thus, it can be related to the context in which it is inserted. It is verified in the descriptive analysis that there is a wide distribution of educational establishments in the study area, which can generate this inverse proportion of travel distance. The indicator of accessibility to schools (A1) was inserted into the GPC conceptual model due to empirical evidence showing that areas with a higher number of young people greatly impact cycling levels, with students being one of the target groups for cycling. However, what may have led this study to a less relevant behavior of this indicator within the proposed conceptual model is because the study area has a wide distribution of educational facilities.

Another consideration is that the area in which this thesis was applied is a "champion" area, and in these areas, the behavior of age tends to be different than in starter cycling cities. Research shows that children to the elderly use the bicycle in similar quantities in the Netherlands (Pucher & Buehler, 2008; City of Amsterdam 2003b, as cited in Cavenett, 2010), a trend that has been confirmed in this thesis. In the research area, there is a similar trend of bicycle use among the different age groups. This trend also tends to answer the question of the age indicator (P1), which is based on the concept of several authors who claim that the most cycling-friendly groups are younger ages. In the Dutch context, the groups seem to have a similar tendency, which is why the indicator, when analyzed, seems to have a coefficient with an inversely proportional relationship. However, even if inversely proportional, it is identified as statistically significant in the most of cycling demand models (I.11, II.11, IV.11), expect for the model (III.11) with total number of bicycle trips (qty_{t1}).

Accessibility to centralities (A2), when analyzed separately from the conceptual model, does not appear to be relevant (model I.2 and model II.2) for the distance of trips (km_{t1} and km_{t2}). The easier the accessibility to centralities, the greater the number of trips (model III.2 and model IV.2). However, this indicator has higher coefficients among total cycling demand (model I.11 and model III.11) than per capita (model II.11 and model IV.11), and these coefficients are inversely proportional. This indicator is based on the concept that denser urban areas host more bicycle trips, although this only appears to be statistically relevant for total kilometers traveled by bicycle (km_{t1}). The inverse influence for the study area of indicator A2 can be explained because most of the study area has relatively high bicycle demand rates even though it is not within a centrality. Yet, it should be added that in the study area, there is easy access to centralities, which may tend to explain the inverse proportion and the statistical non-significance in some models.

Table 23 – Model Overview

Source: Elaborated by the author from the data provided by BooST (2021)

	A1	A2	A3	A4	A5	A6	P1	P2	P4	GPC
Model I.1 to model I.10	+ **		+ **		+ **	+ *		+ **		+ **
Model I.11	-	- .	+	- **	+	+ *	- .	+ **	-	
Model I.13.a		- *		- **		+ *	- *	+ **		
Model I.13.d							- **	+ **		
Model II.1 to model II.10						+ *	- *	+ *	+ *	+ **
Model II.11	-	-	+	- *	+	+ *	- .	+	+	
Model II.12.a				- .		+ *	- .	+ **		
Model II.13.d							- **	+ **		
Model III.1 to model III.10	+ **	+ **	+ **	+ *	+ **	+ **		+ **	+ **	+ **
Model III.11	+	-	+	-	-	+ .	-	+ **	-	
Model III.13.b		- *		- *		+ *		+ **		
Model IV.1 to model IV.10	+ **	+ **	+ **	+ **	+ *	+ **		+ **	+ **	+ **
Model IV.11	+	-	+ *	-	+	+ .	- *	+ .	+ *	
Model IV.12.b			+ *			+ .	- **	+ **	+ *	
Model IV.13.c			+ **				- **	+ **	+ *	

(1) The negative (-) symbol represents an inversely proportional relationship. The positive symbol (+) represents a positive proportional relationship. The "*" symbolizes significance at 0.05. The "**" symbolizes significance at 0.01. The "." symbolizes significance at 0.10.

The accessibility to transportation interfaces (A3) tends to be statistically significant when analyzed separately from the data on the number of trips (qty_{t1} and qty_{t2}) (model III.3 and model IV.3), but within the multivariate models applied, it has low coefficient values and is only statistically significant among the number of trips per capita by bicycle (qty_{t2}) (model IV.11). This indicator is based on the concept that bicycling integrated with public transportation tends to be as competitive as the car and has average weight within the GPC conceptual model. This analysis tends to show that access to transportation interfaces is not as relevant as other indicators within the conceptual model. With some caution, this may suggest that in the study area, since there is a low reach to public transportation interfaces, the presence of these interfaces influences the use of bicycles but not as much as other indicators due to this lack of easy access to interfaces.

Relative accessibility (A4), which defines the car's competitiveness with the bicycle, and the occupation diversity indicator (A6), which is based on the concept that high diversity of use and density increase active mobility, tend to be statistically related. The occupation diversity indicator (A6) tends to be statistically significant in all the forced models (I.11, II.11, III.11, IV.11). The descriptive analysis of this indicator is in line with the conceptual reason it was included in the GPC model, diversity of use increases when population density also increases, which increases active mobility, especially cycling demand. However, the relative accessibility indicator (A4) has inversely proportional coefficients (model I.11, II.11, III.11, IV.11) and significant coefficients only in the multivariate models corresponding to the travel distance (model I.11 and model II.11). This indicates that the car's competitiveness with the bicycle is only relevant when analyzing the distance traveled, but this has no statistically significant influence when evaluated in the multivariate model that tends to be related to the amount of travel (model III.11 and model IV.11). Even if the relative accessibility indicator and occupation diversity are related, it suggests conducting further research on the reason for this relationship since they do not seem to have a theoretical concept easily explained when put together.

The indicators population density (P2) and connectivity (A5) also tend to be related. The indicator of population density (P2) is the one that seems to have the most relevant coefficient when applied in multivariate models (I.11 and III.11) to explain the total number of bicycle trips (qty_{t1}) and total kilometers traveled by bicycle (km_{t1}), this follows the trend of the weight proposed for the indicator in the conceptual model, which has the highest value. The population density (P2) also confirms the assumption established by the GPC that higher population densities tend to have higher cycling demand. The connectivity (A5) indicator, which considers that smaller blocks facilitate active mobility, does not appear to be statistically significant for the multivariate models (I.11, II.11, III.11, IV.11). However, the assumption of the GPC that these sites are generally located near densely populated centers tends to be confirmed. With some caution, the population density (P2) and connectivity (A5) indicators are statistically linked because connectivity is greater in densely populated areas.

The motorization rate (P4) tends to be statistically significant only in the multivariate model (IV.11) that has number of trips per capita by bicycle (qty_{t2}), which with above average coefficients shows that higher rates of car ownership tend to influence the amount of travel. However, the non-significance of this statistic test may, with some caution, be because countries like the Netherlands have a very diversified modal shift, i.e. there are high amounts of motor vehicle travel and high amounts of travel by active modes, especially by bicycle.

There is a tendency for the target population indicators to have higher explanatory power than the target area indicators. The indicators referring to the target area tend to have coefficients not so statistically relevant when applied together with all GPC indicators. Attention is drawn to the indicator referring to occupation diversity (A6), which is the only indicator with a statistically significant coefficient among all the multivariate models with cycling demand data as the dependent variable. In summary, the indicators in the multivariate model tend in some cases to follow the trend of being stronger or weaker as they do in the conceptual model. However, the weights established for the analyses, in general, are varied and do not present a similar trend as that presented in the conceptual model, for example, which has only weights one, two and three. In the models developed in this thesis, these weights tend to be continuous.

5
FINAL CONSIDERATIONS

The objective of this thesis was to trial the conceptual model validity of the Gross Potential for Cycling. This was done through descriptive, multivariate, and bivariate analyses. The Gross Potential for Cycling tends to be explained up to 32.4% when related to cycling demand data. This 32.4% explanation is the amount that GPC explains the total number of bicycle trips (qty_{t1}) (model III.10). This explanation value changes as the cycling demand variables are changed to number of trips per capita by bicycle (qty_{t2}), total kilometers traveled by bicycle (km_{t1}), and kilometers traveled per capita by bicycle (km_{t2}). These are explained by GPC respectively by 22.8%, (model IV.10), 10.5% (model I.10), and 4.5% (model II.10). The explanatory power of the GPC, together with the correlation tests (model III.10 and model IV.10) set as high effect for the cycling demand coefficients, especially for the number of trips (qty_{t1} and qty_{t2}), reveal that the GPC has a good tendency to indicate the potential number of bicycle use in starter cycling cities, as shown by a high correlation ($p = \pm 0.500$). However, even with the high correlation, the models tend to explain less than half of the number of bicycle use concepts. This lack of explanation shows that there are still other indicators that can be considered to increase the explanatory power of the models.

Considering the bivariate analyses performed, in which the GPC indicators were individually analyzed as independent variables and the cycling demand data as dependent variables, it was possible to observe some indicators that were not statistically significant for the explanatory power of cycling demand. These, in some cases, were confirmed when performing multivariate analysis, modeled with all the GPC indicators as independent variables, and cycling demand data as dependent variables. In these multivariate models, the GPC conceptual model has been tested. Though, when all indicators are forcibly inserted into the model, not all are statistically significant. This lack of significance indicates that some indicators could be removed from the model without reducing its explanatory power. This could make the model simpler to be applied in starting cities since it would decrease the amount of data needed to calculate the conceptual model of the GPC. This trend can be observed in the model optimization tests, in which when travel distance data are added as dependent variables (model I.13.d and model II.13.d), the indicators age (P1) and population density (P2) tend to have together an explanatory power of almost 80% relative to a model with up to five variables (model II.12.a and model IV.12.b).

Furthermore, some indicators tend to have a high tendency to statistical similarity when related. For example, the indicator of relative accessibility (A4) and occupation diversity (A6), which present a correlation with high effect and that in the factor analysis show indicators with clustering potential. A correlation with high effect also occurs between population density (P2) and connectivity (A5). Such indicators appear to be statistically similar, and in the case of population density (P2) and connectivity (A5) that, in addition to statistical, with caution, appear to have spatial similarities too, could be further analyzed to become single indicators.

Among the conceptual model presented by the GPC, some indicators tend to have the same tendency applied in the GPC weights, as is the case of population density (P2), which in most models appears to be the indicator with the highest weight. This indicator weights three in the GPC conceptual model, defined as the weight with the highest value. Other indicators, however, tend to have in the multivariate analysis performed in this work weights tending to be from lower to higher among the models (I.11, II.11, III.11, IV.11), while in the GPC conceptual model, these have lower values. As is the case of the indicator referring to occupation diversity (A6) which has statistical significance among the models tested in the multivariate analysis. The weights of the indicators also, differently from the GPC conceptual model that has weights with discrete values; in the models tested in this thesis, these tend to have continuous values. Thus, using discrete weights can lead to a tendency to obtain less similar values with cycling demand than continuous weights.

