Master Thesis

Shared mobility

Who are the users, where are these modes used, what are the trip characteristics and what are the motives for using?

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Abstract

The availability and use of shared electric mopeds, bicycles and cars has risen over the years. However, a lot is still unknown about where, when, why and by whom these modes are used. Therefore, this study focusses on identifying users, reasons for using, travel behaviour and the locations where shared mobility is used. This is done by conducting a user and non-user survey in Rotterdam and The Hague identifying the user characteristics and reasons for (not) using shared mobility. Furthermore, a spatial regression analysis is conducted into the effects of the built environment and demographics on the use and availability of shared mobility. Finally, by using the results of the survey and spatial analysis, longitudinal trip data is studied to identify travel behaviour of shared mobility users. Shared mobility users were in general young, highly educated and had good digital skills. People used shared mobility to increase the flexibility in travelling and to increase accessibility. Preference for the use of a privately owned vehicle was the main reason for not using shared mobility. Furthermore, limited availability of shared cars and the high costs were found to be a main disadvantage. The spatial analysis had similar results to the survey, with the inclusion of diverse land use increasing the use of shared mobility. Shared mobility was used more for work and longer trips compared to private vehicles and less for educational purposes. Furthermore, shared bicycle and moped trips were predicted to replace walking and public transport trips. Large differences were not observed in general travel behaviour between different frequency groups. The results of this study suggest, among other things, that shared mobility needs to be made a more inclusive mode of transport. Increasing the availability, lowering the costs, and making shared mobility easier to use for older or lowly educated people will increase the inclusivity and use of shared modes.

Executive Summary

The availability and use of shared electric mopeds, bicycles and cars has risen over the years. However, a lot is still unknown about where, when, why and by whom these modes are used. Therefore, the following is studied: (1) the user characteristics of the three shared modes, (2) the reasons for (not) using shared mobility, (3) the effect of the built environment and demographics on the use and availability of shared mobility, (4) the trip characteristics of trips likely made by shared mobility and (5) the travel behaviour of different shared mobility user frequency groups.

User characteristics

In the first part of this research, user characteristics of shared car, bicycle and moped users have been identified. This is done by conducting a survey in Rotterdam and The Hague. The survey, setup by the SmartHubs project, was distributed in three phases; (1) digital and assisted at strategic locations in Rotterdam and the Hague, (2) distribution of flyers in Rotterdam and (3) distribution via LinkedIn. Two different analyses are conducted on the results of this survey, one being an analysis on the use of shared mobility modes and two being an analysis on the frequency of use.

The effect of certain demographic characteristics of the respondents, such as age, income and digital skills, were studied with two types of regression models. A logistic regression model, indicating the probability that a person used shared mobility the previous year, and a multinomial logistic regression model, analysing the frequency of use, were used to identify the different user characteristics influencing the use of shared modes. Correlation between the different characteristics was checked, before determining the best model based on AIC.

The logistic regression model shows high education levels and digital skills to be positively associated with the use of all shared modes. People with children, elderly and people that owned cars were found to be less likely to use one of the shared modes. People that are in the possession of a driving license are more likely to use shared cars or mopeds compared to people without a driving license. Furthermore, males are more likely to use a shared moped than females. The multinomial logistic regression shows a strong effect of increased digital skills, which made a person more likely to be a frequent user compared to non-frequent and no-users. Similar results were found for higher age groups for shared moped users.

Reasons for (not) using shared mobility

Reasons for and against using shared mobility modes are discussed in the second part of the research. Respondents, of the same survey as used in the first part of the research, were asked what their reasons for (not) using shared mobility were. The reasons for (not) using shared mobility were distinguished per mode.

The main reason for using shared cars, bicycles and mopeds was the fact that they provide more flexibility in travelling. The following reasons for use were also given users of all modes: increased accessibility, it reduces travel time, and shared cars and bicycles are easy to use. Costs were named as an important reason to not use shared mobility. However, preference for the use of a privately owned vehicle outweighs the other reasons. Furthermore, limited availability of shared cars was found to be a main disadvantage. Shared mopeds were also deemed unsafe, and people did not know how to use that vehicle. Suppliers of these vehicles and governmental bodies could thus improve the use by lowering the costs of all modes, increasing the availability of shared cars, providing training regarding the use of shared mopeds, and improving the safety of shared mopeds.

Spatial analysis

Thirdly, the effect of the built environment and demographics on the use and availability of shared mobility was studied. This was done by developing two negative binomial regression models based on demographic and land use data. The first model predicts the availability of shared cars per neighbourhood in the three largest metropolitan areas in the Netherlands (Amsterdam, Rotterdam-The Hague and Utrecht). The second model predicts the number of trips made with shared mopeds and bicycles in Rotterdam and The Hague. The demographic dataset included variables such as the age distribution of an area, the density and the household compositions. The land use dataset included for example, the percentage of the area belonging to a certain land use class, the land use mixture of the area and the number of public transport stops in an area.

After removing correlated variables and determining the significant variables, results show that higher urbanization level and mixed land use lead to a higher availability of shared cars. Higher shares of low and middle education levels, households with children, people older than 65 years old and males negatively associate with the number of available shared cars in a neighbourhood. High density, a higher average WOZ values, a higher number of public transport stops and a higher percentage of forest, commercial and recreational land use are positively associated with shared bicycle and moped trips. On the other hand, higher shares of people over 45 years old, households with children and males have a negative association with shared bicycle and moped trips.

Trip characteristics shared mobility

The fourth part of this research discusses the characteristics of trips that have a high likelihood of being made with shared mobility. For this part a trip dataset called the Nederlands Verplaatsingspanel (NVP) is used. The NVP collects travel data through a smartphone app. Travel data of approximately 10.000 people is collected in this dataset and generally viewed as representative for Dutch travel behaviour.

The NVP was used in the following ways to find the trip characteristics of shared mobility users. For all trips within this dataset, the number of trips likely to be made by shared mobility are determined based on the traveller characteristics and the origin of the trip. A proportion of trips is determined based on the spatial analysis. The trips of the users with the highest likelihood according to their socio-demographic background were selected as high likely trips made with shared modes and analysed.

It was found that shared car trips are more likely to be made for work and recreational purposes and less for shopping purposes. Shared car trips are also more likely to be longer than 20 kilometres. Shared bicycle and moped trips were combined in this part of the research because of data constraints. Trips for work or shopping purposes have a higher share for shared bicycle/moped trips than for bicycle trips in general. Recreational and educational trips have lower shares. Shared bicycle and moped trips are more often between 2.5 and 10 kilometres and less shorter trips than bicycle trips in general. Furthermore, shared bicycle and moped trips are predicted to replace walking and public transport trips and not car trips.

Travel behaviour shared mobility frequency groups

Finally, the general travel behaviour of different shared mobility user frequency groups is analysed. In this part, the probability a certain user falls within a specific user group (not, non-frequent and frequent) is calculated for all users in the NVP. Their trips are weighted based on this probability. The trip characteristics being the mode of transport, trip motives and trip distances are then analysed based on these weights.

Large differences were not observed in the travel behaviour and trip characteristics of the different user groups. However, shared bicycle and moped no-users were found to travel more often by bicycle and for work, whilst shared bicycle non-frequent users and shared moped frequent users travelled more often by public transport and for shopping purposes. Frequent shared bicycle users and non-frequent shared moped users travelled more by car and for recreational purposes. The no user of shared cars was found to travel more by car and for work purposes. Frequent shared car users travelled more often by public transport and for shopping and recreational purposes. Trip distances were not found to differ between the different user groups.

Discussion and conclusion

This research has provided a better understanding into the users, locations of use, reasons for (not) using and trip characteristics. Governmental bodies and shared mobility providers are advised to use this research, as they can learn from the findings. Firstly, shared mobility is not found to be inclusive. Secondly, reasons for not using shared mobility can help the providers to improve their modes. Furthermore, it is important that the availability of shared cars is increased.

It is advised that further research is conducted into the characteristics of shared mobility trips by using the same set of people for all different analysis and by studying known trips of shared mobility modes. Furthermore, the study of actual shared mobility trips could give an even better understanding of the trip characteristics of shared mobility trips. Also, an increase in unique users in the NVP will help these types of studies in the future.

Preface

This thesis marks the end of my time as a Civil Engineering student at the University of Twente. In the past six months I have been working on this research on shared mobility, and why, where, by whom and for what it is used as a mode of transport. I have conducted this assignment on behalf of Goudappel and the University of Twente and I hope that my research can contribute to their work in the future.

Throughout my research, I have had the support of many people around me, for which I am very grateful. I would like to thank my supervisors for their guidance and feedback. From Goudappel these were: Bernike and Johan, it has been a pleasure to collaborate with you both, especially when I had difficulties with my research in any way you were always there to brainstorm or discuss what I could do best. You both, together with a lot of other colleagues, have helped me to explore what working at Goudappel entails. Also working at the office in Deventer and the Hague, something I was not able to do during my Bachelor thesis research due to the coronavirus outbreak, has helped me in getting a better overview of how it is to work in such an environment. From the University of Twente, I would like to thank Anna Grigolon and Karst Geurs, thank you for your guidance and different point of views to help me scope and finalise my research.

I hope you will enjoy reading this report.

Daan Knijnenburg

Enschede, October 2023

Content

1. Introduction

In the past decades, the number of travelled passenger kilometres has increased (International Transport Forum, 2021). However, this comes with a cost to the environment, since the Greenhouse gas emissions (GHG) from the transportation sector have increased over 75% from 1990 to 2017 (Climatewatch, 2017). This increase has made transport among the highest emitting sectors in the world, with a share of 17% of the total GHG emissions being emitted in the world (Statista, 2022). To reduce the emissions in this sector, a global climate action pathway has been set up that is focused on reducing the transport demand, shifting to more environmentally friendly modes, making the transport sector more resilient and improving the efficiency of the different modes (Marrakech Partnership, 2021).

The availability and use of shared mobility, such as shared electric mopeds, bicycles and cars has risen over the years in order to contribute to making the transport sector more resilient and efficient (Heineke, Kloss, Möller, & Wiemuth, 2021). However, research of the Dutch Knowledge institute for Mobility policy (KiM) showed that the presence of these shared modes hardly lead to less car ownership and use, whilst the use of public transport, personal bicycles and walking was even reduced because of the presence of shared mobility modes (Jorritsma, Witte, González, & Hamersma, 2021). The presence of shared mobility modes has also led to nuisance in the cities, which made some Dutch cities considering tightening the regulations or even remove certain shared modes from their cities (Pointer, 2022). Although the rapid development of shared mobility brings its problems, the possible benefits to environmental and social sustainability goals are still high (Shokouhyar, Shokoohyar, Sobhani, & Gorizi, 2021).

To contribute to the environmental and social goals, it is important to get a better understanding of the use of shared mobility. Mouratidis (2022) has contributed to this by studying shared mobility user characteristics and built environment characteristics of user's residential locations. However, this is the only study doing so and it has some limitations in applying the results. An addition of shared mobility trip data and the built environment characteristics of the areas of origin and destination of these trips will also contribute to understanding the use of shared mobility better.

Therefore, this research will identify the user characteristics of current shared mobility users, potential users and no-users via a survey. Also, built environment characteristics influencing the presence and use of shared mobility modes will be studied. Furthermore, longitudinal travel data will be assessed to identify travel patterns based on the user groups and on a trip likelihood that is derived from built environment, demographics, the availability of shared mobility and trip data.

2. Study area

The metropolitan area of the four largest cities in the Netherlands will be used as a study area. These cities are Amsterdam, Rotterdam, The Hague, and Utrecht. The metropolitan areas of these cities are shown in Figure 1. These cities have been selected since they have a high density, which leads to more use of shared mobility modes and a high availability of shared mobility modes (Mouratidis, 2022). According to the CROW (2023), the cities together have approximately 10,000 shared mobility vehicles within their cities, which is almost twice as much as the rest of the Netherlands combined. Furthermore, these cities have a large number of trips starting and ending in the cities, because of their high number of residents (approximately 7.3 million (CBS, 2022)) which makes sure that there are a sufficient number of trips to study.

The metropolitan area Rotterdam - The Hague, as shown in blue in Figure 1, is of specific interest, since a survey will be conducted within this area. This area consists of twenty-one municipalities around Rotterdam and The Hague who decided to bundle their forces to improve their economy, accessibility and growth (Metropoolregio Rotterdam-Den Haag, 2023). By collaborating, the policies and visions of the area aligns and the possibilities for especially the smaller regions within the area increase (OECD, 2016).

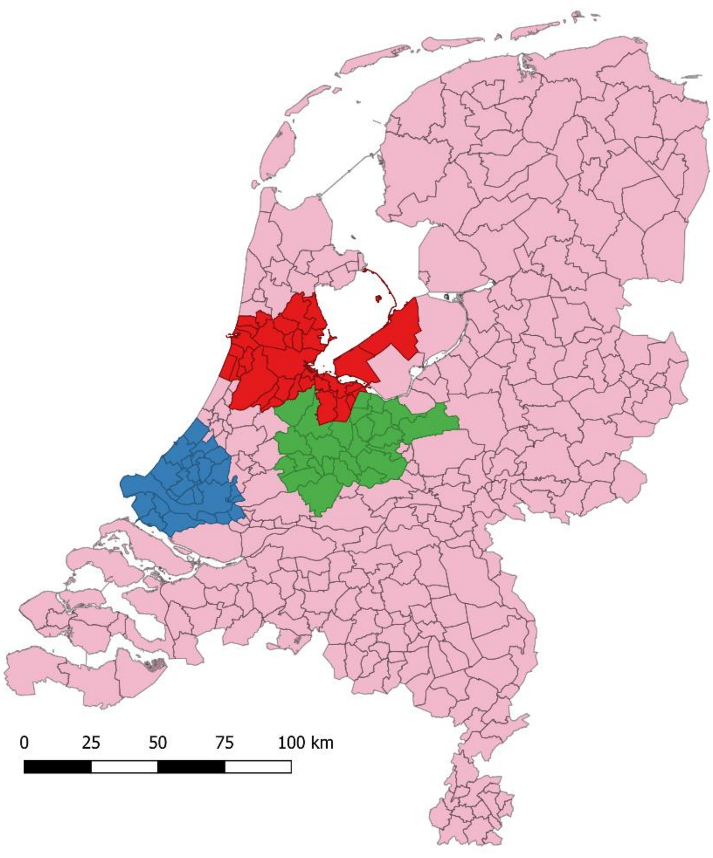

Figure 1 – The metropolitan areas of Rotterdam - The Hague (blue), Amsterdam (red) and Utrecht (green) within the context of the Netherlands

3. Research questions

To assess the potential of shared mobility within the metropolitan areas of Rotterdam – The Hague, Amsterdam and Utrecht, five research questions have been set up. The potential of shared mobility is assessed based on user groups and trip characteristics. These are determined based on survey data and longitudinal travel data.

1. What are characteristics of shared mobility users in the Rotterdam – The Hague area?
2. What are reasons for people to (not) use shared mobility modes?
3. What is the effect of built environment factors and demographics on the use of shared mobility modes?
    a. What is the effect of built environment factors and demographics on the location of shared cars?
    b. What is the effect of built environment factors and demographics on the origins and destinations of trips made with shared mopeds/bicycles?
4. What are the trip characteristics of trips that have a high likelihood to be made by shared mobility in the studied metropolitan areas based on the built environment factors and demographics of the originating area, and the characteristics of the user?
5. What are the general trip characteristics of the identified user groups of shared mobility in the studied metropolitan areas?

4. Theoretical Background

The probability for people to use a specific mode of transport is based on multiple factors, which has led to multiple studies being conducted into the determinants for individuals to choose a specific mode. Ton et al. (2020) for example determines four categories of factors influencing mode choice, availability of modes, trip characteristics, network characteristics and individual characteristics. Scheiner & Holz Rau (2007) also identify a relation with lifestyle since that factor plays an important role in location decisions which in turn influences travel mode choice. There are also mode specific factors influencing mode choice. For example for active modes, Heinen et al. (2010) and Hunt & Abraham (2007) have determined that weather characteristics and built environment also influence mode choice.

In the following sections specific determinants are discussed. Firstly, the effect of individual characteristics will be discussed, which will correspond to the study into the user characteristics and the effects of demographic and land use conducted in this research (Research question 1 and 3). Secondly, the influence of trip characteristics will be discussed. This relates to the third research question. Thirdly, the effects of availability of different modes are discussed, which relates to the first and third research questions. Fourthly, the effect of cultural background is discussed. Finally, the influence of built environment on mode choice and use is discussed. This relation is also studied in this research in the third research question.

4.1. Individual characteristics

Individual characteristics consist of all determinants related to the socio-demographics of a person. Socio demographic factors that are often used in mode choice studies are age, gender, and education level. According to Ton et al. (2020) people older than 50 years use more active modes to commute compared to younger people. Whilst Wang et al. (2021a) and Becker et al. (Becker, Ciari, & Axhausen, 2017) found a decrease in shared mobility utility when age increased.

Furthermore, Vij et al. (2013) concluded that men were more likely to use the car compared to women, who according to Heinen et al. (2010) and Ton et al. (2019) tend to choose the bicycle more often and according to Wang et al. (2021b) are more willing to use carsharing. Women are, however, less likely to use shared mopeds (Laa & Leth, 2020).

Next to that Ton et al. (2020) found that cars are less used by individuals with lower education levels and the bicycle and train are more attractive for an individual with a high education level. However, Calastri et al. (2019) and Muñoz et al. (2016) did not found a significant relation with education levels. Shared mopeds and cars are used more by highly educated persons (Ciari, Weis, & Balac, 2016; Laa & Leth, 2020).

Another possible determinant is the income. Income influences mode choice, since lower incomes are more likely to use car sharing and public transport, whilst private car use and shared bicycles are more frequent amongst high incomes (Vossebeld, 2022; Paulley, et al., 2006; Barri, et al., 2021; Winters, Hosford, & Javaheri, 2019).

Also, the size and composition of the household are found to be a determinant. The presence of children in the household increases the probability of including walking and the car in the experienced choice set and reduces car sharing. Besides that, also an individual living in a household consisting of one or two persons is more likely to include walking or car sharing in the experienced choice set compared to an individual living in a larger household. (Ton, et al., 2020; Celsor, 2007)

Finally, the digital skills of an individual can influence the use of a certain mode, especially shared modes. Durand et al. (2022) argued that the increased reliance on smartphones increases inequality due to not everyone being able to derive all its benefits. For similar reasoning, public transport use is also positively associated with increased digital skills. Horjus et al. (2022) found that the intention to use shared transport (so public transport and shared mobility) was higher for people with higher levels of digital skills, although they also mentioned that digital skill level tends to be correlated with age and education so including this variable should be done with care. Both studies only looked at the effect of digital skills on shared modes all together and also no other studies were found where the effect of digital skills was studied for a specific shared mode.

4.2. Trip characteristics

Determinants related to trip characteristics are for example, the travel time, costs, and distance. Active modes are generally used less when the distance (and thus time) increases (Heinen, van Wee, & Maat, 2010), whilst the use of cars increases with the distance (Buehler, 2011). The different types of public transport are all designed for specific distances and also used for these purposes.

Travel costs also influence mode choice. Higher ticket prices for public transport for example lower the use of these modes, although this mainly depends on the user type (Paulley, et al., 2006). This can also be seen for car use: when the fuel price increases less trips are made, although this mainly holds for short trips (Schuitema, Steg, & Vlek, 2007). Travel costs also influence shared mobility, since e-scooter are used more often because of their use costs being perceived to be low (Sanders, Branion-Calles, & Nelson, 2020).

4.3. Availability of modes

The availability of a certain mode is an important determinant for using a mode. Factors like driving licences, car ownership, bicycle ownership and proximity to modes are all possible determinants. Having a driver's license is for example positively associated with the inclusion of the car and shared car in the mode choice set and also use (Ton, et al., 2020; Vossebeld, 2022).

Ownership of a car or bicycle relates positively to the use of that specific mode, whilst reducing the use of other modes (Muñoz, Monzon, & Daziano, 2016; Heinen, van Wee, & Maat, 2010). Especially the use of shared mobility modes is affected by this factor (Bachand-Marleau, Lee, & El-Geneidy, 2012). Owning a bicycle positively relates to including the bicycle in the choice set, which is in line with literature (Heinen et al., 2010; Muñoz et al., 2016).

Urban density is another determinant for mode choice. Lower urban density makes it less likely for public transport to be used as a mode due to limited accessibility of this mode (Ton, et al., 2020). Higher urban density in general leads to less car trips and more use of active modes, shared mopeds and shared bicycles due to the high proximity to services (Heinen, van Wee, & Maat, 2010; Bachand-Marleau, Lee, & El-Geneidy, 2012). Furthermore, in more dense urban areas the use of car sharing is increased, due to the higher chance of parking problems and the fact that people in this area are perceived to be less dependent on private cars (Vossebeld, 2022).

4.4. Culture and attitude

The culture and attitude of people also affects the mode choice. The individual opinions regarding for example sustainability can affect the travel behaviour by using greener modes of transport more often (Buehler, 2011). Also, cultural backgrounds can influence mode choice. People from a non-western origin tend to cycle less for example (Haustein, Kroesen, & Mulalic, 2020). The relation of these characteristics with mode choice is often not included in studies, however Scheiner and Holz-Rau

(2007) found a relation between certain lifestyles and the residential location choice, urban form and travel mode. However, the lifestyle of a person is difficult to determine and often subjective.

4.5. Built environment

The built environment also has it effects on mode choice. Parking facilities, public transport stations and land use are examples of built environment factors that can influence mode choice (Ewing & Cervero, 2001). Car parking facilities near the destination or the origin of a trip have a positive effect on car use (Christiansen, Engebretsen, Fearnley, & Usterud Hanssen, 2017). However, car parking facilities near the route of a cyclist also have a negative effect on the use of bicycles (Heinen, van Wee, & Maat, 2010). Shared mobility modes such as mopeds and bicycles are also used more in areas with less car parking facilities (Vossebeld, 2022). A lack of car parking facilities can increase the willingness to use public transport, however the presence of a Park and Ride's (a specific type of car parking facilities providing day-time parking at public transport stops) increases public transport use (Lidström Olsson, 2021). Bicycle parking facilities also effect the choice of using certain modes of transport. The presence of a sufficient amount of bicycle parking spaces increases the use of bicycles and public transport (Rijkswaterstaat, 2023b).

Distance to public transport stops has a negative effect on the use of public transport, meaning that the longer the distance to a stop, the less a user is inclined to use that mode (Lunke, Fearnley, & Aarhaug, 2021). Van Kuijk et al. (2022) concluded that shared mobility is used frequently near a public transport station as first and last mile mode. Also, bicycles are chosen frequently as preferred mode around public transport stops (Saelens, Sallis, & Frank, 2016). Furthermore, the number of transit stops in a neighbourhood also has a positive effect on the use of shared cars, since the availability of shared cars is found to be higher in these areas (Khan & Machemehl, 2017).

A mixed land use has been found to have a negative effect on car use and a positive effect on walking and cycling, since within a mixed land use neighbourhood the proximity to different activities is high (Landis & Reilly, 2002). A high proximity to different activities can also lead to an increase in use of shared scooters and bicycles (Cohen & Shaheen, 2016). Also, specific land use areas can influence mode choice. Close proximity to shopping areas have a positive effect on bicycle use, whilst having a negative effect on car use (Landis & Reilly, 2002). The relation between specific land use areas and shared mobility modes is however still unknown.

4.6. Overview of the effects of different factors on mode choice

In the previous sections the effects of different factors on the use of different modes have been discussed. In Table 1 an overview is provided of these effects. The findings of the different user characteristics and the findings of the spatial analysis will be compared to these findings in literature to compare the results and effects of different determinants.

Table 1 - Effects of mode choice determinants on the use of a specific mode

Influencing factor	**Car**	**Bicycle**	**Public Transport**	**Shared Car**	**Shared bike or scooter**
Age	-	Positive	-	Negative	Negative
Men	Positive	-	-	-	-
Women	-	Positive	-	Positive	Negative
Education level	Negative	Positive	Positive	Positive	Positive
Income level	Positive	-	Negative	Negative	Positive
Children in household	Positive	-	-	Negative	-
Digital skills	-	-	Positive	Positive	Positive
Household size	-	-	-	Negative	-
Travel distance	Positive	Negative	-	-	Negative
Driver's license	Positive	-	-	Positive	-
Car ownership	Positive	Negative	Negative	Negative	Negative
Density	Negative	Positive	Positive	Positive	Positive
Car parking facilities	Positive	Negative	-	Negative	Negative
Distance to transit stop	-	Positive	Positive	Positive	Positive
Mixed land use	Negative	Positive	-	Positive	Positive

5. Research framework

This research will follow the steps as visualised in Figure 2. To answer the research questions, three main analyses will be conducted to assess the potential of shared mobility modes. These three parts are shown in the different colours in the figure. The blue part of the framework contains the survey, whilst the green part of the framework shows the analysis of the locational data. The orange part of the framework contains the trip characteristics analysis based on the data of the "Nederlands Verplaatsingspanel" (NVP). The purple box in the framework depicts the conclusion of this research. In the subsections of this chapter, a brief overview of the method per research part is given. The more detailed methods are described in the subsequent chapters answering the research questions that are linked to those chapters.

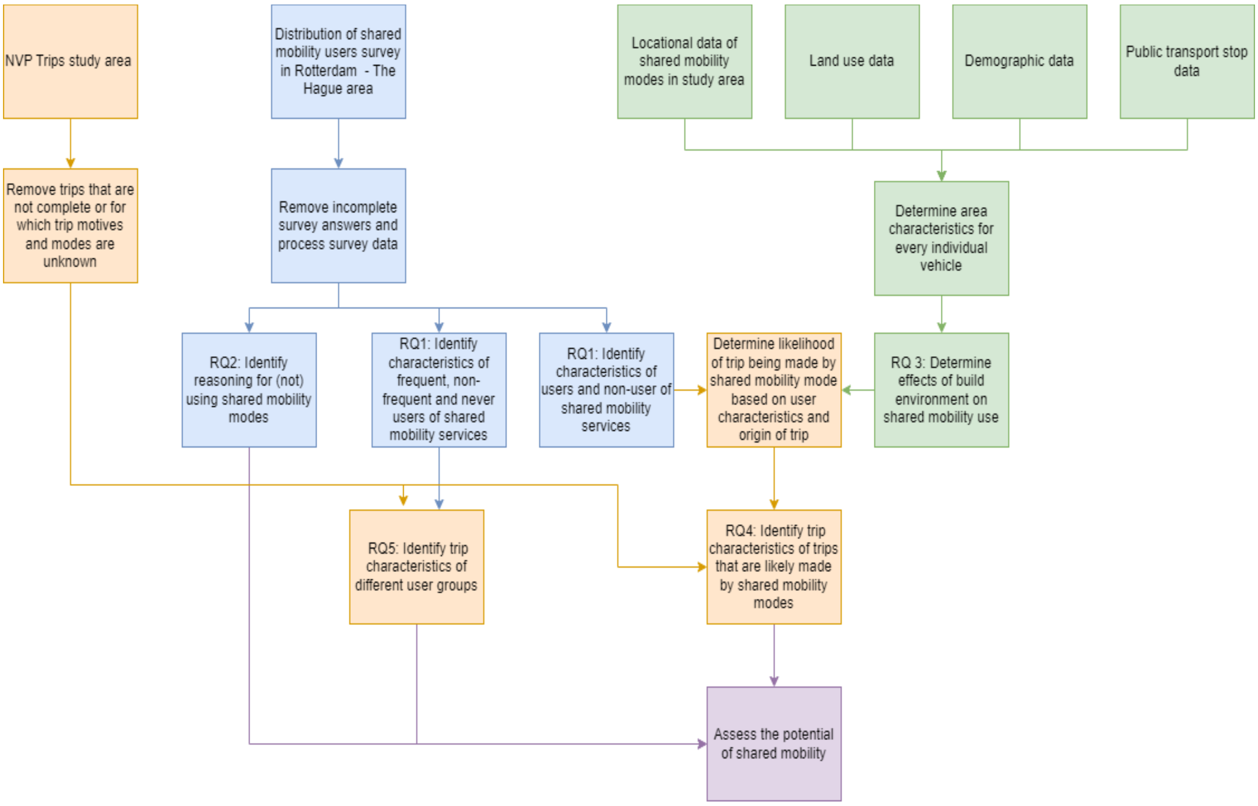

Figure 2 - Research framework

5.1. Survey

As shown in Figure 2, the research is split up into three parts. In this section the method of the blue part of the research framework is discussed. The first part of this research uses a survey by the SmartHubs project (SmartHubs, 2023). The aim of this survey is to get a better understanding of current travel behaviour and the opinion on mobility hubs of the respondents. The survey consists of questions about the demographic background, the travel behaviour, digital skills, shared mobility hub use and stated preference for different hub designs. This survey was distributed prior to the start of this research in the Rotterdam-The Hague metropolitan region digitally and on specific locations throughout the city to increase the sample size of people not using phones.

Extra respondents were gathered during this research by distributing flyers (see Appendix A) at strategic locations in Rotterdam. These locations are the Rotterdam Central station, Blaak, Beurs, Eendrachtsplein and Hofplein. These locations were chosen based on a short analysis of shared car parking locations and trips made by shared mopeds and bicycle (CROW, 2023). During three weekdays, flyers were distributed at these locations at different times of the day to achieve a sufficient number of respondents. The survey has also been shared on LinkedIn.

To identify the frequency of using shared mobility modes, a frequency question (visualised in Appendix B, Figure 51), is used. Three groups are made based upon the responses, (1) frequent users, (2) non-frequent users and (3) non-users. This aggregation is done due to a limited number of observations in the highly frequent groups and since the frequency of using shared mobility is in general low in the Netherlands (Jorritsma, Witte, González, & Hamersma, 2021). Frequent users are defined as people using shared mobility modes more than once a month. This threshold is determined based on 2.7 trips on average per person per day and shared mobility modes making up 2 percent of the modal split in the Netherlands making the use on average approximately 20 times per person per year (Stumpel & Weperen, 2022; CBS, 2023e). Non-frequent users are defined as people using shared mobility at least once a year and not more than once a month, whilst the rest of the people is defined as non-users. A more detailed method on determining these user groups and the resulting characteristics associated with every user group are discussed in Chapter 6.

Besides an analysis of the characteristics of different user groups, the characteristics of persons using or not using shared modes is studied. The process in determining these characteristics is similar to the user groups and also the same survey questions are used. However, all users are assigned to two groups, (1) users and (2) non-users. The detailed method and results are again discussed in Chapter 6.

The survey is also used to answer the second research question, the reasons for (not) using shared mobility. Questions about the reasoning for not using shared mobility were already included within the SmartHubs survey (see Appendix B, Figure 55, Figure 56 and Figure 57). However, an additional set of questions has been added about reasons for using shared mobility (see Appendix B, Figure 52, Figure 53 and Figure 54). Based on the answers on these questions, conclusions can be drawn on this research question. The results are discussed in Chapter 7.

5.2. Spatial analysis

The second part of this research, depicted in green in Figure 2, is a study into the effects of built environment and demographics on the availability and use of shared mobility modes. Firstly, data on trips with and parking locations of shared mobility vehicles are gathered together with demographic data and built environmental data for the entire study region. The data used in this research is shown in section 8.2.

After collecting the data, a regression analysis is conducted to assess the effects of the different variables on the use and availability of shared cars, bicycles and mopeds. The considerations for using a regression model and detailed methodology for this analysis are discussed in section 8.1. Based on the regression analysis, multiple models are set up to determine the effect of the different variables on the different modes and also for the different study regions. The results of this part of the research give an answer to the third research question and the corresponding sub questions and are discussed in section 8.3.

5.3. Trip characteristics

The final part of this research, shown in orange in Figure 2, is an analysis of the characteristics of trips likely made with shared modes. In this part trips of the NVP are assessed based on the user characteristics found in the first part of the research and the spatial analysis conducted in the second part of the research.

The NVP is a panel that collects travel data through a smartphone app. This app is developed by Mobidot in 2013 and the NVP started their data collection procedure in 2019. The NVP is an initiative of not only Mobidot, but also Dat.mobility and Kantar, of which Dat.mobility creates insights into the travel behaviour and Kantar is responsible for the recruitment of a representative group of people using the app. This group is selected and recruited from a panel from Kantar of up to 200.000 participants. A set of approximately 10.000 participants is selected from this panel who using the app provide an overview of their trips throughout the day. This app determines the modes and the motives for these trips automatically, which makes this type of data collection less work for the participant compared to surveys. The app can also be used for distributing specified surveys to understand specific travel choices of the users and to collect additional information on certain topics. (Dat.mobility, 2022)

The NVP classifies a trip as a travel by one mode. Since a person can use multiple modes to travel from A to B, the NVP classifies the different trips involved in getting a person from their origin to their destination as a journey. On a day, a person may make multiple journeys before returning to their home (or sleeping) address. Within the NVP, this set of journeys is classified as a tour.

For every trip in the NVP, general information of the participants is known, which entails a range of socio-demographic variables, like age and gender, but also household characteristics. Furthermore, during the trip general information (like speed, distance and mode) is gathered, but also geographical data (start and end point, points on route and used streets) and externalities (like costs and weather) are saved. Mobidot stores data of the last 91 days which can be directly accessed, whilst Dat.mobility stores the entire trip dataset since the start in 2019. With this data, Dat.mobility can visualise demand overviews per hour and day of the week, but also modal splits and modal shift data can be visualised on a detailed level. An example of the applicability of this data was the monitoring of the impact of COVID-19 safety measures on the travel behaviour in the Netherlands (van der Drift, Wismans, & Olde Kalter, 2022).

Two different analyses are conducted on the NVP trips. Firstly, an analysis is done on this dataset to determine the trip characteristics of trips with a high likelihood of being made with shared modes. This is done for the shared car and a combination of the shared moped and bicycle. Trip characteristics such as trip distance, motive and mode are assessed to see whether certain trips have a higher likelihood of being made with shared mobility than others. The detailed methodology and results for the fourth research question are discussed in Chapter 9.

The second analysis on the NVP trips is a study into the general trip characteristics of the different user groups as determined in Chapter 6. For this part, again the modes of transport, trip motives and trip distances are studied to see whether there is a difference in travel behaviour between the user groups. The results of this part are discussed in Chapter 10.

6. Identify user groups of shared mobility

The identification of the characteristics of different shared mobility frequency user groups and the use of shared mobility is the first part of the research. This chapter presents the methodology used to identify these characteristics and elaborates on the results of the first research question: *what are characteristics of shared mobility users in the Rotterdam – The Hague area?*

6.1. Methodology

In order to identify the effect of certain characteristics on the use of shared mobility two regression analysis are conducted. First, the probability of an individual belonging to a certain shared mobility frequency class is analysed (frequent, non-frequent and not). Secondly, it is analysed which determinants affect whether an individual uses shared cars and shared mopeds/bicycles (yes or no). To determine this, a discrete outcome model is used. This type of regression modelling depicts the probability of a certain individual to choose a given option (Labbé, Laporte, Tanczos, & Toint, 1998).

In a discrete outcome model, the dependent variable is a categorical variable, which for the frequency of use entails whether an individual is a frequent user of shared mobility, non-frequent user or no user of shared mobility. Commonly used discrete outcome models are Logistic Regression, Probit Regression, Multinomial Logit Model and Ordered Logit/Probit Model (Washington, Karlaftis, & Mannering, 2003). As the dependent variable in the frequency of use model consists out of three categories, a multinomial and an ordered logit model can be used. A multinomial logit model is used when the dependent variable is unordered, for example for choices between different modes of transport (Agresti, 1996). The results of both regression models were analysed, in which an unordered relation in the dependent variable was observed. It was found that the effect of the different independent variables on the different user groups was not similar to the intersects and led to high prediction errors. Since these prediction errors were less severe when using a multinomial logit model, the multinomial logit model is used. The regression equation for a multinomial logit model is presented in Equation 1.

$$p_j = \frac{\exp\left(\beta_{0j} + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k\right)}{1 + \exp\left(\beta_{0j} + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k\right)} \qquad \text{Eq. 1}$$

Where p_j represents the probability of the dependent variable falling into category j, the β_{0j} represents the intercept term for category j, the rest of the β's represent the coefficients per independent variable and the X's represent the independent variable values (Agresti, 1996).

For the question whether an individual uses shared mobility, with a binary dependent variable indicating the use, a logistic regression model is best suited (Fávero, Belfiore, & Souza, 2023). In Equation 2, a logistic regression formula is shown. It is similar to the ordered logistic regression equation, however, the output is given as the probability of y being classified as 1.

$$p(y) = \frac{1}{1 + \exp\left(\beta_{0j} + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k\right)} \qquad \text{Eq. 2}$$

Independent variables will be selected based on a few criteria. Firstly, the correlation between the different independent variables is analysed. The correlation is assessed based on the Cramer's V test, a test to assess the strength of an association between two categorical variables (Akoglu, 2018). The values of this coefficient range from 0 to 1, where variables have a high correlation when the values are higher than ± 0.5 (Cohen J. , 1977). When this is the case, one of the two variables should be dropped.

After correlation is verified, a heuristic algorithm is used to assess which selection of independent variables is used to best determine the dependent variable (Calcagno, 2022). The algorithm undertakes an genetic screening, which is an intelligent probabilistic search algorithm which simulates the process of evolution by taking a population of solutions and only developing the highly fit solutions further into new solutions based upon predetermined criteria until a satisfactory solution is found (Chu & Beasley, 1997). In this case the criterion for the algorithm is the Akaike Information Criterion (AIC), which is a statistical measure that balances model fitness and complexity in selecting the best selection of variables. The higher the AIC value becomes, the worse a model performs (Akaike, 1985). Based upon this algorithm the importance of individual independent variables can be assessed based upon the times a variable is included within the best performing models. An importance of more than 95% is chosen for an independent variable to be included within the final model in order to limit the complexity.

6.2. Results

Based on the methodology described above, the survey has been distributed and analysed and the regression models have been set up. The results of these aspects of the research are described in the following section.

6.2.1. Survey results

During this research a survey is used, which was introduced in Section 5.1. The survey had 900 responses in total. The survey was distributed in three phases: (1) initial distribution (N = 805, response rate = unknown), (2) distribution by flyers (N = 66, response rate = 10.3%) and (3) distribution via LinkedIn (N=29). The initial distribution conducted by the SmartHubs project was done digitally and assisted, whilst the survey was only conducted digitally for the respondents gathered by flyers and LinkedIn. The flyers were distributed on 4, 6 and 7 July from 7:30 till 18:00 at Rotterdam Central station, Beurs and Blaak. No flyers were distributed at the Eendrachtsplein and the Hofplein due to a limited number of people at these locations.

In Table 2, the socio-demographic characteristics of the survey respondents are compared to characteristics of the full population of Rotterdam and The Hague to check the representativeness of the survey sample. Also, the characteristics of the survey respondents are split between both distribution phases.

Both genders are equally distributed within the survey, which is similar to the general population of Rotterdam and The Hague. In this survey the age group of 18-25 is underrepresented, which was the case for both distribution phases. Furthermore, the survey sample has a high bias towards high education and people with a middle income, whilst low and middle education levels and people with low income are underrepresented. The bias towards high education can be explained by the second distribution, in which 62.3% of the sample is highly educated. The bias towards middle income levels can be caused by the categories in the survey not corresponding to income levels used by the CBS and the municipality of Rotterdam.

Since the bias towards high education and middle income can have a strong effect on the results of the regression analyses, weighing the survey results can increase the reliability and validity (Dey, 1997). In this research the survey results are not weighed, however the effect of adding weights is assessed on the use of shared cars. In Appendix L, Table 20 the results are shown. From these results it can be observed that there is a limited difference between the results of weighted responses and the non weighted responses (see Table 4). Especially, the coefficients do no differ much, however digital skills were not included in the weighted model and gender was.