Attention should be drawn to indicators such as age (P1), which has an inversely proportional relationship when applied to the context of the study area, so the higher its value, the more negatively it influences the dependent variable. The inversely proportional variation of the age indicator is mainly since there is a high similarity between the cycling demand rates of the different age groups, which does not meet the assumptions established among the choice of age (P1) for the conceptual model of the GPC. Among this study, other indicators also tend to have inversely proportional coefficients that mostly tend not to match the assumptions established by the GPC. This mostly happens because the conceptual model of the GPC is being tested in a "champion" area.

In summary, applying the GPC tool in a "champion" context can provide enough cycling demand information to trial the conceptual model validity of the Gross Potential for Cycling. This analysis would not be possible in a starter city, as it does not have enough cycling demand data to perform statistical tests with sufficient effective samples to validate the GPC conceptual model. However, from the analysis performed in this study, it is also possible to highlight the resilience of the tool to be applied in other cycling contexts beyond starter cycling cities. Nevertheless, it is observed that the behavior of some indicators for the context in which this was applied proved to be irrelevant or even inversely proportional, but it does not mean that these are not appropriate for the starter context. Indicators may behave differently when applied to different concepts. In this case, this research serves as a guideline for validating the Gross Potential for Cycling tool.

5.1. FUTURE RESEARCH

For future work, it is suggested to apply this methodology in a "champion" city with more disaggregated bicycle commuting data. Also, if applied in the Dutch context, it is suggested to use other forms of mobility data collection besides the annually applied mobility surveys. For example, travel data could be collected through smartphone applications, such as the SMART[19] project, which is applied in the municipality of Enschede. It is also suggested to apply the tool in a city with all the available data related to the Gross Potential for Cycling indicators so that an analysis can be done with all the indicators without the need to adapt them. It is also recommended, if one day one of the starters cycling cities where the Gross Potential for Cycling tool was applied becomes a "champion" city, to apply the method again, to compare the two evaluation contexts.

[19] Available on: https://smartenschede.nl/diensten/smart-app/.

BIBLIOGRAPHIC REFERENCES

Albertí, Jaume, Alejandra Balaguera, Christian Brodhag, and Pere Fullana-i-Palmer. 2017. "Towards Life Cycle Sustainability Assessent of Cities. A Review of Background Knowledge." *Science of the Total Environment* 609:1049–63. doi: 10.1016/j.scitotenv.2017.07.179.

Aldred, Rachel. 2010. "'On the Outside': Constructing Cycling Citizenship." *Social and Cultural Geography* 11(1):35–52. doi: 10.1080/14649360903414593.

Aldred, Rachel. 2015. "A Matter of Utility? Rationalising Cycling, Cycling Rationalities." *Mobilities* 10(5):686–705. doi: 10.1080/17450101.2014.935149.

Aldred, Rachel, James Woodcock, and Anna Goodman. 2016. "Does More Cycling Mean More Diversity in Cycling?" *Transport Reviews* 36(1):28–44. doi: 10.1080/01441647.2015.1014451.

Altman, Naomi, and Martin Krzywinski. 2015. "Points of Significance: Simple Linear Regression." *Nature Methods* 12(11):999–1000. doi: 10.1038/nmeth.3627.

Arellana, Julián, María Saltarín, Ana Margarita Larrañaga, Virginia I. González, and César Augusto Henao. 2020. "Developing an Urban Bikeability Index for Different Types of Cyclists as a Tool to Prioritise Bicycle Infrastructure Investments." *Transportation Research Part A: Policy and Practice* 139(January 2019):310–34. doi: 10.1016/j.tra.2020.07.010.

Benoit, Kenneth. 2011. "Linear Regression Models with Logarithmic Transformations." *London School of Economics* 1–8.

BooST. 2020. "BooST – Boosting Starter Cycling Cities." Retrieved July 6, 2020 (https://boost.up.pt/en/).

BooST. 2021. "Gross Potential for Cycling for 276 Four-Digit Postal Areas in the Netherlands."

Brömmelstroet, Marco te. 2013. "Performance of Planning Support Systems: What Is It, and How Do We Report on It?" *Computers, Environment and Urban Systems* 41:299–308. doi: 10.1016/j.compenvurbsys.2012.07.004.

Buehler, Ralph, and John Pucher. 2012. "Cycling to Work in 90 Large American Cities: New Evidence on the Role of Bike Paths and Lanes." *Transportation* 39(2):409–32. doi: 10.1007/s11116-011-9355-8.

Buehler, Ralph, John Pucher, and Adrian Bauman. 2020. "Physical Activity from Walking and Cycling for Daily Travel in the United States, 2001–2017: Demographic, Socioeconomic, and Geographic Variation." *Journal of Transport and Health* 16(December 2019):100811. doi: 10.1016/j.jth.2019.100811.

Buxton, Richard. 2008. "Correlation." 1–8.

Bypad. 2008. "Cycling , the European Approach." *Total Quality Management in Cycling Policy. Results and Lessons of the BYPAD-Project* (October).

Carse, Andrew, Anna Goodman, Roger L. Mackett, Jenna Panter, and David Ogilvie. 2013. "The Factors Influencing Car Use in a Cycle-Friendly City: The Case of Cambridge." *Journal of Transport Geography* 28:67–74. doi: 10.1016/j.jtrangeo.2012.10.013.

Cavenett. 2010. "Amsterdam Cycling?" 53(9):1689–99. doi: 10.1017/CBO9781107415324.004.

CBS. 2015. "Indeling van Nederland in 22 Grootstedelijke Agglomeraties En Stadsgewesten [Division of the Netherlands into 22 Metropolitan Agglomerations and Urban Districts].” 20–21.

CBS. 2016. “Kerncijfers per Postcode [Key Figures by Zip Code].”

CBS. 2018. *Onderweg in Nederland (ODiN) 2018: Onderzoeksbeschrijving*. Netherlands.

CBS. 2019a. “Lengte van Fietspaden Naar Wegtype, 2019 [Length of Bike Lanes by Road Type, 2019].” *CBS*. Retrieved (https://www.cbs.nl/nl-nl/maatwerk/2020/38/lengte-van-fietspaden-naar-wegtype-2019).

CBS. 2019b. *Onderweg in Nederland (ODiN) 2018 Onderzoeksbeschrijving [Onderweg in Nederland (ODiN) 2018 Research Description]*.

CBS. 2020a. “Mobiliteit; per Persoon, Vervoerwijzen, Motieven, Regio’s [Mobility; by Person, Modes, Motives, Regions].” *CBS*. Retrieved March 28, 2021 (https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84710NED/map?ts=1617055253087).

CBS. 2020b. *Onderweg in Nederland (ODiN) 2019 Onderzoeksbeschrijving [Onderweg in Nederland (ODiN) 2019 Research Description]*.

CBS, and RWS. 2018. *ODiN 2018*. Onderzoek Onderweg in Nederland - ODiN 2018.

Cervero, Robert, Steve Denman, and Ying Jin. 2019. “Network Design, Built and Natural Environments, and Bicycle Commuting: Evidence from British Cities and Towns.” *Transport Policy* 74(September 2018):153–64. doi: 10.1016/j.tranpol.2018.09.007.

Chagas, Eduardo Federighi Baisi. 2017. *Regressão No SPSS [Regression in SPSS]*. Marília.

Chevalier, Aline, and Leiqing Xu. 2020. “On the Applicability of a Western Bikeability Index in the Chinese Context.” *International Review for Spatial Planning and Sustainable Development* 8(1):59–93. doi: 10.14246/IRSPSD.8.1_59.

Cook, R. Dennis, and Sanford Weisberg. 1999. *Applied Regression Including Computing and Graphics*. New York: John Wiley&Sons.

Copenhagenize Index. 2019. “Copenhagenize Index 2019.” Retrieved October 19, 2020 (https://copenhagenizeindex.eu/about/the-index).

Daoud, Jamal I. 2018. “Multicollinearity and Regression Analysis.” *Journal of Physics: Conference Series* 949(1). doi: 10.1088/1742-6596/949/1/012009.

Dill, Jennifer, and Nathan McNeil. 2013. “Four Types of Cyclists?” *Transportation Research Record* (2387):129–38. doi: 10.3141/2387-15.

Eesa, Adel S., and Wahab Kh. Arabo. 2017. “A Normalization Methods for Backpropagation: A Comparative Study.” *Science Journal of University of Zakho* 5(4):319. doi: 10.25271/2017.5.4.381.

Federal Highway Administration. 1998. “The Bicycle Compatibility Index: A Level of Service Concept , Implementation Manual.” 44.

Field, Andy., and Lorí. Viali. 2000. *Descobrindo a Estatística Usando o SPSS [Discovering Statistics Using SPSS]*. 2nd ed. edited by Artmed. Porto Alegre: Bookman.

Fietsersbond. 2018. “Fietsstad 2018: De Top 100 [Cycling City 2018: The Top 100].” *Fietsersbond*. Retrieved April 22, 2021 (https://www.fietsersbond.nl/fietsstad/fietsstadverkiezing-

2018/fietsstad-2018-top-100/).

Fietsersbond. 2020a. “Fietsstad 2020: De Top 100 [Cycling City 2020: The Top 100].” *Fietsersbond*. Retrieved April 22, 2021 (https://www.fietsersbond.nl/fietsstad2020/fietsstad-2020-de-top-100/).

Fietsersbond. 2020b. “Fietsstad 2020: Hoe Scoort Jouw Gemeente? [Cycling City 2020: How Does Your Municipality Score?].” *Fietsersbond*. Retrieved April 22, 2021 (https://www.fietsersbond.nl/fietsstad2020/fietsstad-2020-hoe-scoort-jouw-gemeente/?utm_medium=email&utm_source=sharpspring&sslid=MzcwNzG2NDAxNTM2AQA&sseid=MzIwNDc2MDUzMA0C4-36-49-49-79-794-79-49-79 -856d36b-49-457).

Fietsersbond. 2020c. “Veenendaal Verkozen Tot Fietsstad 2020 [Veenendaal Elected Bicycle City 2020].” *Fietsersbond*. Retrieved January 13, 2021 (https://www.fietsersbond.nl/nieuws/fietsstad-2020-winnaar/).

Gemeente Enschede. 2021. “Voorstel Gemeenteraad [Proposal City Council].” 1–4.

Glavić, Draženko, Miloš N. Mladenović, and Marina Milenković. 2019. “Decision Support Framework for Cycling Investment Prioritization.” *Journal of Advanced Transportation* 2019(1):1–15. doi: 10.1155/2019/7871426.