Table 2 - Comparison of socio-demographic characteristics of survey respondents and population of Rotterdam and The Hague (CBS, 2023d; Gemeente Rotterdam, 2023)

Variable	**Population of Rotterdam**	**Population of The Hague**	**Sample full survey**	**Sample first distribution phase**	**Sample second distribution phase**
Number of people	655,106	565,205	712	635	77
Gender					
Male	49.4%	49.8%	49.9%	48.2%	63.6%
Female	50.6%	50.2%	50.1%	51.8%	36.4%
Age group[1]					
18-25	13.2%	15.1%	8.9%	8.7%	10.4%
25-39	30.6%	36.0%	32.4%	30.4%	49.4%
40-54	22.7%	30.9%	25.1%	25.5%	22.1%
55-64	14.3%		12.2%	12.0%	14.3%
65 and older	19.2%	17.9%	21.3%	23.5%	3.9%
Education level[2]					
Low	30.7%	30.1%	25.7%	28.0%	14.3%
Middle	37.4%	34.3%	21.2%	22.7%	23.4%
High	31.9%	35.6%	53.1%	49.3%	62.3%
Income level[3]					
Low	44.2%	41.5%	17.3%	17.6%	6.5%
Middle	37.0%	21.0%	60.6%	65.2%	9.1%
High	18.8%	30.5%	22.1%	17.2%	84.4%

Note: 1. Age group percentages have been calculated without taking people under 18 years old into account. Also, age categories of The Hague are 15-25, 25-45, 45-65 and 65 and older.
2. Education levels have been defined similarly to the CBS **(CBS, 2023d)**.
3. Low income is set at maximum monthly income of 1600 euro **(CBS, 2021)**. High income is set from 4801 euro and higher **(CBS, 2023a)**.

As discussed in Section 5.1, three user groups are determined. In Figure 3, the number of respondents per user group per mode of transport are shown. This figure shows that the non-users are represented the most for all shared modes and that especially for the shared car only a small number of frequent users (50 out of 711 total users) have filled out the survey. When comparing the percentages of respondents per user group with results of a travel survey on a national scale from MuConsult (2021), who determined that 5% of the respondents had used a shared bicycle or car and 3% a scooter at least once in 2020, the percentage of people using a shared vehicle is higher in this sample. However, the supply of vehicles has increased rapidly over the past years, so the research of MuConsult can be outdated (Ministerie van Infrastructuur & Waterstaat, 2023).

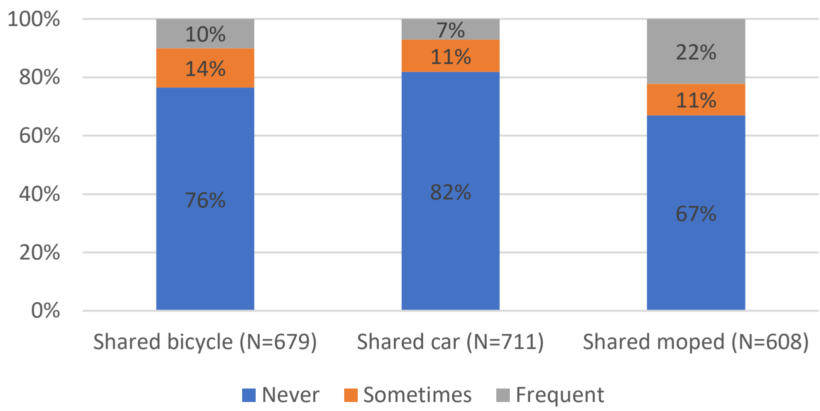

Figure 3 - Percentages of total number of respondents per shared mobility user group per mode of transport

6.2.2. Final model frequency of shared mobility use

There are various characteristics of respondents gathered in the survey, of which the definition can be seen in Appendix C, Table 10, however not all are included in the final regression model. To determine the independent variables to include into a regression model to predict the frequency of shared mobility use by an individual, firstly the Cramer's V score between the different characteristics of a respondent in the survey is calculated. The outcome per variable of the Cramer's V score can be found in Appendix D, Table 11. From these scores, occupation could be seen to have a high relation with age groups (0.49), whilst also having relatively high scores when tested against education level and income level (0.31 and 0.38 respectively), therefore the occupation of an individual is not included in a model when education or income is included. Since income and education are expected to be correlated and show a medium correlation (0.28) also income and education are not included in one model together.

After determining correlation between independent variables, the heuristic algorithm has been used to determine the most important variables. Whilst manually taking the exemptions of the correlation test into account, the most important variables according to this algorithm have been selected and are shown in Table 3, with corresponding regression coefficients and standard error (between brackets). High education, zero children, having a drivers license, age between 25 and 39 and the female gender have been selected as reference scenarios. These have been chosen as reference scenario based on the fact that they are the most occurring category. Furthermore, digital skills level 1 has been set as a reference scenario, as it was expected that with increased digital skills the likelihood of being a frequent or non-frequent user increase compared to the no user which is the reference category for the multinomial regression.

Table 3 - Regression output multinomial logistic regression predicting frequency of shared mobility use

	Shared car	Shared bicycle	Shared moped
Non-frequent			
Intercept	-0.17 (0.23)	**-2.03**** (0.76)	**-2.74*** (1.07)
Low education	**-1.12**** (0.41)	**-0.91**** (0.34)	**-0.88*** (0.40)
Middle education	-0.55 (0.42)	**-1.42**** (0.47)	**-1.00**$^{\cdot}$ (0.54)
1 child	-0.04 (0.43)	-0.06 (0.40)	**1.18**** (0.38)
2 children	0.48 (0.44)	-0.25 (0.46)	0.44 (0.45)
More than 2 children	**-14.09***** (0.00)	**1.40*** (0.56)	**1.21**$^{\cdot}$ (0.64)
No driving license	**-1.30**** (0.47)		0.04 (0.80)
Age below 25	-0.71 (0.49)	0.23 (0.39)	0.73 (0.55)
Age of 40 – 54	**-0.81*** (0.34)	**-0.52**$^{\cdot}$ (0.30)	**-1.00**** (0.35)
Age of 55 – 64	**-2.08**** (0.76)	**-0.83**$^{\cdot}$ (0.48)	**-1.99**** (0.77)
Age of 65 and older	**-1.07*** (0.43)	**-2.40**** (0.75)	**-1.92**** (0.66)
Male			0.23 (0.30)
Number of owned cars	**-1.12***** (0.23)	**-0.37**$^{\cdot}$ (0.20)	-0.26 (0.24)
Digital skills Level 2		**1.36**$^{\cdot}$ (0.75)	1.72 (1.05)
Digital skills Level 3		**1.65*** (0.76)	**1.98**$^{\cdot}$ (1.05)
Frequent			
Intercept	**-1.50***** (0.32)	**-3.10**** (1.05)	**-2.68*** (1.07)
Low education	-0.22 (0.39)	**-0.87*** (0.38)	-0.37 (0.32)
Middle education	0.06 (0.44)	**-2.34**** (0.76)	-0.48 (0.43)
1 child	**0.96*** (0.39)	**1.13**** (0.37)	0.44 (0.34)
2 children	0.61 (0.51)	**0.76**$^{\cdot}$ (0.44)	-0.51 (0.43)
More than 2 children	**-13.61***** (0.00)	0.01 (1.11)	-1.68 (1.08)
No driving license	**-0.94**$^{\cdot}$ (0.52)		**-16.09***** (0.00)

Age below 25	-0.00 (0.51)	-0.09 (0.51)	**1.34**** (0.41)
Age of 40 – 54	-0.36 (0.38)	**-0.75*** (0.36)	**-1.33***** (0.30)
Age of 55 – 64	-0.58 (0.55)	-0.43 (0.54)	**-2.49***** (0.56)
Age of 65 and older	**-1.64*** (0.66)	-0.91 (0.58)	**-16.87***** (0.00)
Male			**0.62*** (0.25)
Number of owned cars	**-0.78**** (0.27)	-0.27 (0.23)	-0.23 (0.20)
Digital skills Level 2		1.35 (1.04)	**2.25*** (1.05)
Digital skills Level 3		**2.49*** (1.04)	**2.97**** (1.05)
AIC	785.58	856.73	828.48
BIC	895.18	974.26	960.79
Log Likelihood	-368.79	-402.36	-384.24
Deviance	737.58	804.73	768.48
McFadden R^2	0.128	0.161	0.251
Number of observations	711	679	608

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

6.2.2.1. Results shared car

As visualised in Table 3, multiple variables have been deemed to make a statistically significant impact on predicting the shared mobility use frequency group. The log odds of being a non-frequent user of a shared car decrease when a respondent has had a low education compared to high education. This significant effect is similar to the findings of Ton et al. (2020) and Becker et al. (2017).

The second significant characteristic is the possession of a driver's license. The log odds of being a non-frequent or frequent user of shared cars increases when a respondent has a drivers license, which corresponds to the logic of having to own a driver license to rent a car as a driver, whilst also corresponding to literature (Vossebeld, 2022).

Furthermore, higher age groups, compared to the reference scenario of 25 till 39 years old, also showed a decrease in use of shared cars. Specifically, the age group of 65 year and older and the age group 55 until 64 years old showed a large decrease (-1.64 and -2.08 respectively) in log odds of being a frequent (for 65 years and older) and non-frequent (for 55-65 years old) user of shared cars compared to the reference scenario. This again corresponds with literature that states that young and middle-aged people use shared cars more than older adults (Prieto, Baltas, & Stan, 2017).

Having one child is statistically significant in increasing the log odds of a respondent being a frequent user of shared cars. This contradicts literature, which states that households with children are less likely to use shared cars over their own vehicles (Ton, et al., 2020). However, children increase the dependency on a car, which can therefore increase the likelihood of people that do not own a car choosing to use a shared car (Chapman, Eyckmans, & Acker, 2020).

It can be seen that the households with more than 2 children variable have a very high negative coefficient. This is due to the fact that in the survey sample no respondents with more than 2 children have indicated to be a non-frequent or frequent user of shared cars the past year.

Finally, the number of owned cars per household significantly impacts the frequency of using a shared car as it has a negative impact on the log odds of being a non-frequent or frequent user of shared cars. This corresponds with literature who also concluded this (Mouratidis, 2022).

In this research gender is not deemed to be a significant influence on the use of shared cars, whilst Hjorteset and Böcker (2020) and Prieto et al. (2017) did conclude this in their research. This can be caused by the small sample of shared mobility users in this research (129 respondents against 1500 in the study of Hjorteset and Böcker and 900 in the study of Prieto et al.), but also the method and setup of the survey used in their research can affect the results. Hjorteset and Böcker for example asked respondents for the likelihood of using car sharing services on a finer scale (1 till 7) and Prieto studied the use instead of frequency.

6.2.2.2. Results shared bicycle

The characteristics of shared bicycle users differ from shared car users, since having a drivers license was not found to be a significant influence on the frequency of use. This can be explained by the fact that a drivers license is not needed for using a shared bike, as is the case for being the driver of a shared car or shared moped.

Low education was again deemed to be a significant education category as was the case for shared car users, but for shared bicycle users also middle education significantly effects the frequency group. For bicycle users a low education level decreases the log odds of being a non frequent user similarly to shared car users, however low education is also significantly decreasing the log odds for frequent users compared to high education. Respondents with middle education decrease the log odds for non-frequent and frequent users even further (-1.42 against -0.91 and -2.34 against -0.87 respectively). That people without high education make less frequent use of shared bicycles is in line with research of Murphy and Usher (2015) and Ricci (2015). However, these studies do not see the same magnitude of effects as is seen from this model. This can possibly come from the overrepresentation of highly educated respondents in the survey sample.

Higher age groups again show a negative effect on the log odds of being a non frequent shared bicycle user. For frequent users only the age group between 40 and 54 shows a significant negative effect compared to the reference scenario, however the other older age groups also have a negative effect on being a frequent user. This corresponds with literature from Ge et al. (2020) and Becker et al. (2017).

For shared bicycles, the category of number of children per household is an interesting category as 2 or more children is statistically significant in increasing the log odds of being a non-frequent user when compared to having a household without children. Whilst having 1 or 2 children increase the log odds of being a frequent user of shared bicycles. Especially the 2 or more children per household category is interesting due to the possible linkage with shared cargo bikes. Literature has also not reported households with children being of influence on shared bicycle use, which makes this an interesting finding.

The number of owned cars significantly negatively effects the log odds of being a non-frequent user but has a smaller effect on shared bicycle users than it had on shared car users. Bachand-Marleau et al. (2012) found that owning cars had a negative effect on shared bicycle use, which corresponds with the findings of this research. The study of Bachand-Marleau also highlights that the ownership of bicycles could have impacted the use of shared bicycles, however in the Netherlands almost everyone owns a bike and too few distinctions can be made between users on this characteristic because of that, making the variable likely to be largely affected by some specific exceptions.

Gender was again not deemed to be of influence on the frequency of use. Ton et al. (2020) concluded that women were more likely to choose the shared bicycle, however other studies like Fishman (2016), Horjus et al. (2022) and Goodman and Cheshire (2014) concluded the opposite.

An interesting finding in this study is that an increasing level of digital skills significantly effects the frequency of shared bicycle use positively, especially if a person has a digital skills level of 3. A relation between digital skills and shared transport has previously been identified by Durand et al. (2022) and Horjus et al. (2022), however they did not specify this per mode.

6.2.2.3. Results shared moped

The user characteristics per frequency group for shared moped users include all variables that were used in both other models. Having a drivers license was again seen as a significant variable, however only for frequent users, where there were no observations where someone did not have a drivers license. As people need to own a drivers license to be able to rent a shared moped, this is an expected outcome, but not one specifically mentioned in literature.

Interesting are that again low and middle educated respondents had a negative association with the log odds of being a non-frequent user compared to highly educated respondents, indicating again that shared mobility might not be inclusive, as depicted by the Dutch parliament (Ideate, 2023). The findings are also disputed in literature as some studies found highly educated people to use shared mopeds more frequently, whilst others did not find any association between education level and the use (Jiao & Bai, 2020; Mouratidis, 2022; Bielinski & Wazna, 2020). Again, the high number of highly educated respondents in this survey sample need to be taken into account, because it can skew the results.

The log odds that a respondent is a frequent user of shared mopeds increases per age group, showing that especially respondents younger than 25 years old use shared mopeds frequently. The log odds for non-frequent users provide a similar image to the frequent user characteristics, however the age below 25 category is not statistically significant, and the highest age group does have observations in this category for non-frequent users. The findings of this variable correspond with literature from Hosseinzadeh et al. (2021) and Degele et al. (2018).

Number of children per household is significantly affecting the log odds of non-frequent shared moped use, as 1 child and more than 2 children increase the log odds. This relation has not been found in other studies, which mostly do not include it as a factor, but Reck and Axhausen (2021) had added it and found a negative relation. This can possibly be caused by the fact that Reck and Axhausen do not have different frequency groups in their probit model, but only consider the use. Furthermore, it is not a categorical variable, but a nominal variable in their research, which is not possible in this research due to the nature of the possible answers in the Smarthubs survey.

The number of owned cars did not have a significant influence on the log odds of being a (non-) frequent user. This is also similar to literature that shows the relation to be context-dependent (Mouratidis, 2022).

In contrary to the other shared modes, gender is added into this model as a significant influence on the log odds of being a frequent user. Males are more likely to use shared mopeds frequently than females. This corresponds to literature (Laa & Leth, 2020).

Finally, higher digital skill levels were found to have a significant positive effect on the probability of being a non-frequent user and have an even higher effect on the probability of being a frequent user. This effect is again in line with the findings of Durand et al. (2022) and Horjus et al. (2022), however

Garritsen (2022) did found a direct relation between moped use and digital skill levels. He found that with a decrease in digital skill level the intention to use shared mopeds decreased, similar to the findings of this research.

6.2.3. Final model shared mobility use

Besides assessing the relation of the frequency of shared mobility use, also the characteristics of the respondents that use (or do not use) shared mobility have been studied. In this section the differences between the logistic regression studying the characteristics of users and non-users is compared (see Table 4) with the results of the multinomial logistic regression into the shared mobility frequency groups (see Table 3).

6.2.3.1. Results shared car

The first difference between the logistic regression and the multinomial logistic regression (use of shared mobility against frequency of use) is that households without children are not deemed to be of interest anymore in predicting the use of shared cars. This means that although it had a significant positive effect on the log odds of a respondent being a frequent user when the household included one child, combined with the non-frequent user group this effect disappeared. This dispute between findings can also be seen in literature, where some studies suggest that people with children are more likely to use shared cars and others suggest a reduction in use (Amirnazmiafshar & Diana, 2022).

The second, and final difference is that digital skills is found to be a significant predictor in the logistic regression model, whilst being excluded in the multinomial model. This shows that digital skills, especially level 3, is an important characteristic influencing shared car use, as found by Durand et al. (2022) and Horjus et al. (2022). As shared car users need to be able to use an electronic device to use the vehicles this relation is logical, but it is often not included in these studies.

The other variables show similar relations with the use of shared cars as with the effect on the non-frequent and frequent user group. However, the coefficients are in general less high.

6.2.3.2. Results shared bicycle

The shared bicycle logistic regression results show similar coefficients for all variables, as was also the case for most variables of the shared car. Furthermore, no additional variables were found to be significant, but ‘having 2 children’ and ‘age group below 25 years’ were not found to be significant compared to the frequent user group in the multinomial model. This is likely caused by the contradicting findings in the multinomial model on the effect of these variables on the non-frequent and frequent user group.

6.2.3.3. Results shared moped

For the shared moped logistic regression, the number of owned cars has become statistically significant compared to the multinomial logistic regression. It is deemed to have a negative influence on the log odds of using shared mopeds, which corresponds with the results of Reck and Axhausen (2021), who also studied this relation the same way. Other than this and some small coefficient changes, no large differences were found.

Table 4 - Logistic regression results predicting the probability of a person having used shared mobility in the past year

	Shared car	Shared bicycle	Shared moped
(Intercept)	-0.43 (0.43)	**-1.76**** (0.63)	**-1.98*** (0.78)
Low education	**-0.63*** (0.29)	**-0.90***** (0.27)	**-0.56*** (0.27)
Middle education	-0.24 (0.32)	**-1.75***** (0.41)	**-0.67**$^{\cdot}$ (0.37)
1 child		**0.51**$^{\cdot}$ (0.29)	**0.71*** (0.29)
2 children		0.21 (0.34)	-0.16 (0.35)
More than 2 children		**1.11*** (0.54)	-0.09 (0.57)
No driving license	**-1.04**** (0.37)		**-1.52*** (0.77)
Age below 25	-0.45 (0.38)	0.14 (0.34)	**1.22**** (0.39)
Age of 40 – 54	**-0.50**$^{\cdot}$ (0.26)	**-0.61*** (0.25)	**-1.21***** (0.25)
Age of 55 – 64	**-1.26**** (0.44)	**-0.65**$^{\cdot}$ (0.38)	**-2.32***** (0.47)
Age of 65 and older	**-1.15**** (0.37)	**-1.65***** (0.46)	**-3.36***** (0.62)
Male			**0.48*** (0.22)
Number of owned cars	**-0.90***** (0.18)	**-0.32**$^{\cdot}$ (0.17)	**-0.25** (0.17)
Digital skills level 2	0.19 (0.41)	**1.35*** (0.62)	**2.04**** (0.76)
Digital skills level 3	**0.70**$^{\cdot}$ (0.42)	**1.99**** (0.62)	**2.59***** (0.77)
AIC	608.65	634.55	580.12
BIC	658.88	693.32	646.28
Log Likelihood	-293.32	-304.27	-275.06
Deviance	586.65	608.55	550.12
Mc Fadden R^2	0.129	0.179	0.287
Num. obs.	711	679	608

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

7. Reasoning for (not) using shared mobility

The second part of this research focuses on the reasoning for (not) using shared mobility. This chapter will add context to why certain travel choices are made and can also be linked to the characteristics of the users. The results of this part are again based upon the results of the SmartHubs survey. Questions about the reasoning for not using shared mobility (see Appendix B, Figure 55, Figure 56 and Figure 57) and questions about reasons for using shared mobility (see Appendix B, Figure 52, Figure 53 and Figure 54) are used to give an overview of why these users use shared mobility modes and what can be improved or influences their opinion negatively. This chapter answers the second research question being: *what are reasons for people to (not) use shared mobility modes?*

7.1. Reason for using shared mobility

In this section the reasons for using the three different shared mobility modes will be discussed. Firstly, the motives for using a shared car are discussed, followed by the shared bicycle and moped.

7.1.1. Shared car

In Figure 4, the reasons for using a shared car as mode of transport are depicted as a percentage of the total number of responses for these questions. As the number of responses for this question is very low (only 25 out of 129), it is difficult to give a decisive answer to why shared cars are used as preferred mode of transport. However, the ratios between answers can be compared to other studies.

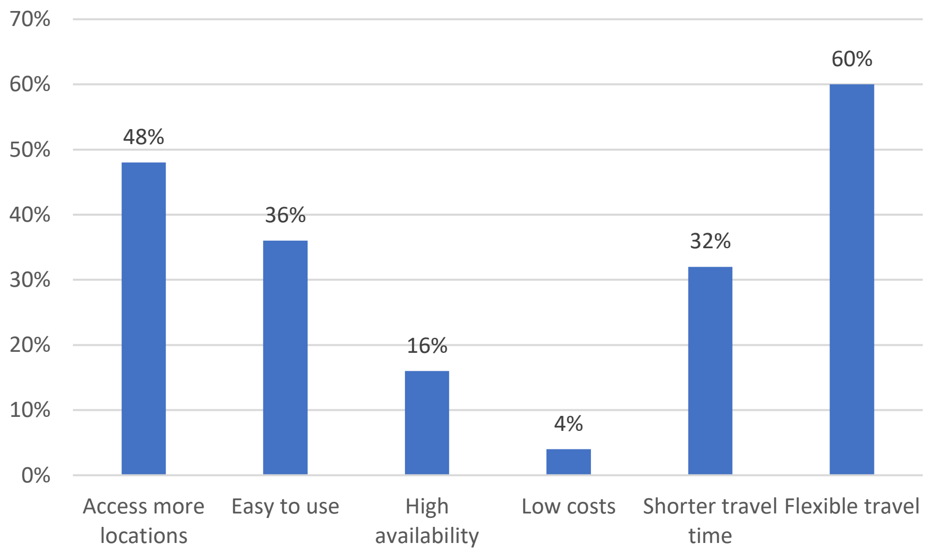

Figure 4 - Percentage of respondents that use shared car (N = 25) per reason for using this mode of transport

From Figure 4 it can be seen that most users preferred this mode because it provided flexibility. This is also supported by Hu et al. (2021), although in their survey it was more often seen as a more convenient way to travel. Dong et al (2020) also indicate flexibility as one of the benefits of shared cars, when comparing it to taxi and public transport. Being able to directly access the destination whilst not having to walk or take another mode of transport is the main reason the flexibility is seen as important. This reason is also linked to the answer: 'access more locations,' which also ranked highly under the respondents. This is also one of the main aims of governments to allow suppliers to make shared cars available within their cities (Rijkswaterstaat, 2023a). Based on this small set of responses, lower costs were not deemed as one of the main reasons for using a shared car, whilst it is one of the arguments made by suppliers and governments to use it (Hu, Javaid, & Creutzig, 2021). It is argued to be cheaper to share a car than to have your own vehicle. However, from this survey this is not yet agreed by its users.

7.1.2. Shared bicycle

The question about why people use shared bicycles has had double the responses of the other two modes. This is probably due to the high amount of people questioned to fill out the survey after renting an OV-fiets at the Rotterdam Central Station. However, the number of responses is still limited.

Figure 5 shows the percentages of respondents using shared bicycles for a specific reason. Similarly, to shared cars, flexible travel and accessing more locations rate the highest. However, the percentages for these answers are approximately 20% higher. In general, this is the case for every given reason compared to the shared car, but the same ranking can be seen between the reasons for shared bicycles compared to share cars.

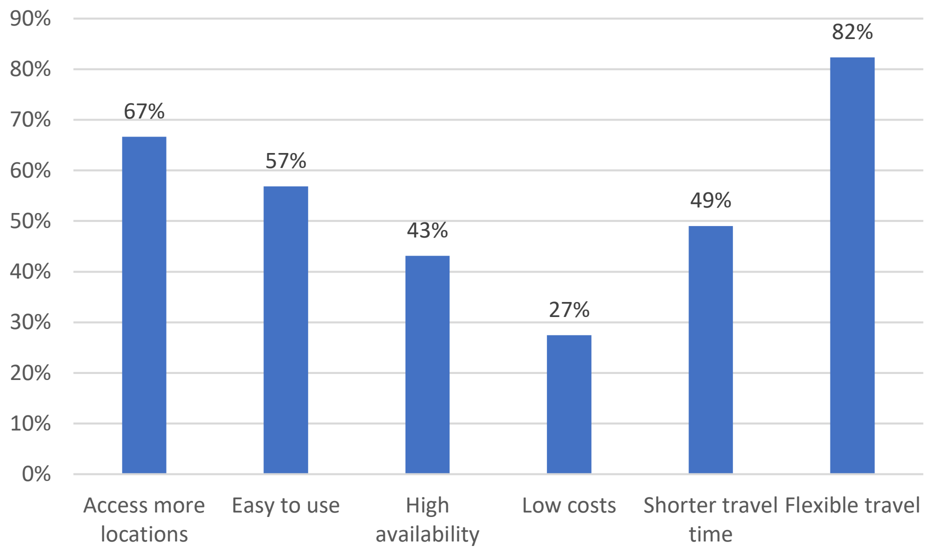

Figure 5 - Percentage of respondents using shared bicycles (N = 51) per reason for using this mode of transport

7.1.3. Shared moped

In Figure 6, the percentage of respondents that use shared mopeds for a specific reason is shown. This question got the least number of responses of all three modes, which makes it difficult to draw conclusions. However, the pattern between the reasons is different compared to the other modes. Although flexible travel scores highest again, shorter travel time is now closely the second most important reason for using shared mopeds. This corresponds to results of Garritsen (2022), who asked a similar question to 98 users. Van Veldhoven et al (2022) also concluded that saving travel time was one of the most important factors for using shared mopeds. Furthermore, it is interesting that this latest study found the influence of other people to be one of the most important reasons, which was not considered in this research.

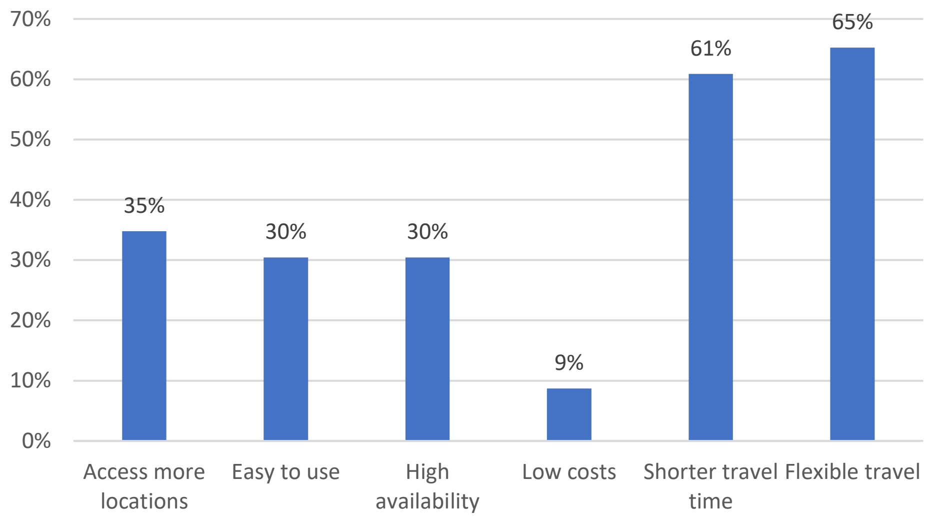

Figure 6 - Percentage of respondents that use shared mopeds (N = 23) per reason for using this mode of transport

7.2. Reason against using shared mobility

In this section, the reasons for not using the three different shared mobility modes will be discussed. Firstly, the motives for not using a shared car are discussed, followed by the shared bicycle and moped.

7.2.1. Shared car

Figure 7 shows the main reasons for non-users of shared cars to not use a shared car. This shows with a clear main reason, being that non-users prefer their own vehicle. Other reasons that score higher are ‘costs’, ‘cannot satisfy travel demands’ and ‘needed to walk too far’. That people think using a shared car is too expensive corresponds with the low amount of people that answered the costs as a main reason for using shared cars, which shows that altering the costs of using a shared car can possibly benefit the use. The other reasons show that currently the availability of the vehicles is too low, since people needed to walk too far to use a vehicle.

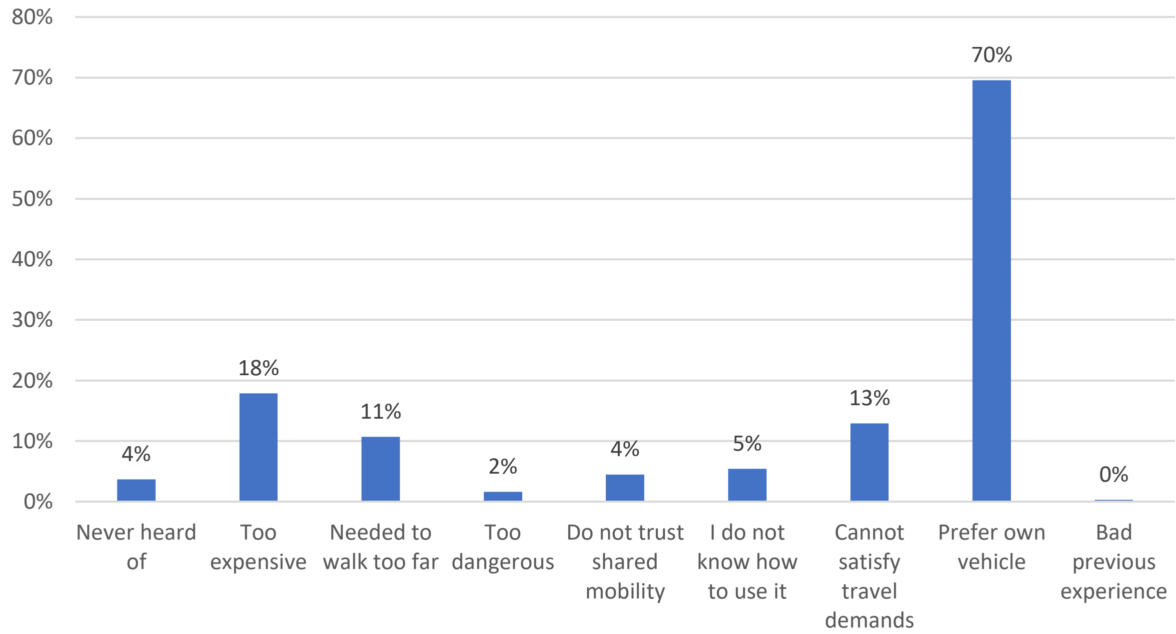

Figure 7 – Percentage of respondents that do not use a shared car (N = 627) per barrier for not using a shared car

7.2.2. Shared bicycle

In Figure 8, a similar pattern for the main reasons for not using shared bicycles can be seen as for the shared car. 70% of the respondents prefers his/her own vehicle. Whilst the other reasons that are mentioned more often are the ‘costs’, ‘cannot satisfy travel demands’ and ‘needed to walk too far’. Literature shows that the limited amount of docking stations, for example the OV-fiets only being able to be docked at train stations, has a negative effect on the use besides the high bike ownership in the Netherlands (Ma, Yuan, Van Oort, & Hoogendoorn, 2020).

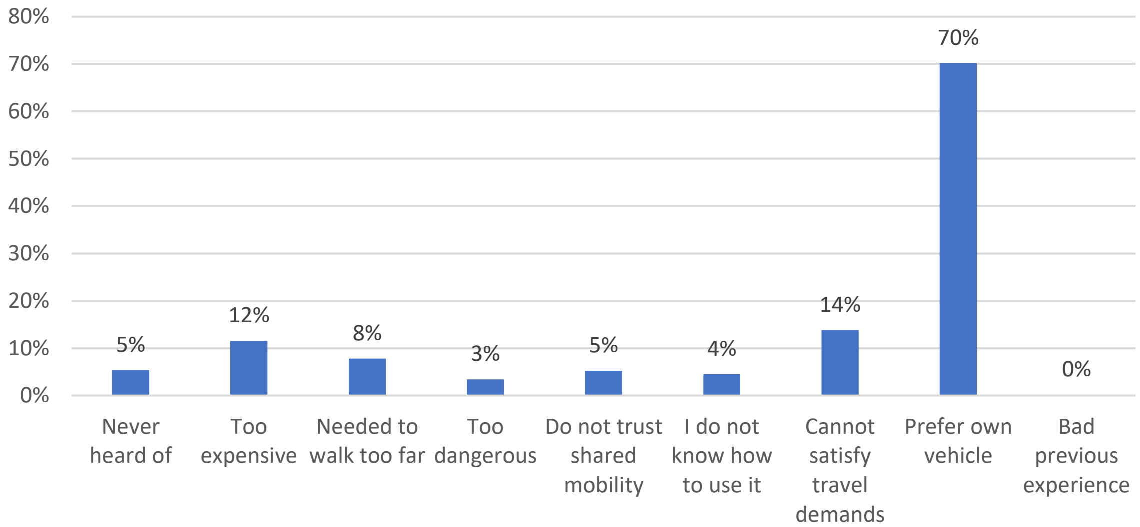

Figure 8 – Percentage of respondents that do not use a shared bicycle (N = 667) per barrier for not using a shared bicycle

7.2.3. Shared moped

In Figure 9, the reasons for not using a shared moped are shown. Most people prefer their own vehicle, however this is a lower percentage of the total than for the other two modes (55% against 70%). The other main reasons are similar to the other modes, however, the reason ‘it is too dangerous’ has a higher percentage for this mode than for the other two (12% against 2 and 3%). Most of the responses in this research have been gathered before the new law obligating helmet use on mopeds, which could have lowered the number of respondents not using shared mopeds because of this reason (Rijksoverheid, 2023).

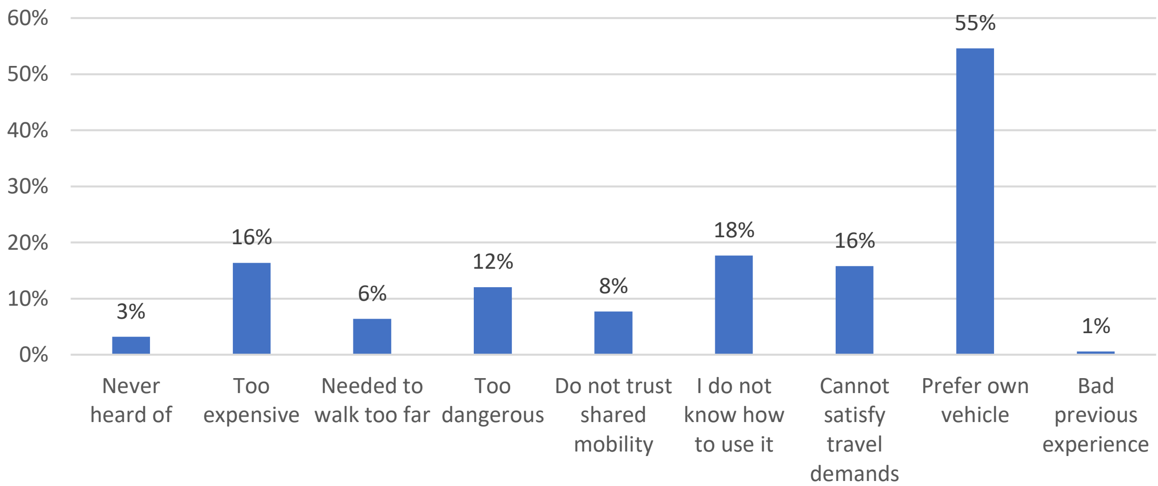

Figure 9 – Percentage of respondents that do not use a shared moped (N = 531) per barrier for not using a shared moped

8. Effect of built environment and demographics on shared mobility use

The third part of this research entails a study into the effect of built environment and demographics of a neighbourhood on the use and availability of shared mobility modes. This chapter elaborates on the methodology for this part, the data used and also discusses the results of the different regression analyses. This chapter will answer the third research question: *what is the effect of built environment factors and demographics on the use of shared mobility modes?*

8.1. Methodology

As discussed in Chapter 4 the built environment and demographics of a neighbourhood influence the likelihood of people travelling by a certain mode of transport. To assess the effects of built environment and demographics on shared mobility, a generalized linear model (GLM) will be used. This is an extension of linear regression that allows a model to be build based on a linear relationship between the independent and dependent variables, whilst their underlying relationship is not linear (Nelder & Wedderburn, 2018). Frequently used GLM's are a Poisson model and a Negative Binomial Model. These models are used when the dependent variable represents count data.

A Poisson model is applied on data that represents rare events with low mean values, that is not overdispersed (variation is equal to the mean) or data that does not exhibit significant clustering (Dean, 1992). Otherwise, a negative binomial model is better suited to analyse the data. The regression equation for a Poisson model can be found in Equation 3 and the negative binomial regression equation in Equation 4.

$$log(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \quad \text{Eq. 3}$$

$$log(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \log(\alpha) \quad \text{Eq. 4}$$

In these equations $log(\mu)$ represents the natural logarithm of the expected value of the dependent variable, the β_0 represents the intercept term, the rest of the β represent the coefficients per independent variable, the X represent the independent variable values and the $\log(\alpha)$ represent the logarithm of the dispersion parameter (Lord & Mannering, 2010).

Two regression models will be setup with the corresponding dependent variables, (1) the number of shared cars within a neighbourhood, (2) the number of shared bicycle and moped trips originating from a PC5 area and (3) the number of shared bicycle and moped trips arriving at a PC5 area. For all models the dispersion will be checked to decided whether a Poisson or Negative Binomial model will be used. Furthermore, the independent variables are selected based on the Pearson correlation factor, which measures the strength and direction of the linear relationship between two independent variables. The correlation coefficient can range from -1 to +1. In which +1 and -1 indicate perfect correlations, whilst 0 indicates no correlation (UCLA, 2023). After checking the correlation between variables, the final set of independent variables is determined based on the heuristic algorithm introduced in Section 6.1.

8.2. Data

For this study multiple data sources are used. The sources per data group are shown in Table 5. The specific information that the sources contain, and preparation of the data is explained in the next sections.

Table 5 - Data sources

Data	**Source**	**Notes**
Shared car	(MyWheels, 2023) (Greenwheels, 2023) GreenWheels	Manual allocated vehicle locations Manual allocated vehicle locations List of locations obtained directly from source
Shared moped/bike	(CROW, 2023)	'Dashboard Deelmobiliteit'
Land Use	(CBS, 2023b)	'Bestand Bodemgebruik'
Demographics	(CBS, 2023d) (CBS, 2023c)	'Kerncijfers Wijken en Buurten 2020' 'Kerncijfers per postcode'
Train stations	(ESRI Nederland, 2023)	
Public transport stops	(University of Groningen Geodienst, 2022)	

8.2.1. Shared cars

The locational data of shared cars in the study area is partially received from GreenWheels, for the cities of Amsterdam, Rotterdam, The Hague and Utrecht, whilst it has been manually supplemented with locational data from all MyWheels vehicles in the study area and with the locations of the rest of the GreenWheels vehicles in the study area.

8.2.2. Shared mopeds/bicycles

The locational data for shared mopeds/bicycles is retrieved for both modes combined from the CROW (2023) for Rotterdam and the Hague. Unfortunately, it was not possible to retrieve the data for the other two metropolitan areas, so therefore it is decided to only use the data for the metropolitan region of Rotterdam - The Hague. Furthermore, both modes are taken together in this dataset, since the main provider for shared bicycles, the NS, does not share its locational data with this dashboard and therefore the number of shared bikes is not complete enough to analyse on its own.

The CROW has provided data of the location of vehicles over the past year and also all trips made with a shared moped or bicycle in the past year (7,119,673 trips). However, not all providers share this data or share data up to a good standard so therefore this data was prepared and altered first. The spokesperson of the dashboard, Bart Roorda, provided a list with providers that are up to standard and providers that are not. Based on this list the data from Go Sharing, Check and HTM was removed, leaving 2,440,546 trips. Furthermore, duplicate trips (21,202 trips were removed), trips of less than 10 seconds (5,121 trips were removed) and trips with average speeds above 45 km/h (436,340 trips) were removed. The speed limit of 45 km/h is chosen based on the maximum speed of a moped being 45 km/h and the assumption that this speed will never be exceeded on average for the entire trip.