Goudappel Coffeng. 2016. “Uitstoot van Mobiliteit [Mobility Emissions].” *Uitstoot van Mobiliteit*. Retrieved April 22, 2021 (https://uitstootvanmobiliteit.nl/index.html).

Greenstein, Ashley Sarah. 2015. “Mapping Bikeability : A Spatial Analysis on Current and Potential Bikeability in Austin , Texas.” 71.

Grigore, Elena, Norman Garrick, Raphael Fuhrer, and Ing Kay W. Axhausen. 2019. “Bikeability in Basel.” *Transportation Research Record* 2673(6):607–17. doi: 10.1177/0361198119839982.

Gu, Peiqin, Zhiyuan Han, Zhejing Cao, Yulin Chen, and Yang Jiang. 2018. “Using Open Source Data to Measure Street Walkability and Bikeability in China: A Case of Four Cities.” *Transportation Research Record* 2672(31):63–75. doi: 10.1177/0361198118758652.

Handy, Susan, Bert van Wee, and Maarten Kroesen. 2014. “Promoting Cycling for Transport: Research Needs and Challenges.” *Transport Reviews* 34(1):4–24. doi: 10.1080/01441647.2013.860204.

Hartanto, Kurniawan. 2017. “Developing a Bikeability Index to Enable the Assessment of Transit-Oriented Development (TOD) Nodes.”

Havlicek, Larry L., and Nancy L. Peterson. 1977. “Effect of the Violation of Assumptions upon Significance Levels of the Pearson R.” *Psychological Bulletin* 84(2):373–77. doi: 10.1037/0033-2909.84.2.373.

Heinen, Eva, Bert van Wee, and Kees Maat. 2010. “Commuting by Bicycle: An Overview of the Literature.” *Transport Reviews* 30(1):59–96. doi: 10.1080/01441640903187001.

Hull, Angela, and Craig O’Holleran. 2014. “Bicycle Infrastructure: Can Good Design Encourage Cycling?” *Urban, Planning and Transport Research* 2(1):369–406. doi: 10.1080/21650020.2014.955210.

Instituto da Mobilidade e dos Transportes Terrestres. 2011. “Colecção de Brochuras Técnicas/Temáticas: Rede Ciclável - Princípios de Planeamento e Desenho [Technical Thematic Brochure Series: Cycling Network - Principles of Planning and Design].” *Pacote Da Mobilidade - Território, Acessibilidade e Gestão de Mobilidade* 41.

Kamel, Mohamed Bayoumi, Tarek Sayed, and Alexander Bigazzi. 2020. “A Composite Zonal Index for Biking Attractiveness and Safety.” *Accident Analysis and Prevention* 137(October 2019):105439. doi: 10.1016/j.aap.2020.105439.

Kellstedt, Debra K., John O. Spengler, Margaret Foster, Chanam Lee, and Jay E. Maddock. 2020. “A Scoping Review of Bikeability Assessment Methods.” *Journal of Community Health* (0123456789). doi: 10.1007/s10900-020-00846-4.

Keypoint Consultancy. 2011. “Goed Op Weg? Van Sturen Naar Faciliteren: Een Evaluatie van Het Enschedese Mobiliteitsbeleid [Well on Your Way? From Steering to Facilitating: An Evaluation of Enschede’s Mobility Policy].” 1–26.

Koglin, Till. 2014. “City Cycling.” *European Planning Studies* 22(1):227–28. doi: 10.1080/09654313.2013.798111.

Krenn, Patricia Jasmin, Pekka Oja, and Sylvia Titze. 2015. “Development of a Bikeability Index to Assess the Bicycle-Friendliness of Urban Environments.” *Open Journal of Civil Engineering* 05(04):451–59. doi: 10.4236/ojce.2015.54045.

Kuiper, Stephan. 2012. “Duurzame Mobiliteit in Enschede [Sustainable Mobility in Enschede].” University of Twente.

Landis, Bruce W., Venkat R. Vattikuti, and Michael T. Brannick. 1997. “Real-Time Human Perceptions: Toward a Bicycle Level of Service.” *Transportation Research Record* (1578):119–31. doi: 10.3141/1578-15.

Lee, Qian Yun, and Dorina Pojani. 2019. “Making Cycling Irresistible in Tropical Climates? Views from Singapore.” *Policy Design and Practice* 2(4):359–69. doi: 10.1080/25741292.2019.1665857.

Van Leeuwen, Niek. 2019. “Statistische Gegevens per Vierkant En Postcode 2018-2017-2016-2015 [Statistical Data by Grid and Zip Code 2018-2017-2016-2015].” 1–32.

Li, Zhibin, Wei Wang, Chen Yang, and Guojun Jiang. 2013. “Exploring the Causal Relationship between Bicycle Choice and Trip Chain Pattern.” *Transport Policy* 29:170–77. doi: 10.1016/j.tranpol.2013.06.001.

Liu, Qiang, Riken Homma, and Kazuhisa Iki. 2019. “Utilizing Bicycle Compatibility Index and Bicycle Level of Service for Cycleway Networks.” *MATEC Web of Conferences* 5. doi: https://doi.org/10.1051/matecconf/201925903005.

Lovelace, Robin, Anna Goodman, Rachel Aldred, Nikolai Berkoff, Ali Abbas, and James Woodcock. 2017. “The Propensity to Cycle Tool: An Open Source Online System for Sustainable Transport Planning.” *Journal of Transport and Land Use* 10(1):505–28. doi: 10.5198/jtlu.2016.862.

Martens, Karel. 2007. “Promoting Bike-and-Ride: The Dutch Experience.” *Transportation Research Part A: Policy and Practice* 41(4):326–38. doi: 10.1016/j.tra.2006.09.010.

McLeod, Sam, Courtney Babb, and Steve Barlow. 2020. “How to ‘Do’ a Bike Plan: Collating Best Practices to Synthesise a Maturity Model of Planning for Cycling.” *Transportation Research Interdisciplinary Perspectives* 5:100130. doi: 10.1016/j.trip.2020.100130.

McNeil, Nathan. 2011. “Bikeability and the 20-Min Neighborhood: How Infrastructure and Destinations Influence Bicycle Accessibility.” *Transportation Research Record* (2247):53–63. doi: 10.3141/2247-07.

McNeil, Nathan, Christopher M. Monsere, and Jennifer Dill. 2015. “Influence of Bike Lane Buffer

Types on Perceived Comfort and Safety of Bicyclists and Potential Bicyclists." *Transportation Research Record* 2520:132–42. doi: 10.3141/2520-15.

Meer, Tom Van Der, and Te Grotenhuis. 2010. "Influential Cases in Multilevel Modeling : A Methodological Comment." *American Sociological Association* 75(April 2006):173–78. doi: 10.1177/0003122409359166.

Mitra, Raktim, and James Schofield. 2019. "Biking the First Mile: Exploring a Cyclist Typology and Potential for Cycling to Transit Stations by Suburban Commuters." *Transportation Research Record* 2673(4):951–62. doi: 10.1177/0361198119837229.

Motta, Bruno Guasti. 2017. "Faculty of Engineering Technology Civil Engineering & Management A Bikeability Index for Curitiba." Faculty of Engineering Technology.

Motulsky, Harvey. 2018. *Intuitive Biostatistics: A Nonmathematical Guide to Statistical Thinking*. 2nd ed. New York: Oxford University Press.

Osama, Ahmed, Maria Albitar, Tarek Sayed, and Alexander Bigazzi. 2020. "Determining If Walkability and Bikeability Indices Reflect Pedestrian and Cyclist Safety." *Transportation Research Record* 2674(9):767–75. doi: 10.1177/0361198120931844.

Pucher, John, and Ralph Buehler. 2006. "Why Canadians Cycle More than Americans: A Comparative Analysis of Bicycling Trends and Policies." *Transport Policy* 13(3):265–79. doi: 10.1016/j.tranpol.2005.11.001.

Pucher, John, and Ralph Buehler. 2008. "Making Cycling Irresistible: Lessons from the Netherlands, Denmark and Germany." *Transport Reviews* 28(4):495–528. doi: 10.1080/01441640701806612.

Pucher, John, Ralph Buehler, and Mark Seinen. 2011. "Bicycling Renaissance in North America? An Update and Re-Appraisal of Cycling Trends and Policies." *Transportation Research Part A: Policy and Practice* 45(6):451–75. doi: 10.1016/j.tra.2011.03.001.

Pucher, John, Jennifer Dill, and Susan Handy. 2010. "Infrastructure, Programs, and Policies to Increase Bicycling: An International Review." *Preventive Medicine* 50(SUPPL.):S106–25. doi: 10.1016/j.ypmed.2009.07.028.

Ros-McDonnell, L., M. V. de-La-Fuente, D. Ros-McDonnell, and M. Cardós. 2020. "Development of a Biking Index for Measuring Mediterranean Cities Mobility." *International Journal of Production Management and Engineering* 8(1):21–29. doi: 10.4995/ijpme.2020.10834.

Rousseeuw, Peter J., and Bert C. van Zomeren. 1990. "Unmasking Multivariate Outliers and Leverage Points." *Journal of the American Statistical Association* 85(411):633–39. doi: 10.1080/01621459.1990.10474920.

Rupprecht, Siegfried, Rafael Urbanczyk, and Michael Laubenheimer. 2010. "Promoting Cycling for Everyone as a Daily Transport Mode."

Schober, Patrick, Christa Boer, and Lothar A. Schwarte. 2018. "Correlation Coefficients: Appropriate Use and Interpretation." *Anesthesia and Analgesia* 126(5):1763–68. doi: 10.1213/ANE.0000000000002864.

Scholen op de kaart. 2021. "Vind En Vergelijk Scholen in de Buurt [Find and Compare Schools in Your Area]." *Kennisnet*. Retrieved April 24, 2021 (https://scholenopdekaart.nl/).

Seltman, Howard J. 2018. *Experimental Design and Analysis*. Vol. 1. Pittsburgh: Carnegie Mellon University.

Al Shalabi, Luai, and Zyad Shaaban. 2006. “Normalization as a Preprocessing Engine for Data Mining and the Approach of Preference Matrix.” *Proceedings of International Conference on Dependability of Computer Systems, DepCoS-RELCOMEX 2006* 207–14. doi: 10.1109/DEPCOS-RELCOMEX.2006.38.

Silva, Cecília, Joana Marques, Tamara Bicalho, and Ana Dias. 2019. “Mapping the Gross Potential for Cycling: A Tool to Support Planning for Cycling in Starter Cities.” *Cycling Research Board 2019* 1–2.