8.2.3. Built environment and Demographics

Variables influencing mode choice have been defined in Section 4. Built environment variables and demographics are amongst these and are of interest to this research. Land use categories, land use mix, train stations and public transport stops are identified as interesting variables and therefore included. Furthermore, neighbourhood data of the CBS and PC5 data of the CBS are used for the demographic data. These datasets include roughly the same number of variables (only income is not included in PC5 data), but the PC5 areas are smaller than the neighbourhood data. Since the number of shared cars is very small compared to the number of PC5 areas, the neighbourhood data is used for this analysis so that the spread between frequencies is increased. Since the locational data for shared mopeds/bicycles is only available for Rotterdam and the Hague, PC5 data is used to increase the number of polygons for this analysis to study the trip data on a more detailed level and decrease the chance of outliers affecting the analysis.

As the number of shared cars (or mopeds/bicycles) per neighbourhood (or PC5) is chosen as dependent variable, all data sources are linked to these areas. Therefore, the number of non train public transport stops and the number of train stations per area, as well as the number of total public transport stops is calculated per neighbourhood (or per PC5 area). To account for difference in area sizes, the number of stops and stations has been divided by the total area.

The CBS 'Bestand Bodemgebruik' has classified 9 main groups of land use, being Transport, built up areas, semi built-up areas, recreational, agricultural, forest and open natural terrain, rivers, ponds and lakes, seas and abroad. All of these main groups have categories which are resorted into new groups to add main groups that are not included in the 'Bestand Bodemgebruik'. The new main groups are commercial and services, industrial, recreational, agriculture, forest and housing. Also, land use classes transport and water were setup, however, these were excluded from the research as they are not of interest to this study. After determining the land use classes, the percentage of area of the neighbourhood covered by every land use class is added as a variable.

Besides the land use classes, a Land Use Mix (LUM) is calculated to depict the availability of different services and land use classes in the neighbourhood. The equation as shown in Equation 5, is used in multiple studies and is called the Shannon Index (Hankey, et al., 2012; Winters, Teschke, Grant, Setton, & Brauer, 2010; Chen, Zhou, & Sun, 2017).

$$LUM = -\Sigma_k[(p_i)\, ln\, (p_i)]/ln\, (k) \qquad \text{Eq. 5}$$

Within this equation, the p_i is the proportion of each of the land uses classes and *k* is the number of those classes present. LUM eventually ranges from 0 to 1, with 0 being homogeneous land use and 1 the most mixed land use.

The demographic variables that are used within this research are retrieved from the CBS neighbourhood dataset of 2020. The more recent versions of this dataset have not been used since they are not fully available for every variable. The demographic variables that are used within this research are shown in Appendix G.

8.3. Results

In this section, the results of two regression analyses will be discussed. Firstly, the effect of built environment and demographics on the availability of shared cars is discussed. This is followed by a regression analysis on the effect of built environment and demographics on shared moped and bicycle trips.

8.3.1. Effect of built environment and demographics on availability of shared cars

In this section, the regression analysis to determine the effect of built environment and demographics on the availability of shared cars per neighbourhood is determined. Firstly, the variable selection will be discussed, followed by a section that provides a description of the data, and finally the finalised regression model is discussed. This section will answer the sub question 3.1: *what is the effect of built environment factors and demographics on the location of shared cars?*

8.3.1.1. Variable selection

In order to set up a final model to accurately predict the number of shared cars per neighbourhood a set of independent variables needs to be chosen that do not have high correlation with each other and are able to make a statistically significant addition to this prediction. Firstly, the Pearson correlation coefficient is calculated for every variable, as can be seen in Appendix H, Table 15 and Table 16.

Based on this coefficient, number of public transport stops per m^2, population density, average household size, number of households and address density were identified to have high correlation with the level of urbanization. Therefore, only one of these variables can be included in the final model. After assessing the different combinations in the heuristic algorithm, it was decided to include level of urbanization, because this variable was deemed to be more important and showed lower AIC scores when included compared to the other variables.

Furthermore, the percentage of 1 person households and the percentage of households without children had high correlation with the percentage of households with children. The 1 person households and households without children were excluded based on literature (Amirnazmiafshar & Diana, 2022).

The percentage of people belonging to the highest 20% income class in the Netherlands is also excluded from the final model based on its high correlation with low income. High income is excluded to use similar variables as in the user characteristics section.

The final variable to be excluded based on the Pearson correlation coefficient is the percentage of agricultural land use, which is excluded due to its high negative correlation with urbanization.

After closely examining the variables that were still included, the average WOZ value, the number of employed workers and the number of self-employed workers were excluded from the final model due to the large amount (over 500) of missing data points.

This left 24 different independent variables, which were tested in different combinations within the heuristic algorithm to test the individual importance, the times a variable was included in a low AIC model. This led to a final set of seven independent variables that were included in the final model, of which the descriptive statistics can be seen in Table 6. In this table, the first column (N) depicts the number of neighbourhoods used in the regression analysis. The second column shows the mean of the corresponding variable over all neighbourhoods. The third column depicts the standard deviation of the variable over all neighbourhoods. The final two columns show the minimum and maximum value of the variable at a certain neighbourhood.

Table 6 - Descriptive statistics of final variable selection

Statistic	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Number of shared cars	2,917	1.20	2.81	0	48
Level of Urbanization	2,917	2.47	1.44	1	5
Percentage of people older than 65 years	2,917	18.80	9.64	0	89
Percentage of households with children	2,917	34.55	12.81	0	80
Percentage of males	2,917	0.50	0.03	0.31	0.89
Percentage of people with middle education level	2,917	0.29	0.08	0.00	0.79
Percentage of people with low education level	2,917	0.19	0.09	0.00	0.65
Land Use Mix	2,917	0.35	0.21	0.00	0.90

8.3.1.2. Final model

In Table 7 the finalised negative binomial regression model predicting the number of shared cars in a neighbourhood is shown for the entire dataset and for all different study areas. In Figure 10, Figure 12, Figure 14 and Figure 16 the predicted number of available shared cars per neighbourhood are shown for the different cities in the study area. The effect of all the included variables will be discussed and the effect of some variables are highlighted besides the figures of the predicted number of available shared cars in all studied cities, whilst the spread of the other variables per city can be found in Appendix M.

In this model it can be seen that Land Use Mix has a statistically significant positive effect on the number of shared cars in a neighbourhood, which corresponds with the research of Zhao et al. (2022). Which is even stronger in the metropolitan areas of Rotterdam – The Hague and Utrecht, whilst not existing for Amsterdam. This can be explained due to the fact that Amsterdam has a low variance in Land Use Mix values per neighbourhood.

The percentage of people with a middle education level in a neighbourhood has a negative effect on the number of shared cars. The percentage of people with a low education level also has this effect, but less severe. This corresponds with research done by multiple researchers as bundled by Amirnazmiafshar and Diana (2022). In Figure 11, the percentage of people with a low education level is shown per neighbourhood in Amsterdam. From this figure, and Figure 10, the negative effect of people with a low education level on the availability of shared cars can be seen. This effect can especially be seen in the north and west of Amsterdam, where neighbourhoods with higher percentages of low educated people score lower than surrounding areas with lower percentages.

For the different metropolitan areas, the effect of middle educated people is less severe in Amsterdam, while the percentage of people with low education is not significant and lower for Rotterdam-The Hague. This can be explained by the difference in number of people with a low education level between these two cities, as more people with low education live in Rotterdam.

The percentage of household with children is seen to have a negative effect on the number of shared cars in a neighbourhood. This is similar for Amsterdam and Utrecht, whilst it is stronger in Rotterdam-The Hague. This can also be seen in Figure 13.

The percentage of people older than 65 years old is also negatively associated with the number of shared cars. This is especially present in the Rotterdam-The Hague area, as visualised in Figure 15. This negative relation can possibly be explained by the results of Section 6.2.2.1 as this showed that people in this age group have a lower probability of using shared cars.

The level of urbanization also has its effect on the availability of shared cars. It has a negative effect, which is logical based on how the level of urbanization is defined. The higher the level of urbanization, the lower the urbanization of a city becomes, which means that higher urbanized areas increase the availability of shared cars, as can also be seen in Figure 17.

The final variable that has a significant effect on the number of shared cars, is the percentage of males in an area. The percentage of males has a negative relation with the number of shared cars, meaning that areas with more females have a higher number of available shared cars. This is in accordance with the research of Wang et al. (2021b).

Table 7 - Final model for predicting the number of shared cars in a neighbourhood

	Full	Amsterdam	MRDH	Utrecht
(Intercept)	**10.43*****	**9.00*****	**16.88*****	**8.98*****
	(0.67)	(0.86)	(1.78)	(1.34)
Land Use Mix	**0.91*****	-0.02	**1.59*****	**1.41*****
	(0.17)	(0.22)	(0.38)	(0.30)
Percentage of people with a middle education level	**-6.70*****	**-5.32*****	**-8.32*****	**-7.58*****
	(0.43)	(0.56)	(1.04)	(0.89)
Percentage of households with children	**-0.04*****	**-0.03*****	**-0.07*****	**-0.03*****
	(0.00)	(0.00)	(0.01)	(0.00)
Percentage of people older than 65 years	**-0.08*****	**-0.07*****	**-0.13*****	**-0.06*****
	(0.00)	(0.01)	(0.01)	(0.01)
Level of urbanization	**-0.70*****	**-0.62*****	**-0.93*****	**-0.71*****
	(0.04)	(0.06)	(0.11)	(0.07)
Percentage of the population that is a male	**-9.99*****	**-8.27*****	**-18.55*****	**-8.01****
	(1.24)	(1.61)	(3.04)	(2.59)
Percentage of people with a low education level	**-1.23****	**-1.79*****	-0.90	**-1.68***
	(0.37)	(0.51)	(0.77)	(0.78)
AIC	6171.70	3118.94	1578.36	1391.30
BIC	6225.50	3165.07	1621.26	1433.53
Log Likelihood	-3076.85	-1550.47	-780.18	-686.65
Deviance	2052.64	1021.25	527.27	510.54
McFadden R^2	0.211	0.193	0.219	0.274
Num. obs.	2917	1243	868	806

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Figure 10 - Number of predicted available shared cars in Amsterdam per neighbourhood

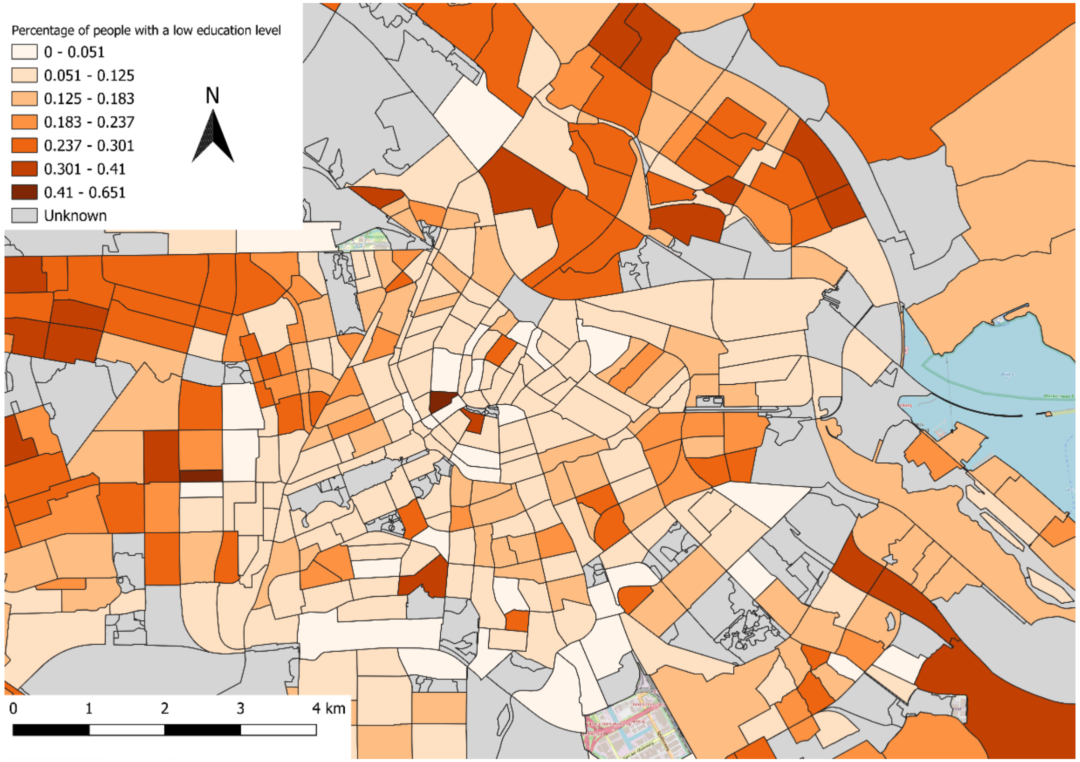

Figure 11 - Percentage of people with low education level in Amsterdam per neighbourhood, where a negative effect can be seen with the predicted number of shared cars in Amsterdam

Figure 12 - Number of predicted available shared cars in The Hague per neighbourhood

Figure 13 - Percentage of households with children in The Hague per neighbourhood, where a negative effect can be seen with the predicted number of shared cars in The Hague

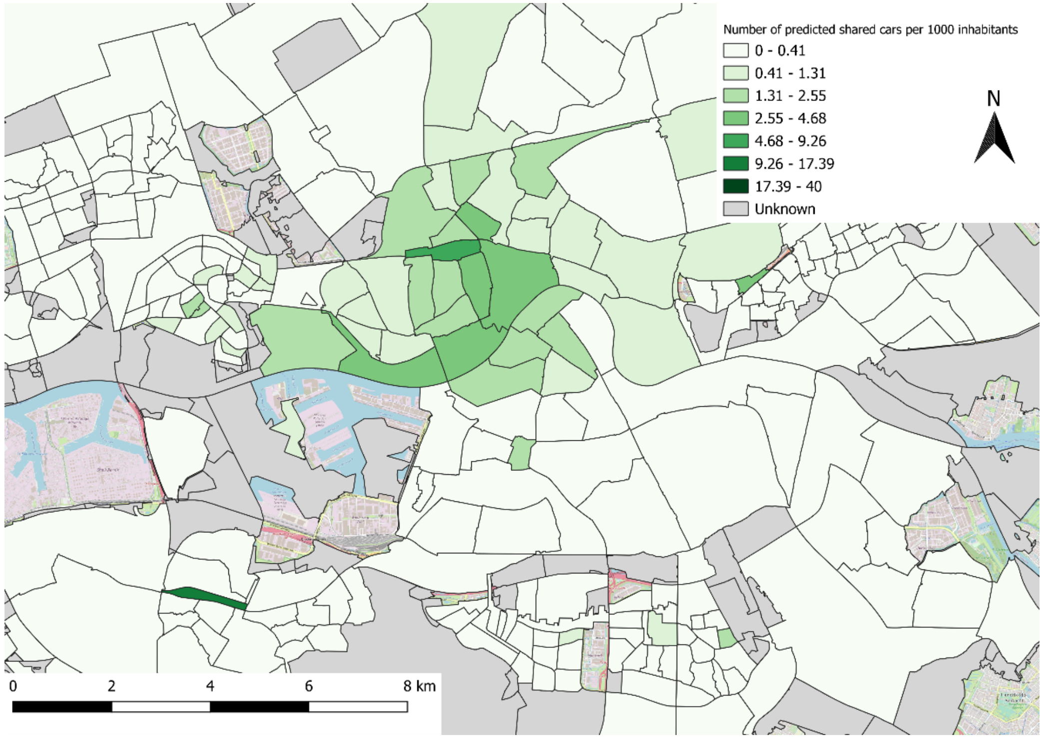

Figure 14 - Number of predicted available shared cars in Rotterdam per neighbourhood

Figure 15 - Percentage of people older than 65 years in Rotterdam per neighbourhood, where a negative effect can be seen with the predicted number of shared cars in Rotterdam

Figure 16 - Number of predicted available shared cars in Utrecht per neighbourhood

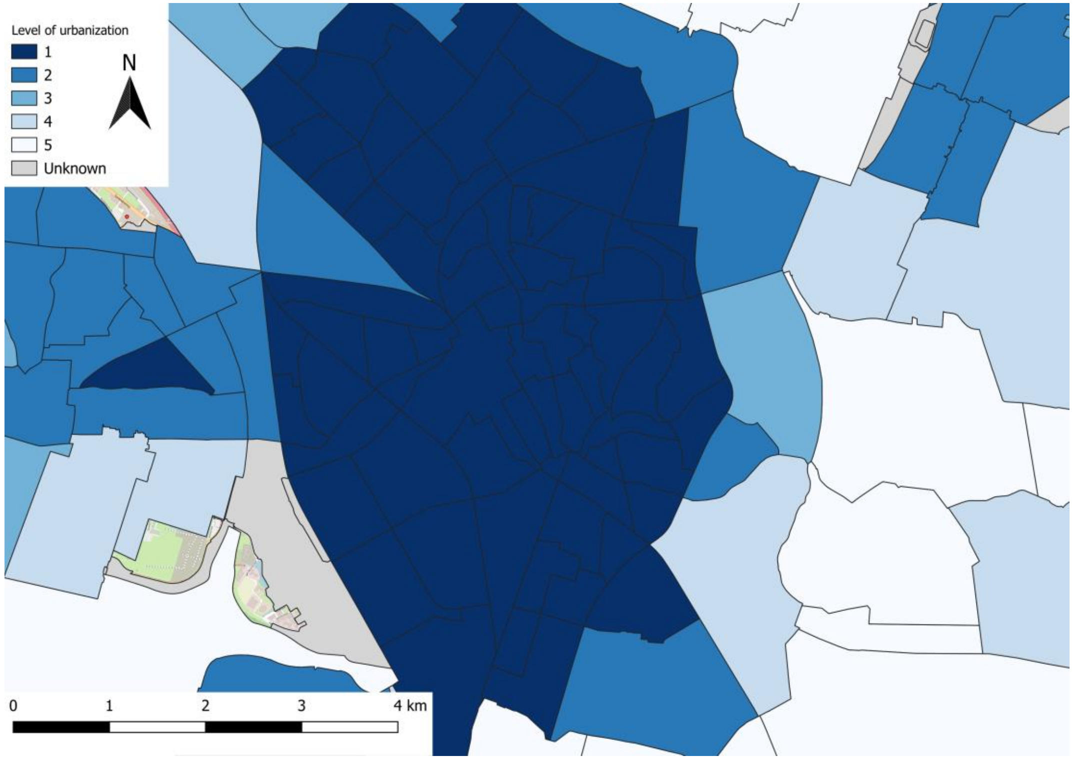

Figure 17 – Level of urbanization per neighbourhood, where a positive effect can be seen with the predicted number of shared cars in Utrecht

8.3.2. Effect of built environment and demographics on shared moped/bicycle trips

This section elaborates on the regression analysis to determine the effect of built environment and demographics on the number of shared moped/bicycle trips per PC5 area. Firstly, the variable selection will be discussed, which is followed by a discussion of the finalised regression model. As the process for determining the variables and setting up the final model is similar for the origin and destination of the trips, the final model for the destination PC5 areas can be found in Appendix J, Table 19. This section, together with Appendix J, will answer the research question 3.2: *what is the effect of built environment factors and demographics on the origins and destinations of trips made with shared mopeds/bicycles?*

8.3.2.1. Variable selection

Similarly to variable selection of the model for the shared cars, the Pearson correlation coefficient is calculated for every variable, as can be seen in Appendix I, Table 17 and Table 18. Based on this coefficient, the level of urbanization was identified to have high correlation with the address density. Therefore, only one of these variables can be included in the final model. After testing the two variables in the heuristic algorithm, it was decided to include address density, because this variable was deemed to be more important and showed lower AIC scores when included compared to the other variable. Furthermore, the number of inhabitants and the number of houses were excluded, because of an expected correlation with the address density.

The percentage of households without children, percentage of one person households, average household size and the percentage of people younger than 14 years old had high correlation with the percentage of households with children. The percentage of households with children was kept in the set of variables and the other were excluded to keep similar variables across the different models.

The education classes have a high correlation with the average WOZ-value. After assessing the different variables within the heuristic algorithm, the education classes were excluded.

The final variable to be excluded based on the Pearson correlation coefficient is the percentage of built-up land use, which is excluded due to its high negative correlation with Land-Use mix and expected correlation with address density.

In order to account for the variables with percentages and nominal variables, such as WOZ, address density and public transport stops, the nominal variables have been normalized. The WOZ-value and address density have been normalised by taking the log of the values and the number of public transport stops per m^2 has been normalised by min-max.