Silva, Cecília, Joana S. Marques, Miguel Lopes, and Ana Dias. 2021. *The Gross Potential for Cycling: Planning for Human Scale Urban Mobility*.

Silva, Cecília, João Teixeira, and Ana Proença. 2019. “Revealing the Cycling Potential of Starter Cycling Cities.” *Transportation Research Procedia* 41(2016):637–54. doi: 10.1016/j.trpro.2019.09.113.

Silva, Cecília, João Teixeira, Ana Proença, Tamara Bicalho, and Isabel Cunha. 2018. “Potential for Cycling Assessment Method - Final Report of the Generation.Mobi Project.” *CITTA*.

Silva, Cecília, João Teixeira, Ana Proença, Tamara Bicalho, Isabel Cunha, and Ana Aguiar. 2019. “Revealing the Cycling Potential of Starter Cycling Cities: Usefulness for Planning Practice.” *Transport Policy* 81(August 2018):138–47. doi: 10.1016/j.tranpol.2019.05.011.

Steinbach, Rebecca, Judith Green, Jessica Datta, and Phil Edwards. 2011. “Cycling and the City: A Case Study of How Gendered, Ethnic and Class Identities Can Shape Healthy Transport Choices.” *Social Science and Medicine* 72(7):1123–30. doi: 10.1016/j.socscimed.2011.01.033.

Transport for London. 2010. “Analysis of Cycling Potential.” 1–55.

Transport for London. 2017. “Analysis of Cycling Potential.” (March):1–56.

Wagenbuur, Mark. 2014. “Enschede, Nominee for Best Cycling City.” *Bycicle Dutch*. Retrieved January 14, 2021 (https://bicycledutch.wordpress.com/2014/02/20/enschede-nominee-for-best-cycling-city/).

Walk Score. 2020. “Bike Score Methodology.” Retrieved December 21, 2020 (https://www.walkscore.com/bike-score-methodology.shtml).

Weisberg, Sanford. 2014. *Applied Linear Regression*. 4th ed. edited by D. J. Balding, N. A. C. Cressie, G. M. Fitzmaurice, H. Goldstein, I. M. Johnstone, G. Molenberghs, D. W. Scott, A. F. M. Smith, R. S. Tsay, and S. Weisberg. Minneapolis: John Wiley & Sons Inc.

Winters, Meghan, Michael Brauer, Eleanor M. Setton, and Kay Teschke. 2013. “Mapping Bikeability: A Spatial Tool to Support Sustainable Travel.” *Environment and Planning B: Planning and Design* 40(5):865–83. doi: 10.1068/b38185.

Winters, Meghan, Gavin Davidson, Diana Kao, and Kay Teschke. 2011. “Motivators and Deterrents of Bicycling: Comparing Influences on Decisions to Ride.” *Transportation* 38(1):153–68. doi: 10.1007/s11116-010-9284-y.

Winters, Meghan, Matt Lerner, Kay Teschke, and Michael Brauer. 2012. *Bike Score: Applying Research to Build Web-Based Tools to Promote Cycling*.

Xing, Yan, Jamey Volker, and Susan Handy. 2018. “Why Do People like Bicycling? Modeling Affect toward Bicycling.” *Transportation Research Part F: Traffic Psychology and Behaviour* 56:22–32. doi: 10.1016/j.trf.2018.03.018.

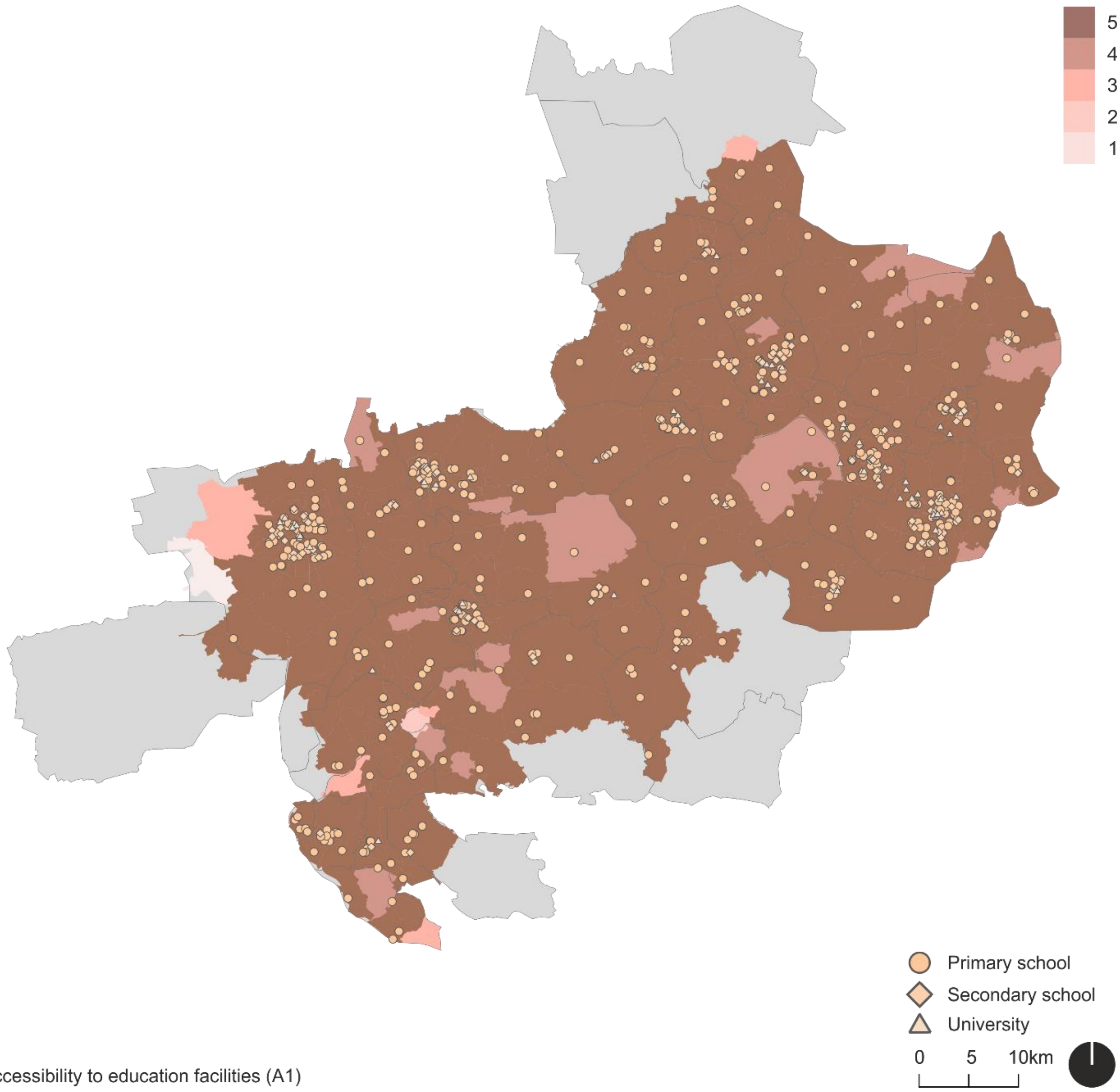
Yang, Lin, Shannon Sahlqvist, Alison McMinn, and Simon J. Griffin. 2010. "Interventions to Promote Cycling: Systematic Review." *BMJ (Online)* 341(7778):870. doi: 10.1136/bmj.c5293.

Yang, Yiyang, Xueying Wu, Peiling Zhou, Zhonghua Gou, and Yi Lu. 2019. "Towards a Cycling-Friendly City: An Updated Review of the Associations between Built Environment and Cycling Behaviors (2007–2017)." *Journal of Transport and Health* 14(February). doi: 10.1016/j.jth.2019.100613.

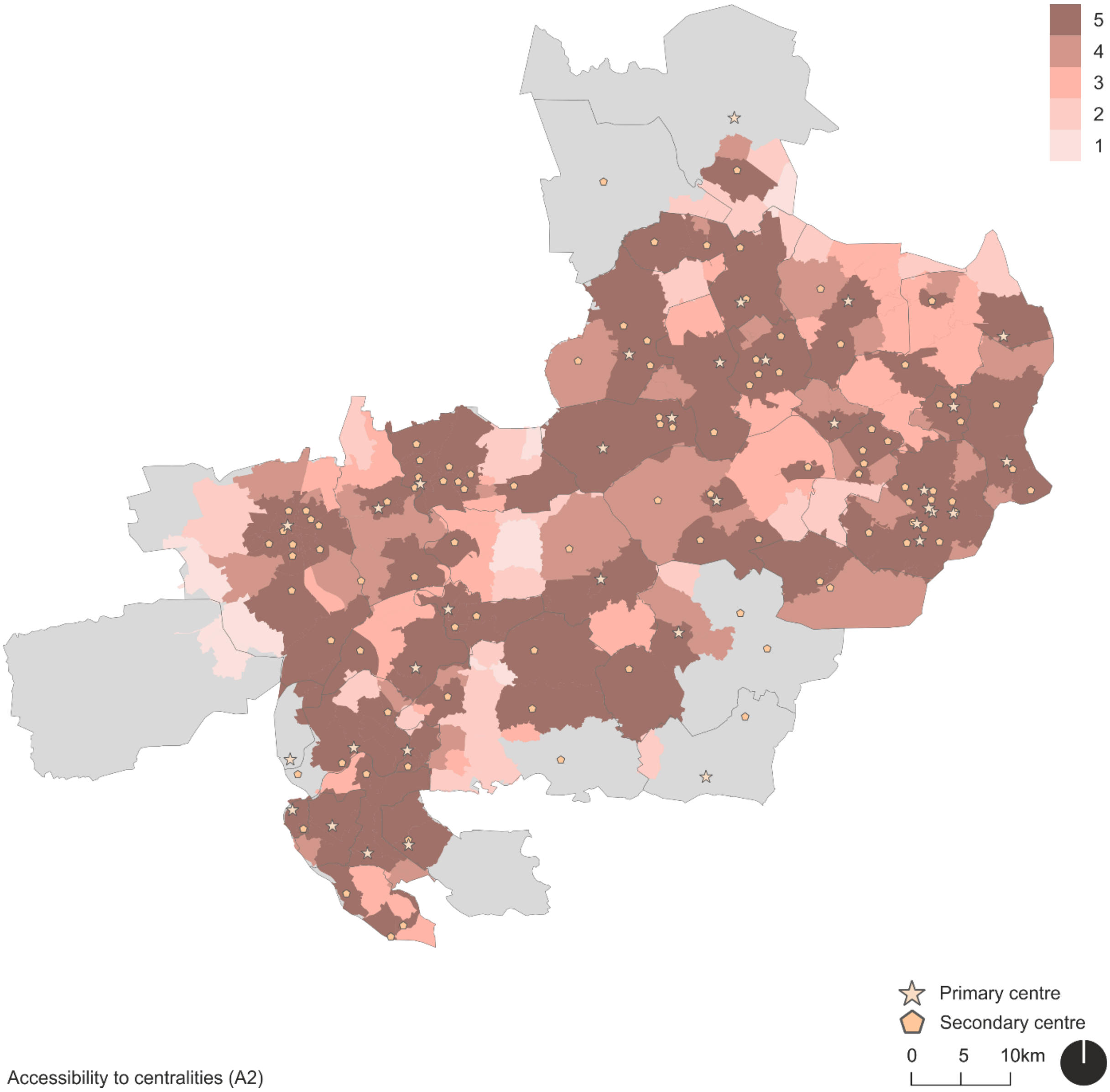
Zayed, Mohamed Anwer. 2016. "Towards an Index of City Readiness for Cycling." *International Journal of Transportation Science and Technology* 5(3):210–25. doi: 10.1016/j.ijtst.2017.01.002.