This left 19 different independent variables, who were tested in different combinations within the heuristic algorithm to test the individual importance. This led to a final set of ten independent variables that were included in the final model, of which the descriptive statistics can be seen in

Table 8. Similarly, to section 8.3.1.1 this table shows the number of observations, mean, standard deviation, minimum and maximum value.

Table 8 - Descriptive statistics final model shared mopeds/bicycles

Statistic	**N**	**Mean**	**St. Dev.**	**Min**	**Max**
Number of shared moped/bike trips	1,877	966.11	2,150.26	1	48,412
Address density	1,877	8.24	0.59	3.40	9.12
Percentage of people between 45 and 64 years old	1,877	25.17	6.23	0.00	66.67
Percentage of people older than 65 years	1,877	16.04	11.91	0.00	100.00
Percentage of households with children	1,877	30.22	14.34	0.00	80.41
Percentage of males	1,877	49.66	4.03	31.39	80.00
Number of public transport stops per m^2	1,877	0.07	0.13	0.00	1.00
Average WOZ value	1,877	5.31	0.50	3.99	7.24
Percentage of forest land use	1,877	1.38	7.96	0.00	88.88
Percentage of commercial land use	1,877	13.69	21.31	0.00	100.00
Percentage of recreational land use	1,877	8.16	14.68	0.00	86.83

8.3.2.2. Final model

In In The Hague and Utrecht, the positive effect of commercial land use can clearly be seen (see Figure 21 and Figure 25).

In Table 9, also some statistics for the goodness of fit and prediction error are shown. The low McFadden R^2 stands out compared to the shared car model. Since the McFadden R^2 shows the improvement of a model compared to a null model (only an intercept), the lower the score, the better the model is compared to the null model . This model therefor shows a good fit compared to the null model.

Table 9, the finalised negative binomial model predicting the number of shared moped and bicycle trips per year per PC5 area is shown. In Figure 18, Figure 20, Figure 22 and Figure 24 the predicted number of shared moped and bicycle trips per year are shown for the PC5 areas in the study area. In the coming section the effect of all included variables is discussed. This is sometimes done with a comparing figure and for all other variables an overview of the distribution per PC5 area per city is provided in Appendix N.

The address density has a positive relation with the number of shared moped/bicycle trips per PC5 area. This is in correspondence with literature of Heinen et al. (2010) and Bachand-Marleau et al. (2012). The two cities, Rotterdam and the Hague differ a bit and both have a stronger positive relation with the dependent variable.

Beside address density, two age groups have a significant effect on the number of shared moped/bicycle trips. These are the age group between 45 and 64 years old and the age group of people older than 64 years old. Both have a similar negative effect on the dependent variable, which is similar for both cities. In Figure 23, an overview is presented of the percentage of people that are 65 years and older per PC5 area in Rotterdam. From this figure, together with Figure 22, the negative effect of this variable is clearly visible.

The percentage of households with children has been identified as a significant negative predictor of shared moped/bicycle trips. This can also be seen in Figure 19 in combination with Figure 18. Furthermore, the percentage of males has a negative effect on the dependent variable.

In previous parts of this research, education or income was deemed to be of importance in predicting the availability and use of shared mobility, however for shared moped and bicycle trips, this is not the case. However, as the average WOZ-value is linked to both, the same type of data is still included in this model. It also has the same effect on the shared moped and bicycle trips, since it has a positive effect on this dependent variable, whilst being correlated with high education and high income.

The number of transit stops per m^2 is also included in this model. This corresponds with literature from Bachand-Marleau et al. (2012) indicating the same whilst relating it to a combination in use as well. As the number of transit stops per m^2 has a positive effect on the dependent variable this could also be implied from this research.

In the model for shared cars, the Land Use Mix was seen as an important predictor, however in this model three different land use classes have been included, being forest, commercial use and recreational use. All three have similar positive effects on the number of shared moped and bicycle trips in a year per PC5 area. In The Hague and Utrecht, the positive effect of commercial land use can clearly be seen (see Figure 21 and Figure 25).

In Table 9, also some statistics for the goodness of fit and prediction error are shown. The low McFadden R^2 stands out compared to the shared car model. Since the McFadden R^2 shows the improvement of a model compared to a null model (only an intercept), the lower the score, the better the model is compared to the null model (Cameron & Windmeijer, 1997). This model therefor shows a good fit compared to the null model.

Table 9 - Final model for predicting the number of shared moped and bicycle trips in a year per PC5 area

	Full	Den Haag	Rotterdam
(Intercept)	-1.29 (0.92)	**-3.21*** (1.42)	**-3.15*** (1.27)
Address density	**0.62***** (0.06)	**0.83***** (0.10)	**0.72***** (0.08)
Percentage of people with the age between 45 and 64 years old	**-0.04***** (0.01)	**-0.03***** (0.01)	**-0.03***** (0.01)
Percentage of people older than 64 years old	**-0.04***** (0.00)	**-0.03***** (0.01)	**-0.04***** (0.01)
Percentage of households with children	**-0.04***** (0.00)	**-0.04***** (0.00)	**-0.03***** (0.00)
Percentage of people that are males	**-0.02*** (0.01)	**-0.03**$^{\cdot}$ (0.01)	-0.02 (0.01)
Average WOZ-value	**1.10***** (0.07)	**1.10***** (0.10)	**1.24***** (0.10)
Number of transit stops per m^2	**1.40***** (0.23)	**1.77***** (0.33)	**1.23***** (0.32)
Percentage of forest land use	**0.02***** (0.00)	**0.02***** (0.00)	0.01 (0.01)
Percentage of commercial land use	**0.02***** (0.00)	**0.01***** (0.00)	**0.02***** (0.00)
Percentage of recreational land use	**0.01***** (0.00)	**0.01*** (0.00)	**0.01**** (0.00)
AIC	25692.31	12228.39	13428.25
BIC	25757.91	12285.23	13485.96
Log Likelihood	-12834.15	-6102.19	-6702.13
Deviance	2116.71	1007.55	1102.32
McFadden R^2	0.0363	0.0340	0.0397
Num. obs.	1749	843	906

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

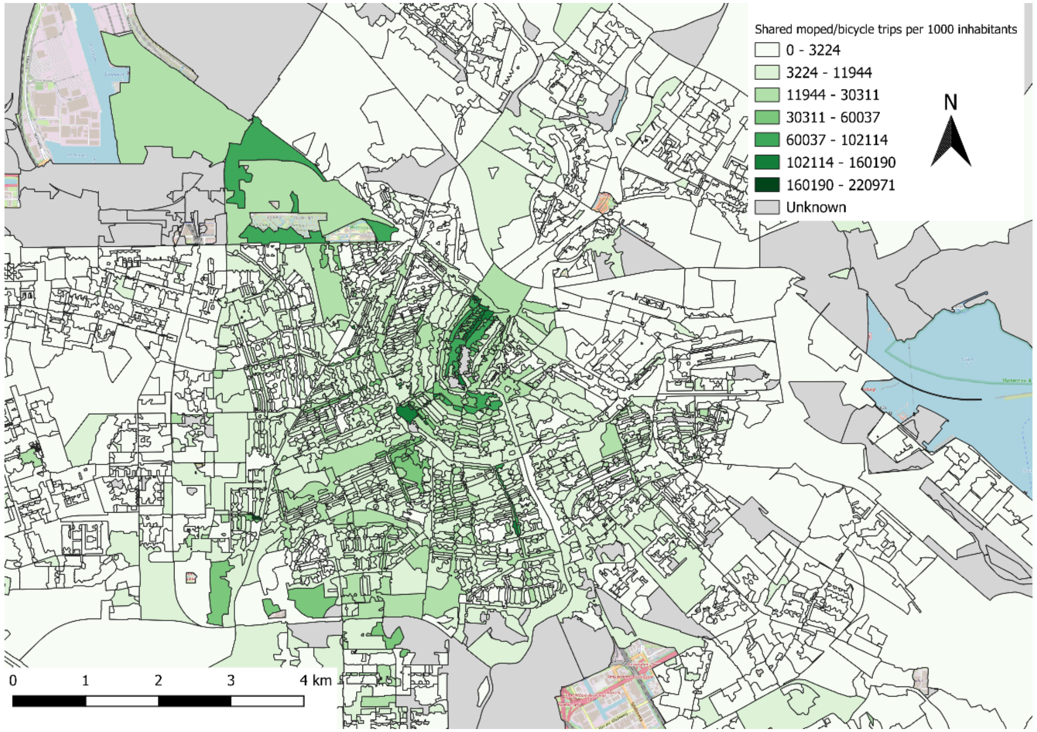

Figure 18 - Predicted number of shared moped/bicycle trips per year in Amsterdam per PC5 area

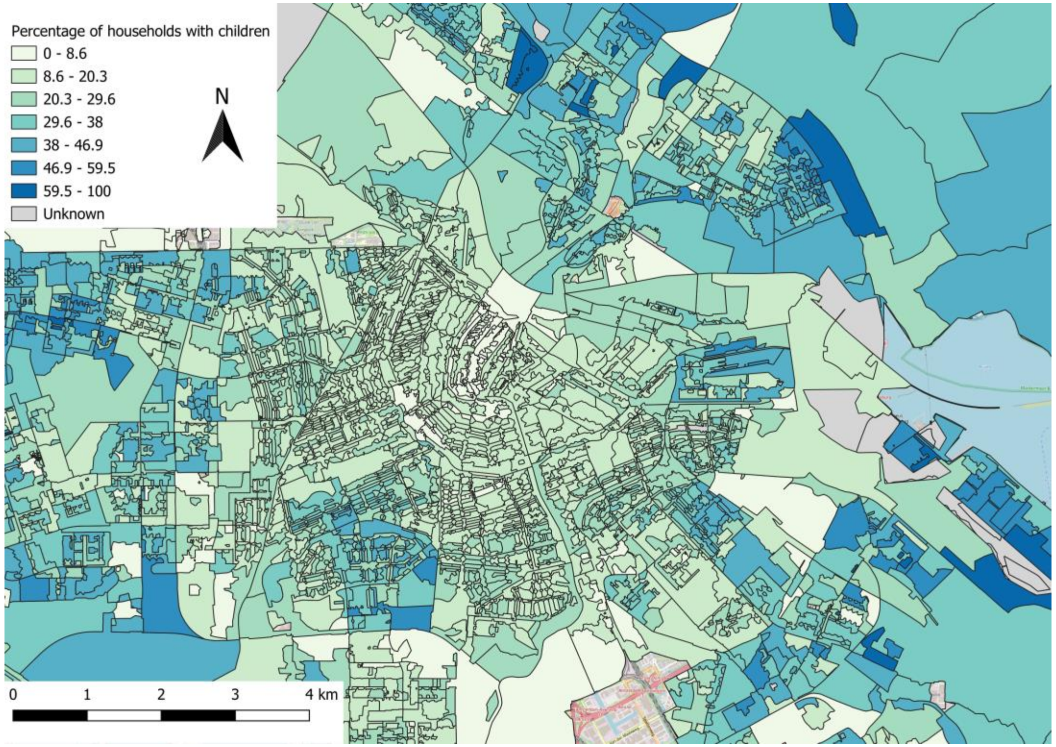

Figure 19 - Percentage of households with children in Amsterdam per PC5 area, a negative relation between this variable and the predicted number of shared moped/bicycle trips can be observed

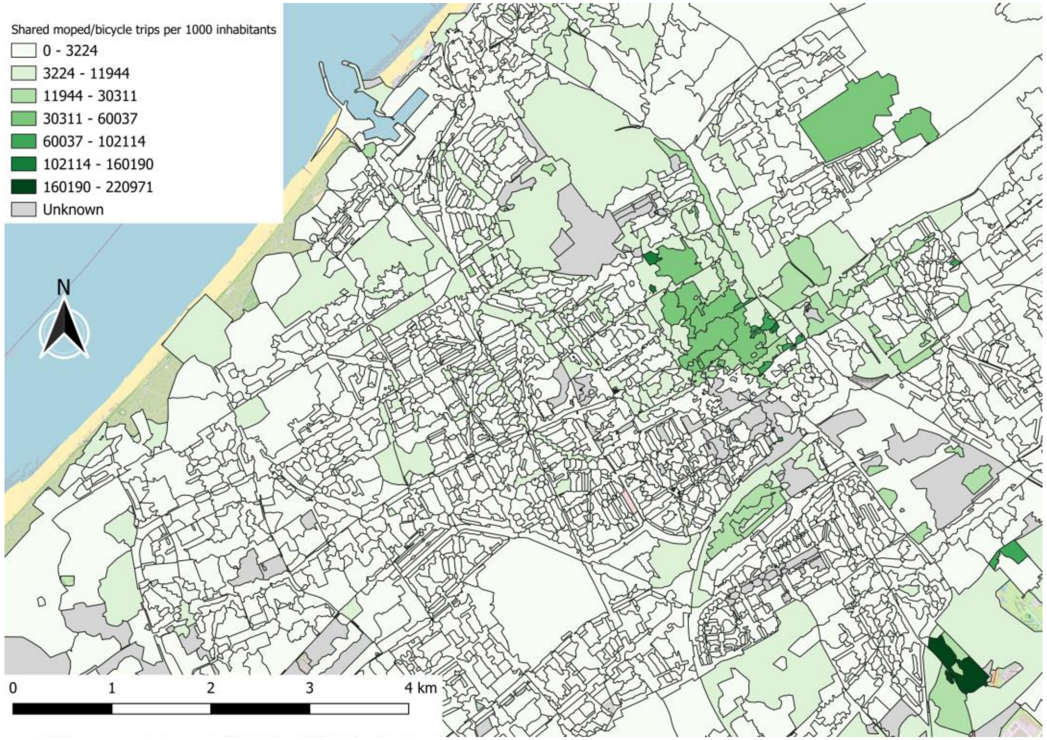

Figure 20 - Predicted number of shared moped/bicycle trips per year in The Hague per PC5 area

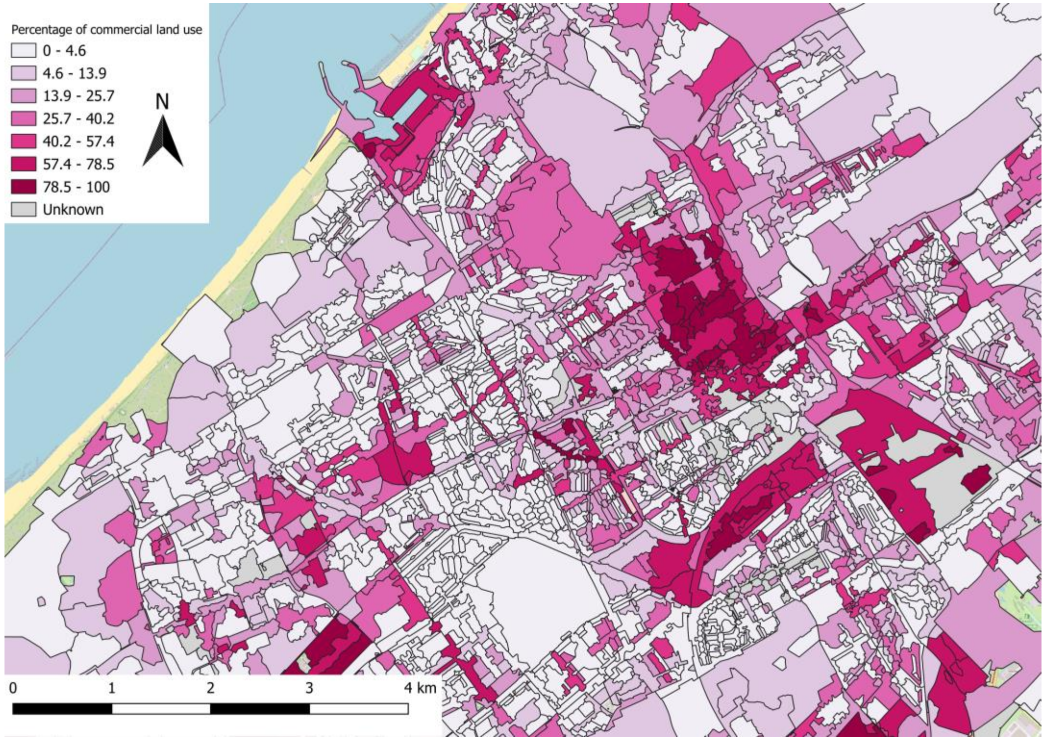

Figure 21 - Percentage of commercial land use in The Hague per PC5 area, a positive relation between the commercial land use and predicted number of shared moped/bicycle trips is observed

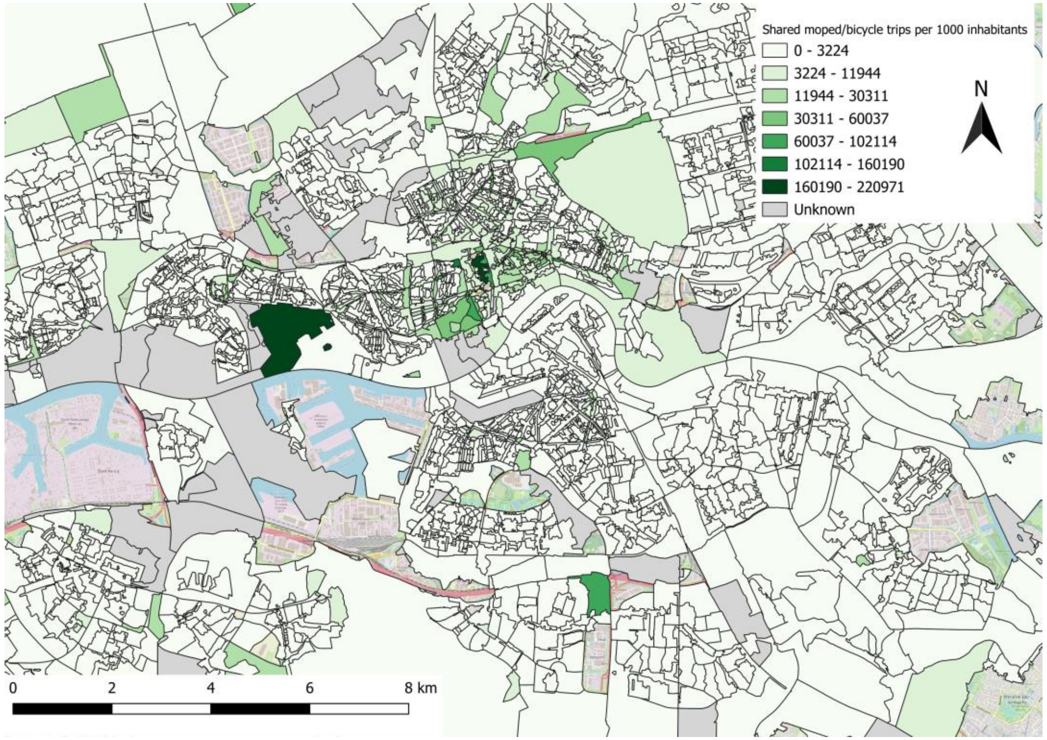

Figure 22 - Predicted number of shared moped/bicycle trips per year in Rotterdam per PC5 area

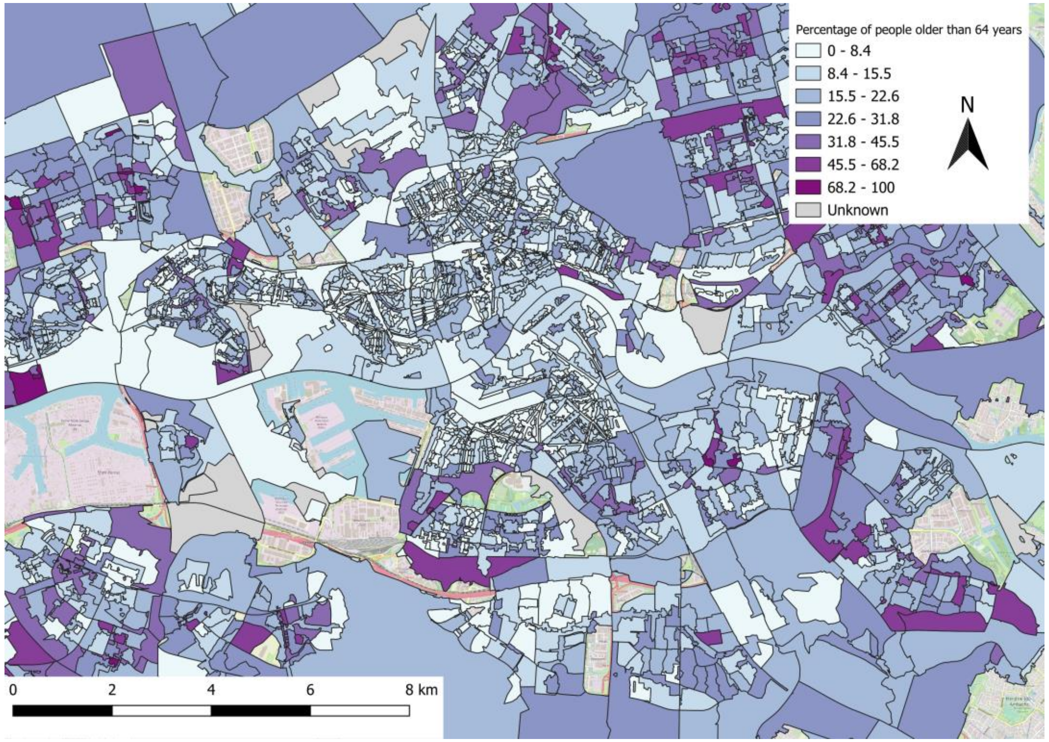

Figure 23 - Percentage of people older than 65 years in Rotterdam per PC5 area, a negative relation between the percentage of people older than 64 years old and predicted number of shared moped/bicycle trips is observed

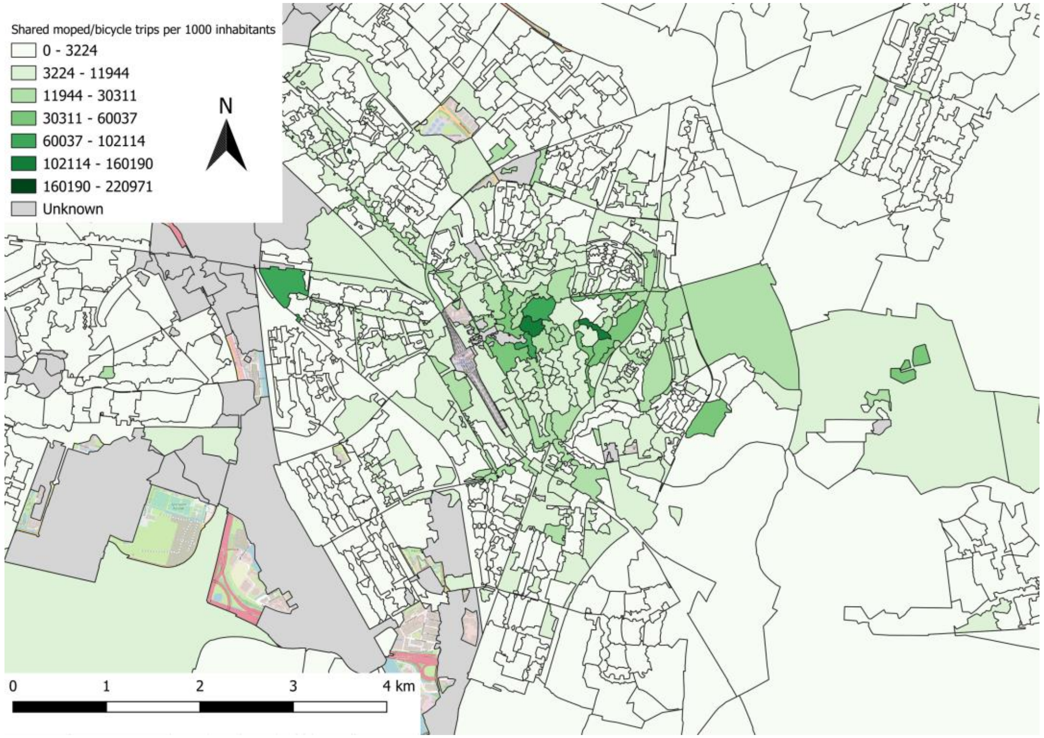

Figure 24 - Predicted number of shared moped/bicycle trips per year in Utrecht per PC5 area

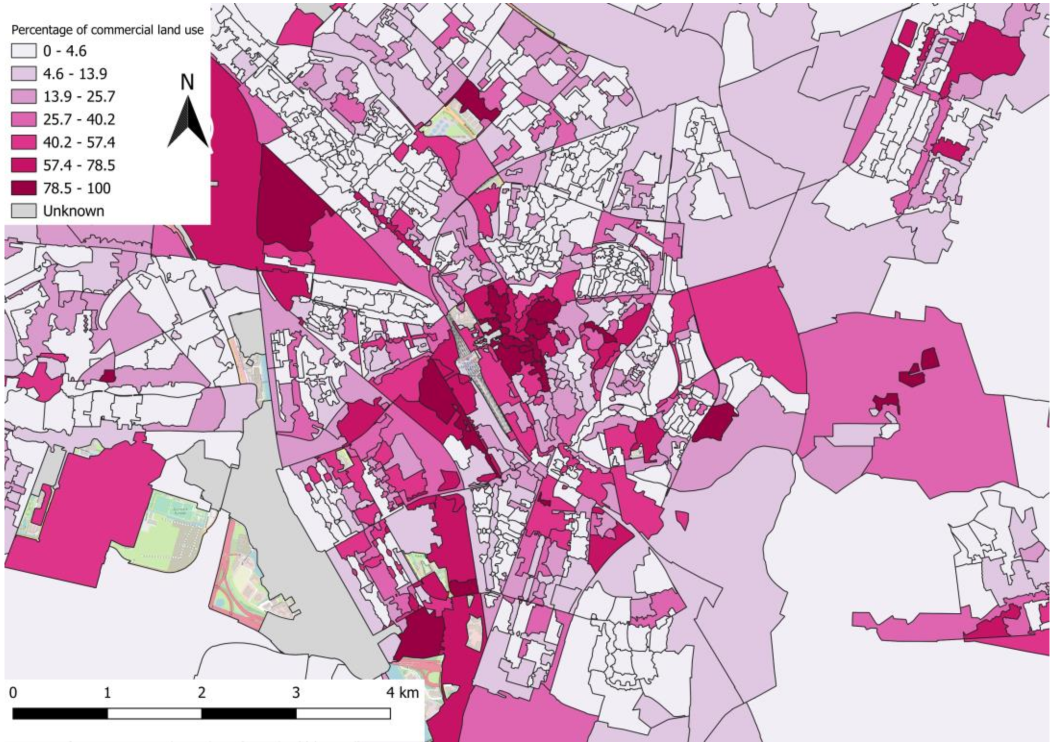

Figure 25 - Percentage of commercial land use in Utrecht per PC5 area, a positive relation between commercial land use and shared moped/bicycle trips is observed

9. Characteristics of trips predicted to be made by shared mobility

In this chapter, the trip characteristics of predicted shared mobility trips will be determined and analysed. Firstly, the methodology is discussed, followed by an introduction to the trip data. Also, the results of this research question are discussed. This chapter will try to answer research question 4: *what are the trip characteristics of trips that have a high likelihood to be made by shared mobility in the studied metropolitan areas based on the built environment factors and demographics of the originating area, and the characteristics of the user?*

9.1. Methodology

After determining the user characteristics and the influence that demographics and the built environment have on the presence and use of shared mobility vehicles, the likelihood of a certain trip being made with a shared mobility mode can be determined. Since the trip data used in this part, data from the NVP as discussed in section 5.3, is different from the studied users and trips in the previous parts of this research, the likelihood is difficult to determine. In literature, trip likelihoods are generally determined with maximum likelihood equations that are optimized for every starting and end point of a trip, based on travel costs and preferences (Vos, 2016). Since this research also takes individual characteristics into account and data constraints limit this method, another approach is undertaken in this research.

The method used in this study to determine the likelihood a trip is undertaken by shared mobility depends on two different components, (1) the predicted share of shared mobility trips in an area of the total number of trips and (2) the probability that the specific user of a trip from that area travels with shared mobility. The first component is dependent on the predicted number of trips made by shared moped/bicycle based on the negative binomial regression equation setup in Section 8.3.2 and the total number of trips made by moped/bicycle. Or in the case of shared cars, the predicted number of available shared cars per area based on the results of Section 8.3.1 and the total number of cars available per area. Based on both values, Equation 6 and 7 are setup to calculate the share of shared mobility trips.

$$P_j = \frac{V_j}{Xj + V_j} \qquad \text{Eq. 6}$$

$$P_j = \frac{O_j}{Tj} \qquad \text{Eq. 7}$$

In Equation 6, P_j is the proportion of trips expected to be made by shared car in neighbourhood j, V_j is the number of shared cars present in the neighbourhood of the origin j based on the regression equation described in section 8.3.1.2 and X_j is the number of privately owned cars in the neighbourhood of the origin j which is based on data of the CBS (2023d). The division of the number of available shared cars by total number of available cars, either private or shared, is assumed to approximate the proportion of trips likely to be made by shared car in the neighbourhood, since it is assumed that the presence of a vehicle is directly linked to the use (de Jong, 1990).

In Equation 7, P_j is the proportion of trips expected to be made by shared bicycle/moped in PC5 area j, O_j is the number of originating shared moped/bicycle trips in PC5 area j based on the regression equation described in section 8.3.2.2, and T_j is the number of expected bicycle and moped trips in PC5 area j based on the ODIN (CBS, 2023e). In this equation the proportion of expected shared bicycle/moped trips is only based on originating trips. A more precise approximation of the proportions of trips per area can be obtained by considering the arriving at a PC5 area, for which the results in Appendix J, Table 19 could be used. However, this research adopts a more simplified approach as suggested in Equation 7, due to the fact that an optimization algorithm needed to allocate all trips per area would only lead to a marginal improvement of the precision due to the limited number of trips available in the NVP per area.

In Figure 26, the method to determine the trips with a high likelihood of being shared mobility trips is shown. Firstly, Equation 6 and 7 are applied to a year of trip data from the NVP to determine the proportion of trips made by shared mobility per area. The proportion is than multiplied by the total number of trips in an area, which leads to the number of trips likely made with shared mobility in area (*n)*. After determining the number of trips of the total of trips per area that are likely to be made with shared mobility, all the trips made in that area are ranked based on the probability that the user of that trips uses shared mode (based on Chapter 6). Finally, the *n* highest scoring trips are selected as trips likely to be made by shared mobility.

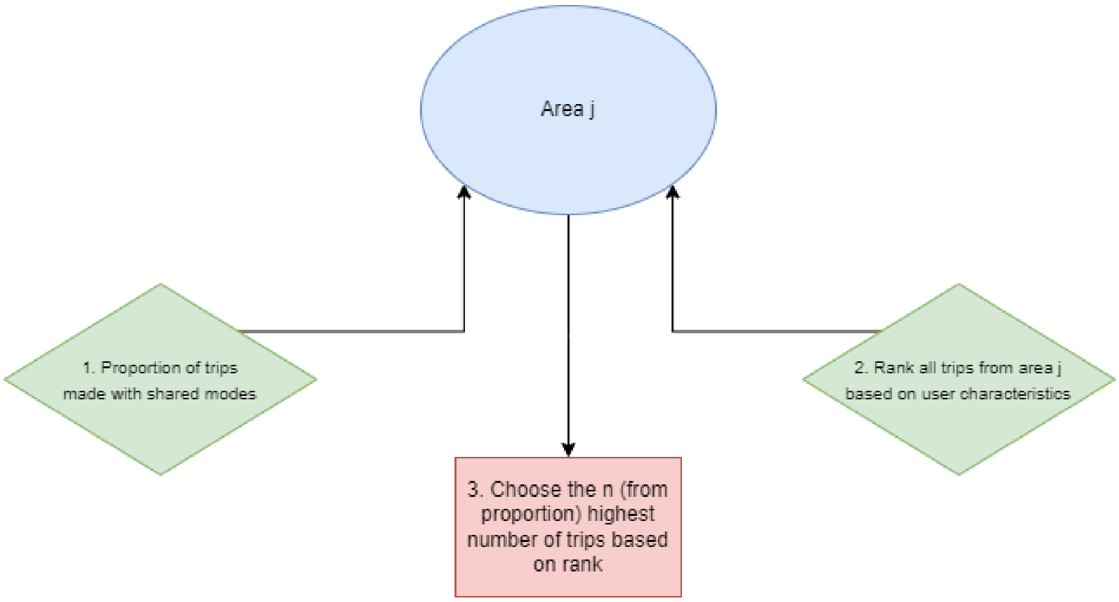

Figure 26 - Method to determine trips that have high likelihood of being shared mobility trips

After determining this for all neighbourhoods, a set of likely shared mobility trips is obtained of which trip lengths, motives and modes will be analysed. An example of how these trips is selected per neighbourhood is provided in Figure 27.

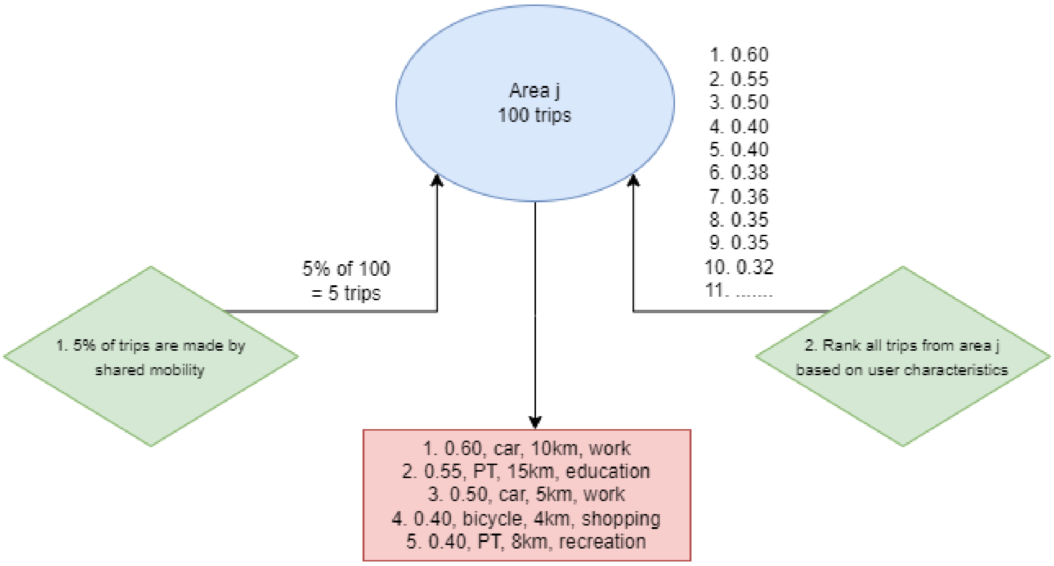

Figure 27 - Example of shared mobility trip selection

9.2. NVP Data

In this section, the dataset of the NVP is discussed. Firstly, the data is processed, and the different processing steps are discussed. Secondly, a general overview of the NVP trip data is given and the NVP data is compared to the ODIN in order to assess the representativeness of the data.

9.2.1. Data processing

Before using the NVP dataset, the data needs to be processed. Data is retrieved of all trips and journeys with an origin or destination within the study area. Furthermore, all associated tours and user information is retrieved. All trips with missing journey ids are removed, as are the trips without tour ids. Furthermore, the duplicate journeys and trips are removed. Besides that, all trips and journeys with a missing or unknown mode or motive are removed. Also trips with modes such as airplane, boat and ferry are removed since these are of no interest due to a low number of observations. The different public transport modes, such as light rail, train, metro, tram and bus are combined into one mode, being public transport.

As the user characteristics identified in Chapter 6 do not have the same format as the user characteristics from the NVP, some variables are changed in the regression model. The variables that are changed are the number of children per household, which is adjusted to household with or without children and the number of cars per household is changed to if a household has a car or not. Based on these adjusted variables, a new regression model has been setup which can be found in Appendix E Table 12.

Also, variables from the NVP have been adjusted to suit the regression model. For example, the seven educational categories have been combined into three categories similar to how the CBS classifies them. Also, age has been transformed into six age groups. To identify different trip distances, a new variable has been made categorising trip distance into six categories, excluding trips smaller than 500 meters.

For the analysis of the shared car trips, a different approach is used as for the shared moped/bicycle trips as both have different characteristics. For example, the trip distance for which a shared car is used ranges from very short trips (<2.5 km) till very long trips (>50km) whilst shared bicycles/mopeds are often used for trips with a distance shorter than 20 kilometres and more often even shorter (Sengül & Mostof, 2021; Rijkswaterstaat, 2023a). Therefore, for the shared bicycle and mopeds two analyses are conducted and for shared car only one. The analyses for shared moped/bicycle are an analysis where only bicycle trips in the NVP are used, and an analysis in which only trips shorter than 20 kilometres are taken into account. In the first analysis, trips which are likely made by shared moped/bicycle are identified. This is done only based on the current bicycle trips in the NVP since it is assumed that shared bicycle or moped trips are currently being classified as bicycle trips, due to the similar travel behaviour. In the second analysis also the other modes of transport are included. In this case the high likely shared moped/bicycle trips are assumed as possibly misclassified bicycle, car, public transport or walking trips. High likely shared moped/bicycle trips can in this analysis also be seen as trips currently conducted by these other modes of which the current mode can be substituted by a shared moped/bicycle.

For the shared cars, distance impacts the use less, discussed in Section 4.2, and therefore only one analysis where only car trips in the NVP are taken into account, is conducted. This due to the fact that car trips are in general less likely to be misclassified, as they have less similar travel patterns to the other modes. However, shared cars are likely classified currently as car trips and therefore these trips are of interest to analyse.

9.2.2. Descriptive statistics

For this analysis a year of trip data is analysed, in which trips are studied that have an origin and destination within the study area. Data is retrieved from July 2022 until June 2023. This time span is chosen since there were no travel restrictions because of the COVID-19 virus (RIVM, 2022). In this year 1,625,799 trips are recorded by 9,196 individual users. After processing the data 768,273 trips remained, which were recorded by 4,673 individual users.

In Figure 28, the modal split of the trips in the NVP is provided. Public transport trips only depict 1.68% of the total number of trips, which is lower than the 2.86% from the general modal split of the Netherlands, shown in Figure 29. The share of the car trips is also lower in the NVP compared to the modal split. The share of cycling trips in the NVP is also lower, but less compared to the other two modes. This is mainly due to the larger share of walking trips, which could be caused by a large amount of short trips being made by foot according to the NVP (see Appendix K, Figure 58) which are generally neglected in the ODIN research of which the modal splits are derived (CBS, 2023e).