APPENDIX I

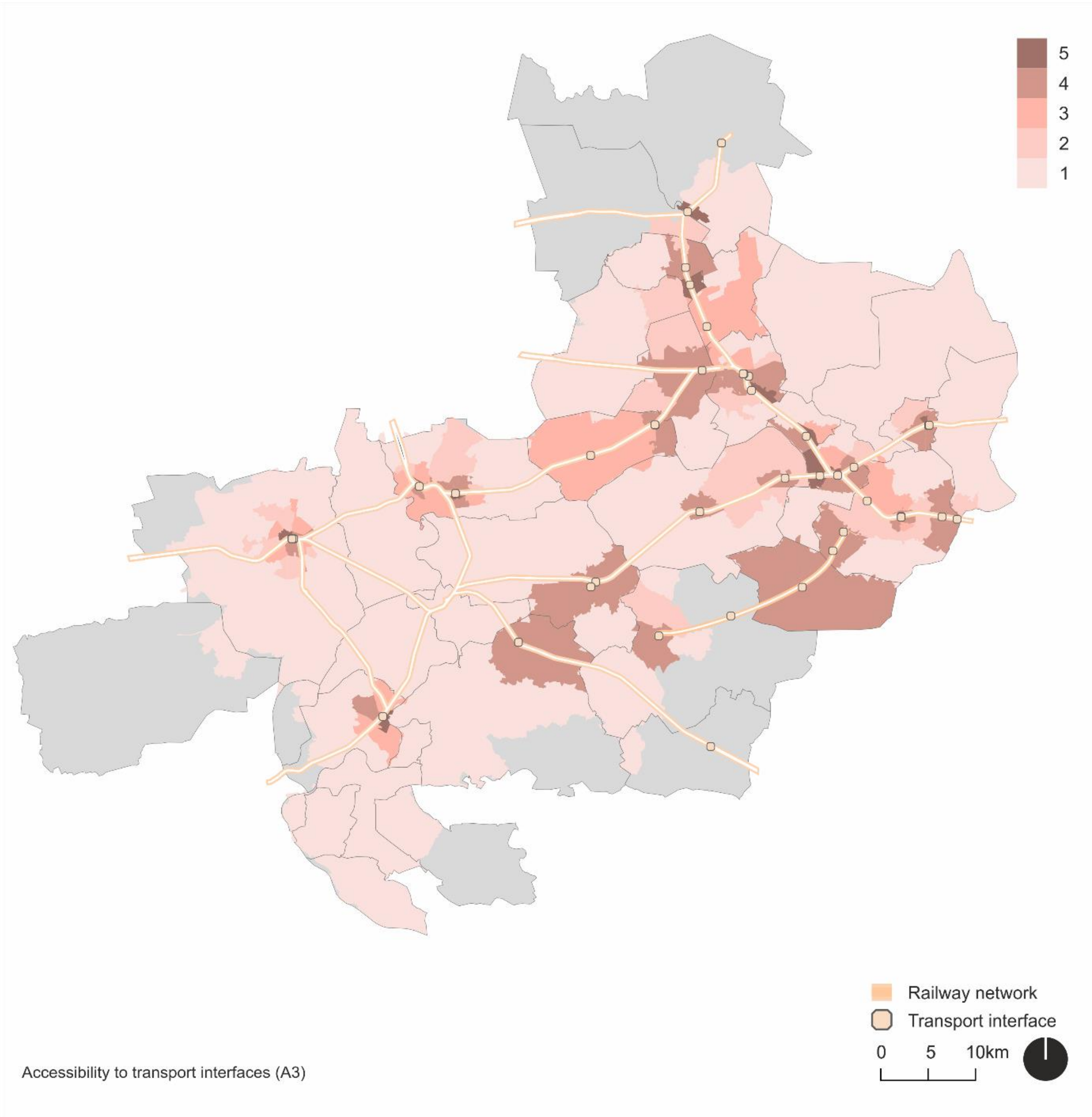
GROSS POTENTIAL FOR CYCLING INDICATORS



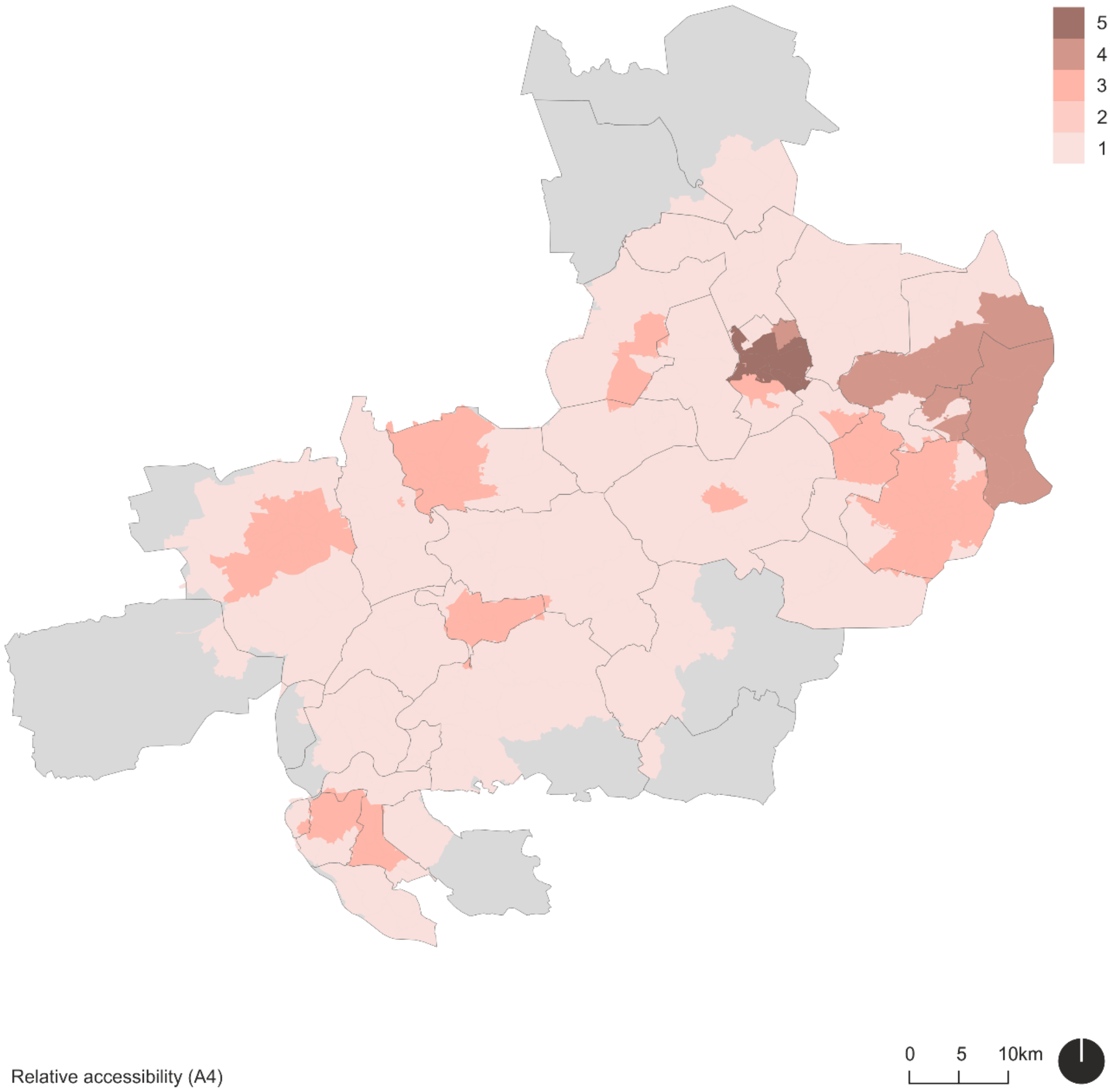
Accessibility to education facilities (A1)



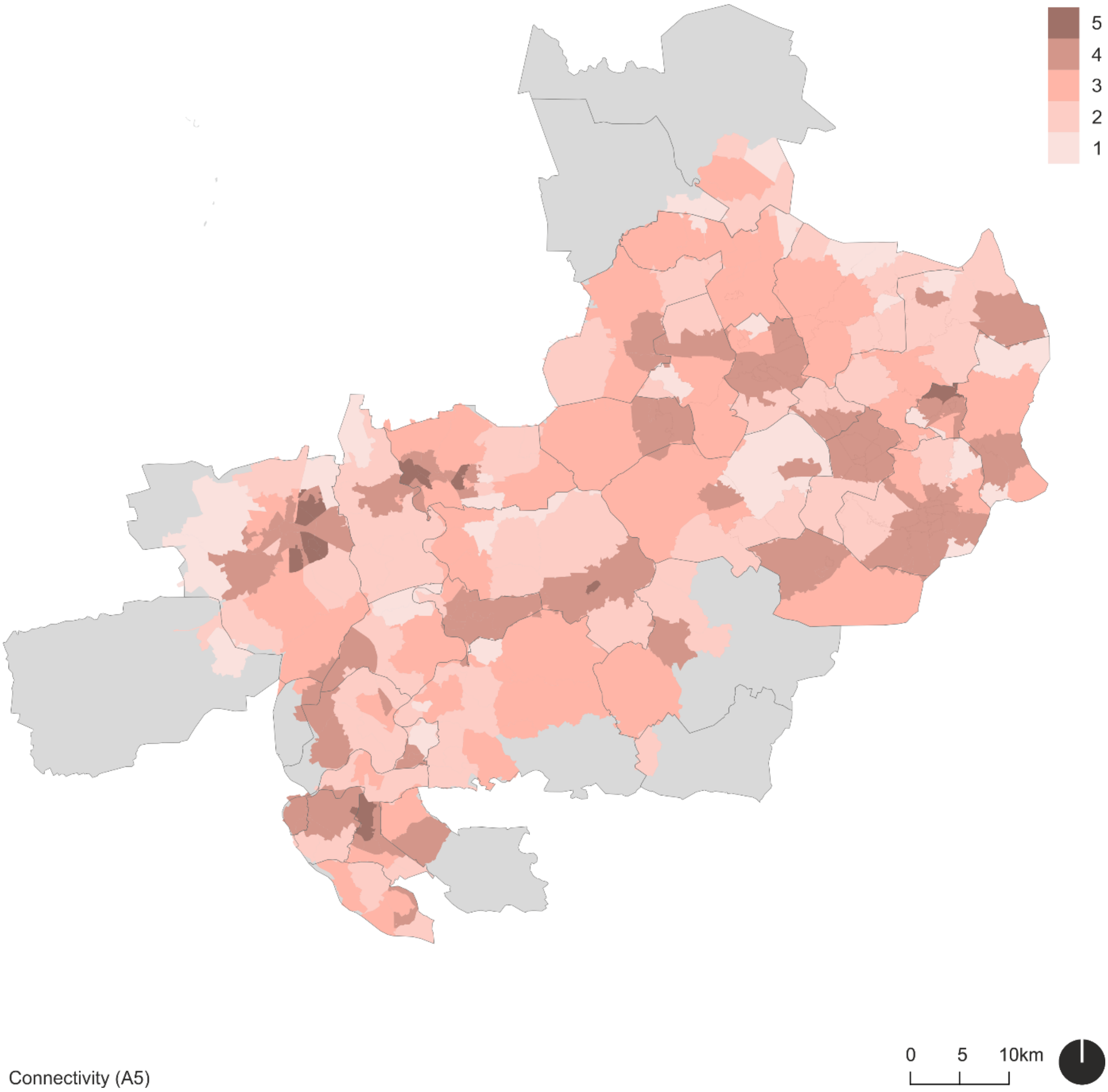
Accessibility to centralities (A2)



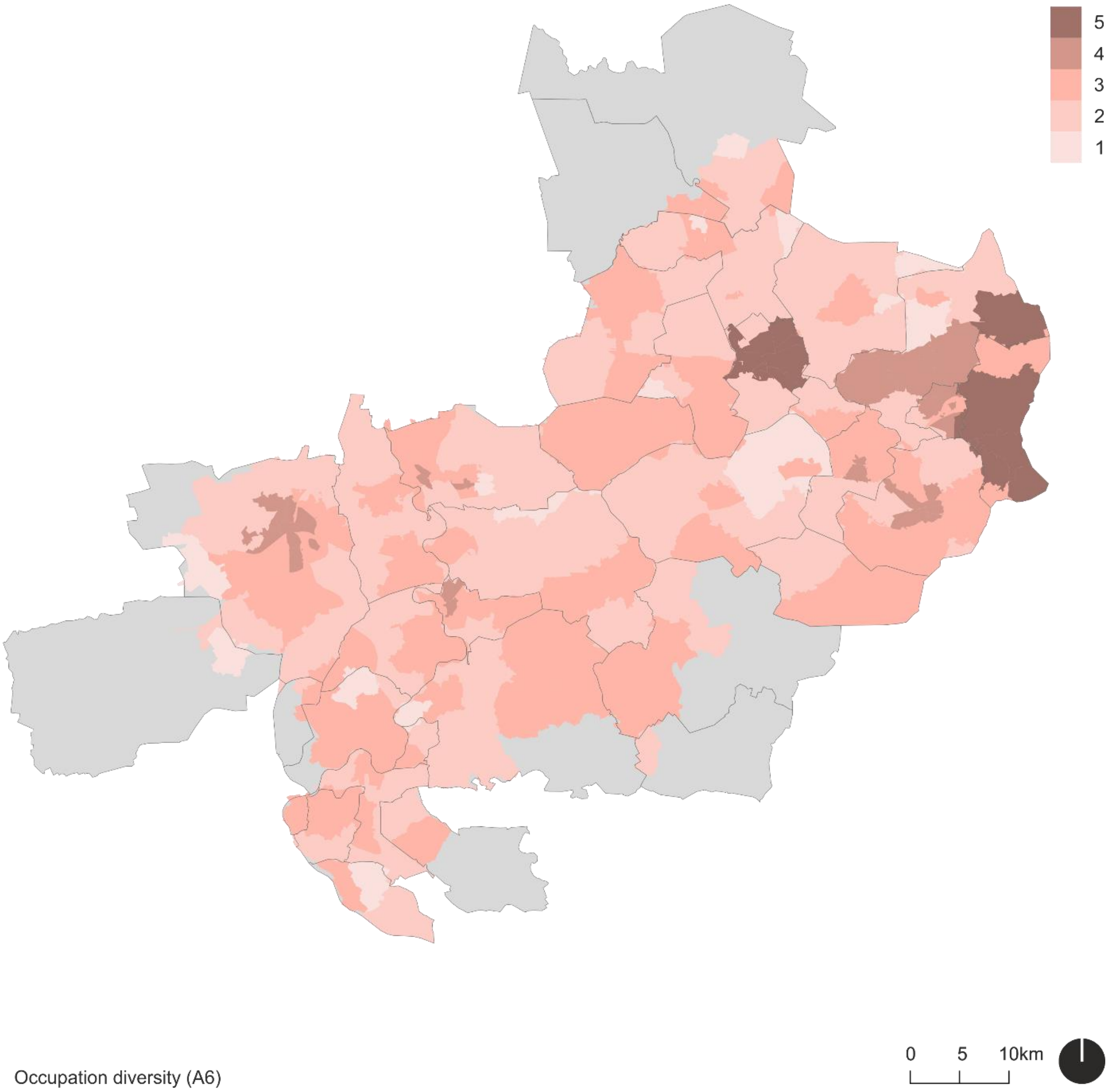
Accessibility to transport interfaces (A3)



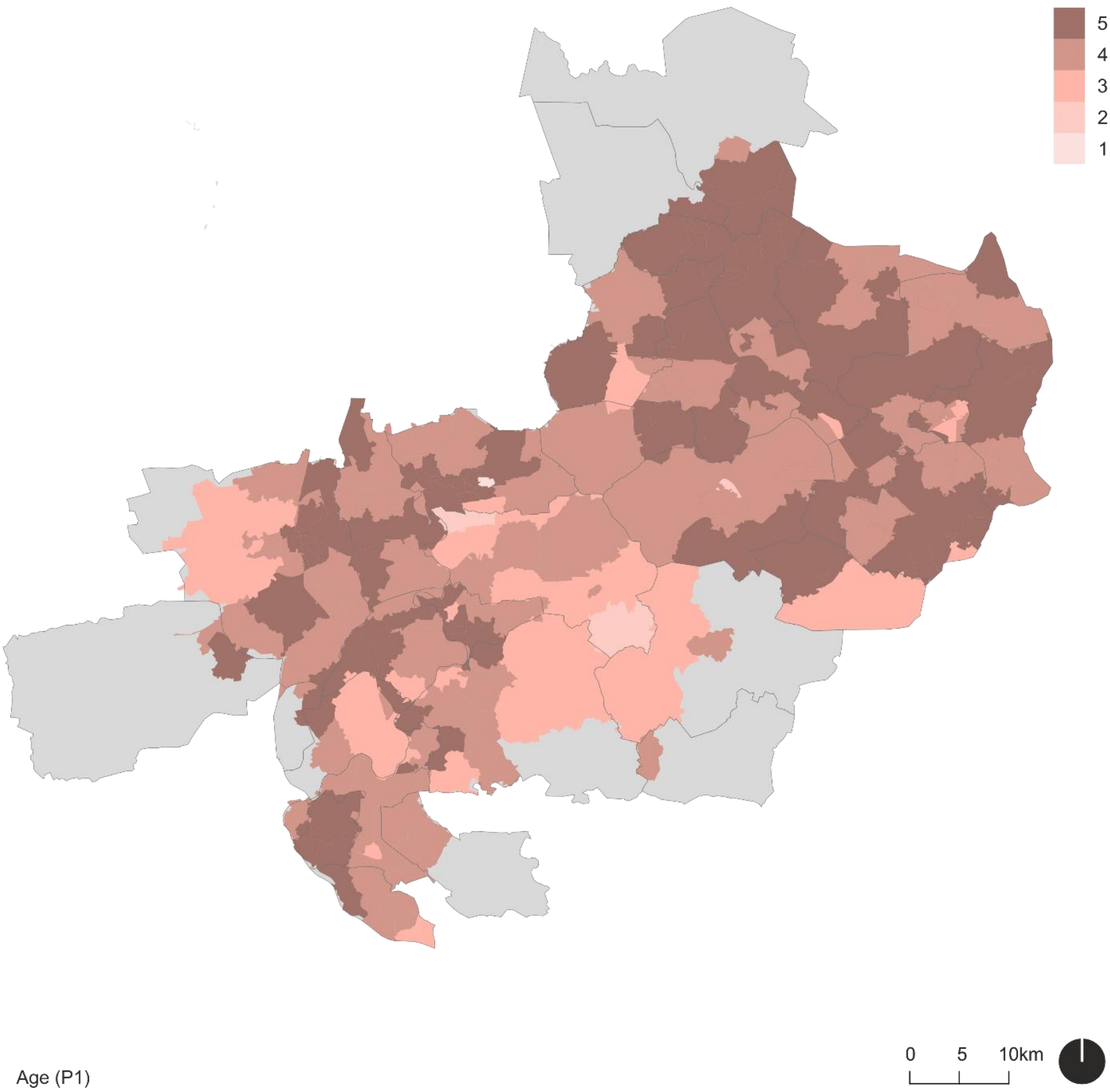
Relative accessibility (A4)



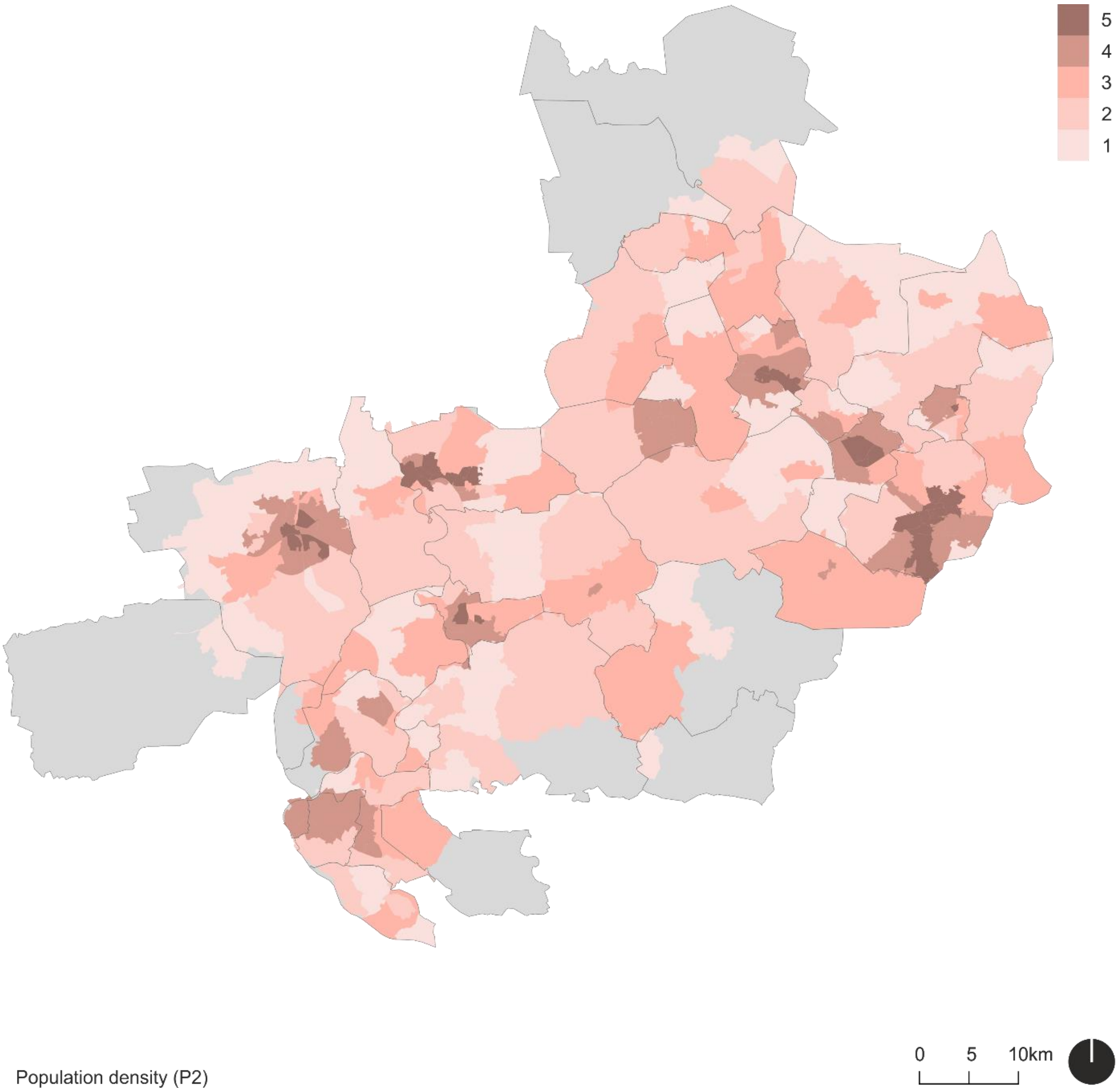
Connectivity (A5)



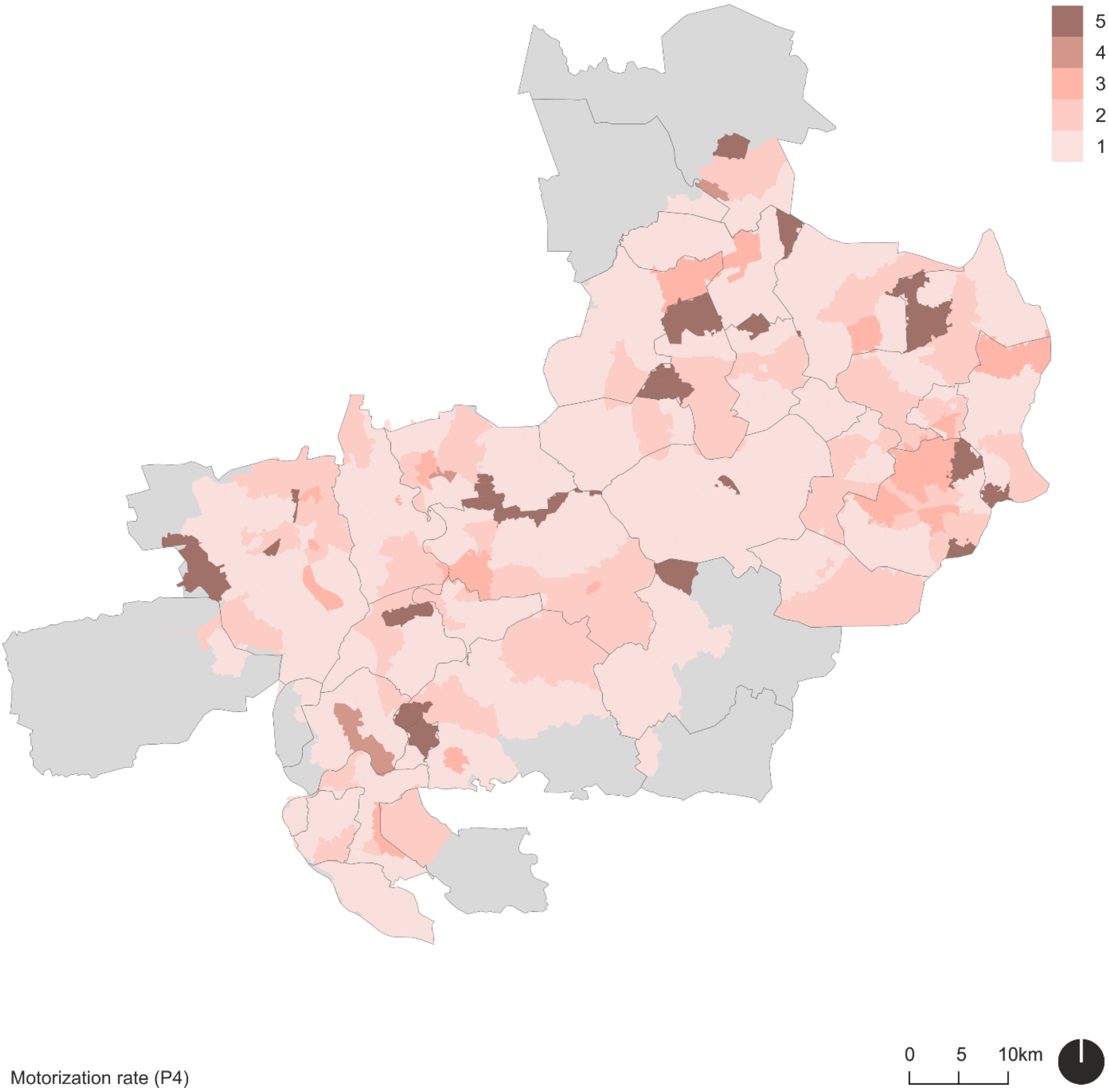
Occupation diversity (A6)



Age (P1)



Population density (P2)



Motorization rate (P4)

APPENDIX II

BIVARIATE STATISTICAL ANALYSIS

Model I.1				
	B	***Std. Err.***	***t***	***sig***
A1	1.810	0.631	2.877	0.005
Constant	-0.411	0.187	-2.120	0.030
Summary statistics	N	136		
	r	0.241 ($p = 0.005$)		
	Adjusted r^2	0.051		

Model I.3				
	B	***Std. Err.***	***t***	***sig***
A3	0.161	0.062	2.616	0.010
Constant	0.299	0.025	11.811	< 0.001
Summary statistics	N	134		
	r	0.222 ($p = 0.010$)		
	Adjusted r^2	0.042		

Model I.5				
	B	***Std. Err.***	***t***	***sig***
A5	0.415	0.112	3.715	< 0.001
Constant	0.097	0.069	1.408	0.161
Summary statistics	N	134		
	r	0.308 ($p < 0.001$)		
	Adjusted r^2	0.088		

Model I.6				
	B	***Std. Err.***	***t***	***sig***
A6	0.266	0.104	2.560	0.012
Constant	0.236	0.050	4.760	< 0.001
Summary statistics	N	133		
	r	0.218 ($p = 0.012$)		
	Adjusted r^2	0.040		

Model I.8				
	B	***Std. Err.***	***t***	***sig***
P2	0.350	0.076	4.614	< 0.001
Constant	0.146	0.046	3.194	0.002
Summary statistics	N	133		
	r	0,374 ($p < 0.010$)		
	Adjusted r^2	0.133		

Model I.10				
	B	***Std. Err.***	***t***	***sig***
GPC	0.579	0.142	4.061	< 0.001
Constant	0.003	0.086	0.039	0.969
Summary statistics	N	133		
	r	0.334 ($p < 0.001$)		
	Adjusted r^2	0.105		

Model II.6				
	B	***Std. Err.***	***t***	***sig***
A6	0.157	0.070	2.255	0.026
Constant	0.173	0.034	5.128	< 0.001
Summary statistics	N	135		
	r	0.192 ($p = 0.026$)		
	Adjusted r^2	0.030		

Model II.7				
	B	***Std. Err.***	***t***	***sig***
P1	-0.169	0.071	-2.368	0.019
Constant	0.371	0.56	6.610	< 0.001
Summary statistics	N	136		
	r	-0.200 ($p = 0.109$)		
	Adjusted r^2	0.033		

Model II.8				
	B	***Std. Err.***	***t***	***sig***
P2	0.111	0.048	2.310	0.022
Constant	0.169	0.029	5.880	< 0.001
Summary statistics	N	134		
	r	0.197 ($p = 0.022$)		
	Adjusted r^2	0.032		

Model II.9				
	B	***Std. Err.***	***t***	***sig***
P4	0.183	0.092	1.991	0.049
Constant	0.220	0.014	15.607	< 0.001
Summary statistics	N	135		
	r	0.170 ($p = 0.049$)		
	Adjusted r^2	0.022		

Model II.10				
	B	***Std. Err.***	***t***	***sig***
GPC	0.103	0.047	2.176	0.031
Constant	0.208	0.077	2.686	0.008
Summary statistics	N	134		
	r	0.228 ($p = 0.008$)		
	Adjusted r^2	0.045		

Model III.1				
	B	***Std. Err.***	***t***	***sig***
A1	3.334	0.619	5.382	< 0.001
Constant	-0.851	0.183	-4.643	< 0.001
Summary statistics	N	131		
	r	0.428 ($p < 0.001$)		
	Adjusted r^2	0.177		

Model III.2				
	B	***Std. Err.***	***t***	***sig***
A2	0.905	0.228	3.974	< 0.001
Constant	-0.412	0.216	-2.184	0.031
Summary statistics	N	134		
	r	0.327 ($p < 0.001$)		
	Adjusted r^2	0.100		

Model III.3				
	B	***Std. Err.***	***t***	***sig***
A3	0.270	0.068	3.974	< 0.001
Constant	0.312	0.027	11.225	< 0.001
Summary statistics	N	134		
	r	0.325 ($p < 0.001$)		
	Adjusted r^2	0.099		

Model III.4				
	B	***Std. Err.***	***t***	***sig***
A4	0.261	0.108	2.410	0.017
Constant	0.283	0.049	5.771	< 0.001
Summary statistics	N	135		
	r	0.205 ($p = 0.017$)		
	Adjusted r^2	0.035		

Model III.5				
	B	***Std. Err.***	***t***	***sig***
A5	0.578	0.110	5.250	< 0.001
Constant	0.015	0.067	0.230	0.819
Summary statistics	N	128		
	r	0.424 ($p < 0.001$)		
	Adjusted r^2	0.173		

Model III.6				
	B	***Std. Err.***	***t***	***sig***
A6	0.595	0.122	4.874	< 0.001
Constant	0.141	0.057	2.506	0.010
Summary statistics	N	131		
	r	0.394 ($p < 0.001$)		
	Adjusted r^2	0.149		

Model III.8				
	B	***Std. Err.***	***t***	***sig***
P2	0.495	0.077	6.411	< 0.001
Constant	0.089	0.045	1.978	0.050
Summary statistics	N	128		
	r	0.496 ($p < 0.001$)		
	Adjusted r^2	0.240		

Model III.9				
	B	***Std. Err.***	***t***	***sig***
P4	0.478	0.176	2.715	0.007
Constant	0.356	0.026	14.293	< 0.001
Summary statistics	N	134		
	r	0.230 ($p = 0.008$)		
	Adjusted r^2	0.046		

Model III.10				
	B	***Std. Err.***	***t***	***sig***
GPC	1.260	0.159	7.930	< 0.001
Constant	-0.117	0.032	7.930	< 0.001
Summary statistics	N	130		
	r	0.574 ($p < 0.001$)		
	Adjusted r^2	0.324		

Model IV.1				
	B	***Std. Err.***	***t***	***sig***
A1	2.116	0.430	4.930	< 0.001
Constant	-0.523	0.127	-4.126	< 0.001
Summary statistics	N	135		
	r	0.393 ($p < 0.001$)		
	Adjusted r^2	0.148		

Model IV.2				
	B	***Std. Err.***	***t***	***sig***
A2	1.022	0.250	4.099	< 0.001
Constant	-0.194	0.072	-2.683	0.008
Summary statistics	N	132		
	r	0.338 ($p < 0.001$)		
	Adjusted r^2	0.108		

Model IV.3				
	B	***Std. Err.***	***t***	***sig***
A3	0.196	0.038	5.180	< 0.001
Constant	0.209	0.015	13.614	< 0.001
Summary statistics	N	131		
	r	0.415 ($p < 0.001$)		
	Adjusted r^2	0.166		

Model IV.4				
	B	***Std. Err.***	***t***	***sig***
A4	0.180	0.067	2.700	0.008
Constant	0.203	0.031	6.545	< 0.001
Summary statistics	N	136		
	r	0.227 ($p = 0.008$)		
	Adjusted r^2	0.045		

Model IV.5				
	B	***Std. Err.***	***t***	***sig***
A5	0.367	0.075	4.863	< 0.001
Constant	0.051	0.047	1.088	0.279
Summary statistics	N	134		
	r	0.390 ($p = 0.049$)		
	Adjusted r^2	0.145		

Model IV.6				
	B	***Std. Err.***	***t***	***sig***
A6	0.426	0.072	5.871	< 0.001
Constant	0.097	0.033	2.963	0.003
Summary statistics	N	128		
	r	0.463 ($p < 0.001$)		
	Adjusted r^2	0.209		

Model IV.8				
	B	***Std. Err.***	***t***	***sig***
P2	0.293	0.054	5.438	< 0.001
Constant	0.111	0.032	3.445	< 0.001
Summary statistics	N	135		
	r	0.426 ($p < 0.001$)		
	Adjusted r^2	0.176		

Model IV.9				
	B	***Std. Err.***	***t***	***sig***
P4	0.419	0.107	3.899	< 0.001
Constant	0.245	0.016	15.360	< 0.001
Summary statistics	N	135		
	r	0.320 ($p < 0.001$)		
	Adjusted r^2	0.096		

Model IV.10				
	B	***Std. Err.***	***t***	***sig***
GPC	0.698	0.112	6.217	< 0.001
Constant	-0.040	0.023	-1.760	0.081
Summary statistics	N	129		
	r	0.483 ($p < 0.001$)		
	Adjusted r^2	0.228		

APPENDIX III

MULTIVARIATE STATISTICAL ANALYSIS

Model I.11				
	B	***Std. Err.***	***t***	***sig***
A1	-0.386	0.590	-0.654	0.514
A2	-0.394	0.223	-1.770	0.079
A3	0.021	0.055	0.382	0.703
A4	-0.413	0.148	-2.795	0.006
A5	0.012	0.187	0.065	0.948
A6	0.341	0.159	2.138	0.035
P1	-0.197	0.104	-1.899	0.060
P2	0.616	0.148	4.176	< 0.001
P4	-0.200	0.130	-1,538	0.127
Constant	0.903	0.489	1.845	0.068
Summary statistics	N	127		
	Adjusted r^2	0.260		

Model II.11				
	B	***Std. Err.***	***t***	***sig***
A1	-0.206	0.344	-0.599	0.550
A2	-0.106	0.130	-0.818	0.415
A3	0.020	0.032	0.614	0.540
A4	-0.160	0.080	-1.993	0.049
A5	0.070	0.109	0.643	0.521
A6	0.203	0.090	2.261	0.026
P1	-0.116	0.061	-1.917	0.058
P2	0.127	0.086	1.479	0.142
P4	0.112	0.075	1.491	0.139
Constant	0.460	0.284	1.620	0.108
Summary statistics	N	130		
	Adjusted r^2	0.116		

Model III.11				
	B	***Std. Err.***	***t***	***sig***
A1	0.396	0.689	0.057	0.808
A2	-0.537	0.260	-2.064	0.567
A3	0.087	0.062	1.387	0.168
A4	-0.247	0.160	-1.539	0.126
A5	-0.086	0.213	-0.404	0.687
A6	0.322	0.174	1.850	0.067
P1	-0.066	0.112	-0.550	0.583
P2	0.745	0.168	4.423	< 0.001 **
P4	-0.210	0.151	-1.387	0.168
Constant	0.138	0.568	0.243	0.809
Summary statistics	N	134		
	Adjusted r^2	0.333		

Model IV.11				
	B	***Std. Err.***	***t***	***sig***
A1	0.257	0.409	0.627	0.532
A2	-0.057	0.154	-0.371	0.711
A3	0.083	0.038	2.220	0.028
A4	-0.109	0.095	-1.149	0.253
A5	0.097	0.128	0.754	0.452
A6	0.198	0.106	1.870	0.064
P1	-0.160	0.071	-2.271	0.025
P2	0.190	0.101	1.882	0.062
P4	0.211	0.089	2.365	0.020
Constant	-0.054	0.338	-0.160	0.873
Summary statistics	N	132		
	Adjusted r^2	0.328		

APPENDIX IV

OPTIMIZATION TESTS

Model II.12.a				
	B	***Std. Err.***	***t***	***sig***
A4	-0.150	0.078	-1.924	0.057
A6	0.199	0.086	2.230	0.022
P1	-0.114	0.059	-1.937	0.055
P2	0.141	0.048	2.974	0.004
Constant	0.205	0.045	4.610	< 0.001
Summary statistics	N	130		
	Adjusted r^2	0.117		

Model IV.12.b				
	B	***Std. Err.***	***t***	***sig***
A3	0.092	0.037	2.517	0.013
A6	0.124	0.072	1.719	0.088
P1	-0.257	0.085	-3.031	0.003
P2	0.320	0.068	4.740	< 0.001
P4	0.165	0.076	2.172	0.032
Constant	0.070	0.021	3.338	0.001
Summary statistics	N	132		
	Adjusted r^2	0.349		

Model I.13.a				
	B	***Std. Err.***	***t***	***sig***
A2	-0.418	0.196	-2.131	0.035
A4	-0.408	0.144	-2.835	0.005
A6	0.327	0.155	2.107	0.037
P1	-0.217	0.100	-2.162	0.033
P2	0.562	0.092	6.094	< 0.001
Constant	0.593	0.167	3.556	< 0.001
Summary statistics	N	127		
	Adjusted r^2	0.267		

Model III.13.b				
	B	***Std. Err.***	***t***	***sig***
A2	-0.496	0.229	-2.167	0.032
A4	-0.302	0.149	-2.025	0.045
A6	0.375	0.161	2.333	0.021
P2	0.711	0.096	7.417	< 0.001
Constant	0.409	0.186	2.198	0.030
Summary statistics	N	134		
	Adjusted r^2	0.332		

Model IV.13.c				
	B	***Std. Err.***	***t***	***sig***
A3	0.096	0.037	2.604	0.010
P1	-0.279	0.085	-3.291	0.001
P2	0.358	0.064	5.567	< 0.001
P4	0.180	0.076	2.366	0.020
Constant	0.086	0.019	4.165	< 0.001
Summary statistics	N	132		
	Adjusted r^2	0.339		

Model I.13.d				
	B	***Std. Err.***	***t***	***sig***
P1	-0.311	0.097	-3.219	0.002
P2	0.470	0.077	6.070	< 0.001
Constant	0.304	0.067	4.510	< 0.001
Summary statistics	N	127		
	Adjusted r^2	0.217		

Model II.13.d				
	B	***Std. Err.***	***t***	***sig***
P1	-0.156	0.057	-2.741	0.007
P2	0.169	0.045	3.777	< 0.001
Constant	0.248	0.039	6.291	< 0.001
Summary statistics	N	130		
	Adjusted r^2	0.093		