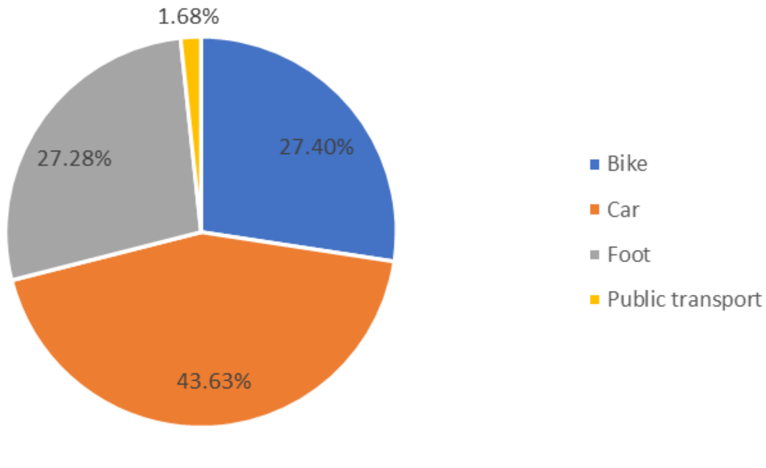

Figure 28 - Percentage of total number of trips per mode in NVP

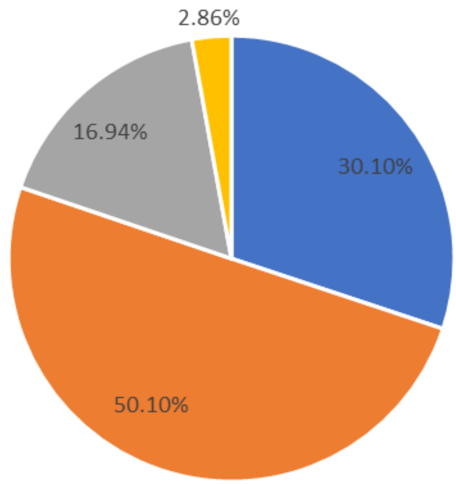

Figure 29 - Modal split ODIN (CBS, 2023e)

In Figure 30, the shares of the total number of trips per motive are shown. From this it can be seen that the majority of the trips made in the NVP are recreational trips, which is similar to the findings of the ODIN, however the magnitude is different (44% against 35%). Shopping and work trips have similar shares of the total number of trips in the ODIN as in the NVP, as shown in Figure 31. Educational trips have a lower share in the NVP, whilst also the other motives are less frequent. The higher share of recreational trips can again possibly be linked to the short walking trips (see Appendix K, Figure 59 and Figure 60), which are in general linked to the recreational motive. (CBS, 2023e)

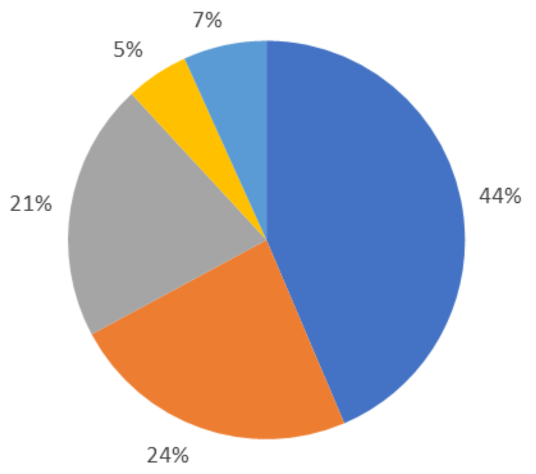

Figure 30 - Percentage of total number of trips per motive in NVP

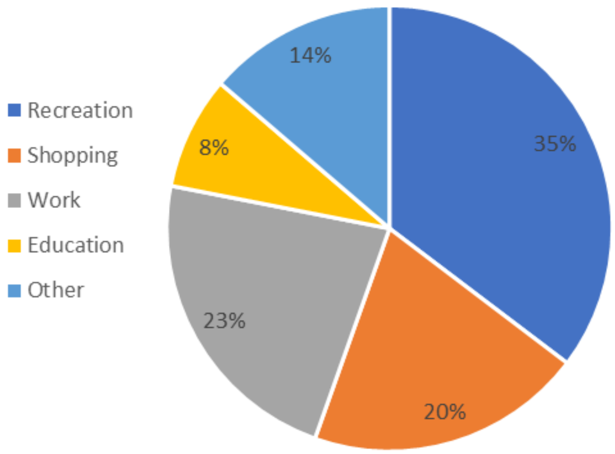

Figure 31 - Percentage of number of trips per motive in ODIN (CBS, 2023e)

In Figure 32, the percentage of trips per distance category is shown. Compared to similar travel data gathered for the Netherlands (see Figure 33), this shows that there is a higher share of shorter trips (under 5km) in the NVP (70% against 59%) (Gemeente Rotterdam, 2023). The other distance categories are therefore less frequent, but show similar patterns, which is the higher the trip distance category, the less frequent it occurs.

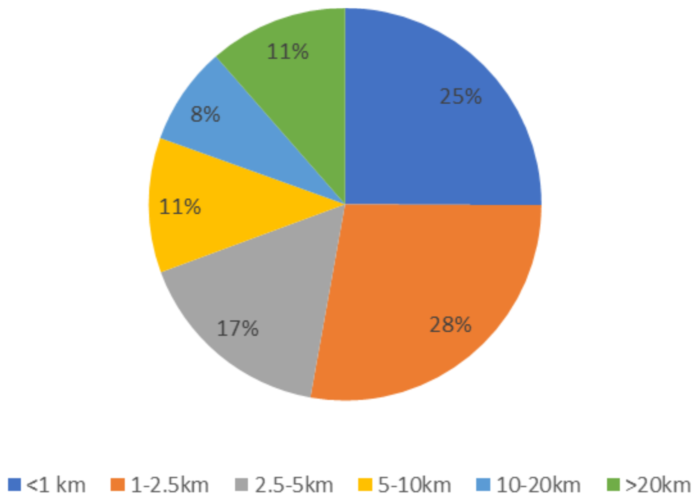

Figure 32 - Percentage of total number of trips per distance category in NVP

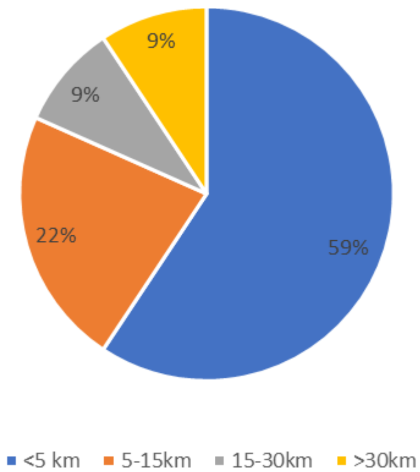

Figure 33 - Percentage of number of trips per distance category in the Netherlands (Gemeente Rotterdam, 2023)

9.3. Results

In this section, the results of the analysis on the trip characteristics of the trips with a high likelihood to be made by shared mobility are discussed. This is done for shared cars separately and shared bicycles and mopeds combined. In this analysis, the trip distance, motive and modes are discussed.

9.3.1. Trip characteristics shared car

For shared cars, the determined trips are all derived from car trips in the NVP as mentioned in Section 9.1. In the NVP set, there are 273,542 car trips. Of these car trips only 362 trips were found to have a high likelihood of being conducted by shared car (0.13%), which is similar to the findings of the Kennisinstituut voor Mobiliteitsbeleid, who found 0.2% of the car trips to be conducted by shared cars (Jorritsma, Witte, González, & Hamersma, 2021).

In Figure 34, the percentage of the total number of trips per motive are shown for the high likely shared car trips and for the car trips in general. From this figure, it can be seen that the shared car is in general more used for work and recreational trips compared to a privately owned car and shopping trips are made less by shared car.

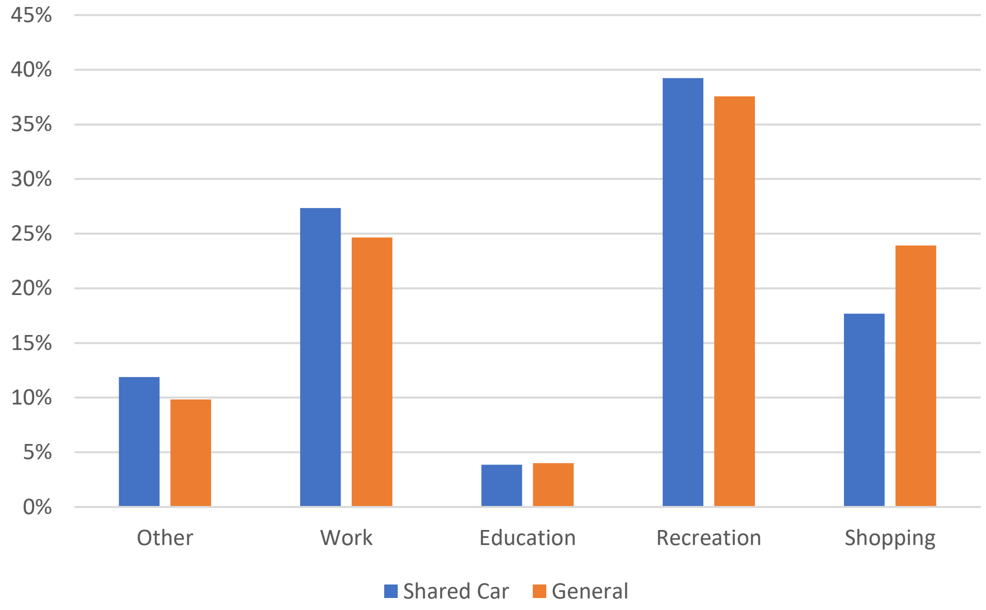

Figure 34 - Percentage of total number of trips per motive depicted for expected shared car trips and car trips of the NVP

In Figure 35, the percentages of the total number of trips per distance category are shown for the high likely shared car trips and for the car trips in general. This figure shows that for especially trips with large distances (> 10 kilometres) shared cars are used more, whilst a person with a private car takes more shorter trips compared to the shared car user. Trips between 1 and 2.5 km are an exception since these have a higher share for shared cars than for private cars.

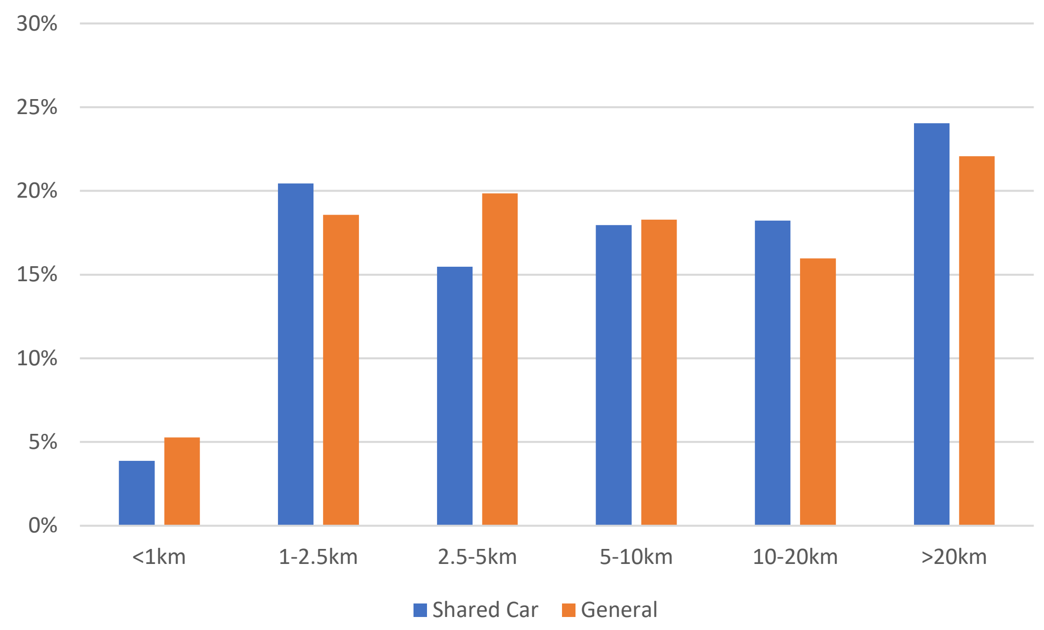

Figure 35 - Percentage of total number of trips per distance category for expected shared car trips and car trips of the NVP

9.3.2. Trip characteristics shared moped/bicycle

Two different analyses are done for shared bicycles, (1) analysis of all bicycle trips and (2) analysis of all trips shorter dan 20 kilometres. These will be discussed in separate sections.

9.3.2.1. Trip characteristics bicycle trips

In the NVP set, there are 204.554 bicycle trips. Of these trips 2,690 trips were found to have a high likelihood of being conducted by shared bicycle (1.32%). This is higher than the findings of the Kennisinstituut voor Mobiliteitsbeleid, who found 0.3% of the bicycle trips to be conducted by shared bicycles (Jorritsma, Witte, González, & Hamersma, 2021). However, this can be explained by the fact that shared moped use is also included in this analysis, which is in general used more than the shared bicycle (18.5 million against 5.2 million trips) (Rijkswaterstaat, 2023c; Duijnisveld, 2023).

In Figure 36, the percentages of the total number of trips are depicted per trip motive for expected shared bicycle/moped trips and bicycle trips in general. From this figure it can be observed that work and shopping trips are conducted more by shared bicycle compared to privately owned bicycle trips, whilst this is the opposite for recreational and educational trips.

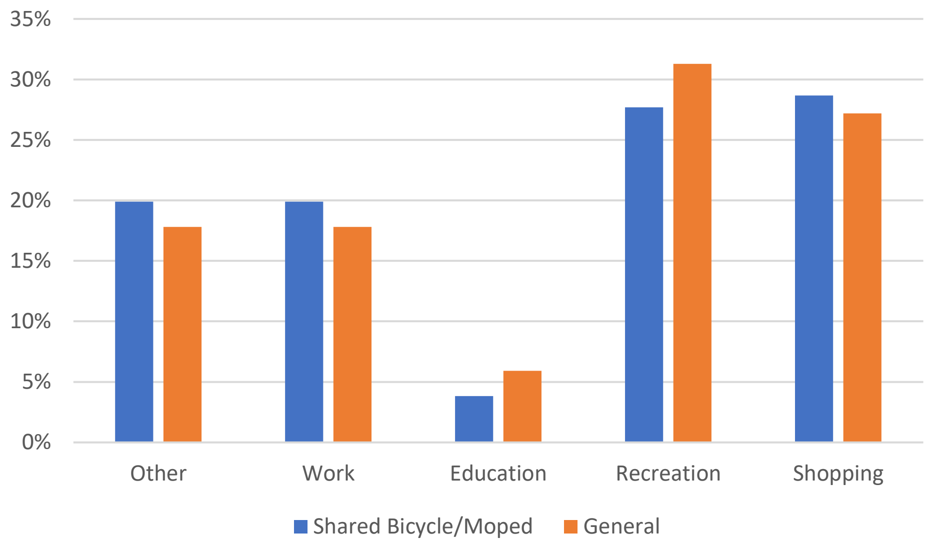

Figure 36 - Percentage of total number of trips per motive for expected shared bicycle/moped trips and bicycle trips of the NVP

In Figure 37, the proportions per distance category of the total number of trips for expected shared bicycle/moped trips and bicycle trips in general is shown. This shows that especially trips between 2.5 kilometres and 10 kilometres are conducted more with shared bicycle than the other distance categories, which is consistent with literature, although also more trips between 1 and 2.5 kilometres were expected (Sengül & Mostof, 2021).

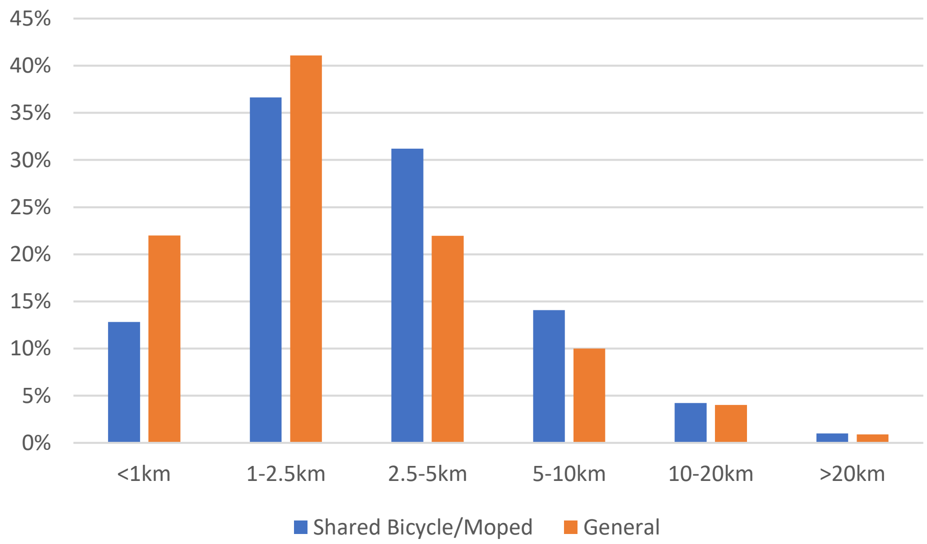

Figure 37 - Percentage of total number of trips per distance category for expected shared bicycle/moped trips and bicycle trips of the NVP

9.3.2.2. Trip characteristics short trips

In the NVP set, there are 669,372 trips that are shorter than 20 kilometres. Of these trips 9,525 trips were found to have a high likelihood of being replaced by shared bicycle/moped or misclassified in the NVP (1.42%). This misclassification can occur for trips made by scooter, as this mode is not included in the NVP. In Figure 38, the percentage of the total number of trips per mode of transport is shown for expected shared bicycle/moped trips and trips of the NVP in general. From this it can be seen that especially public transport and walking trips are predicted to be replaced by shared bicycle/moped trips, whilst car trips are in general less likely to be replaced.

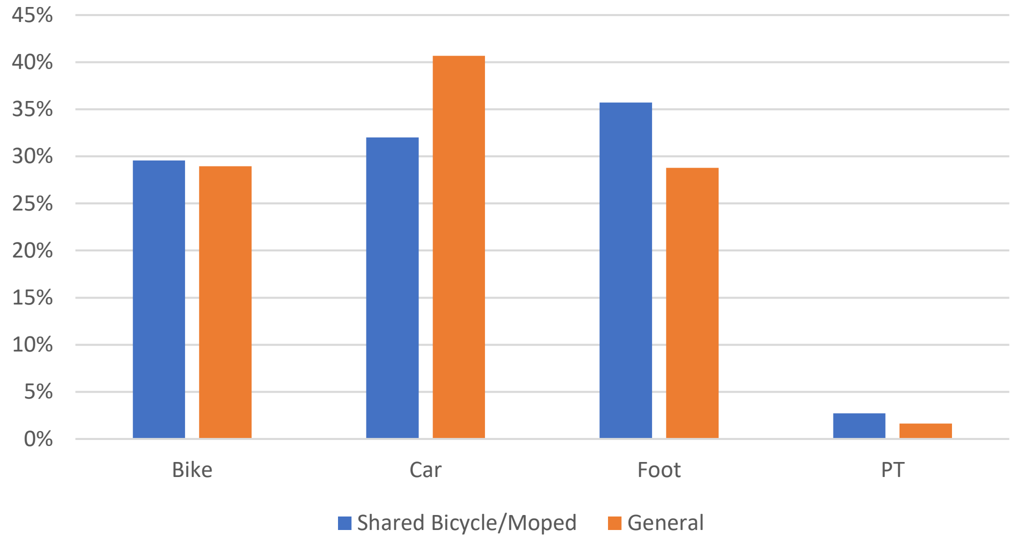

Figure 38 - Percentage of total number of trips per mode of transport for expected shared bicycle/moped trips and NVP in general

In Figure 39, the proportions of the total trips for expected shared bicycle/moped trips and NVP trips in general are shown per motive. From this figure it can be derived that work trips are conducted more often with shared bicycle/moped compared to all trips, whilst recreational and educational trips are less frequent. This is in line with the findings of the analysis in Section 9.3.2.1, as was visualised in Figure 36.

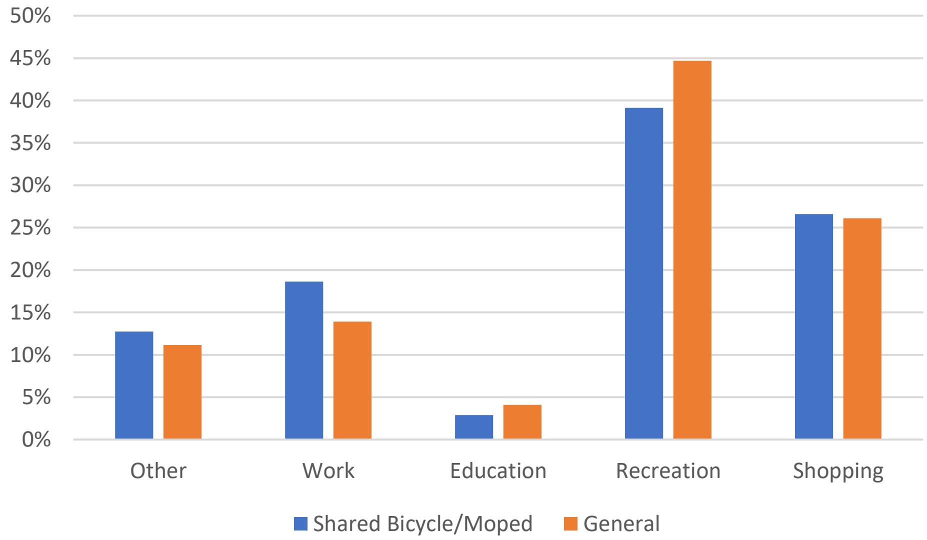

Figure 39 - Percentage of total number of trips per motive for expected shared bicycle/moped trips and NVP trips in general

In Figure 40, the shares per distance category of the total number of trips is shown for both expected shared bicycle/moped trips and NVP trips in general. This figure shows that in general trips between 2.5 and 10 kilometres are conducted more often by shared bicycle/mopeds than in general, which shows a similar image to the other method in the previous section.

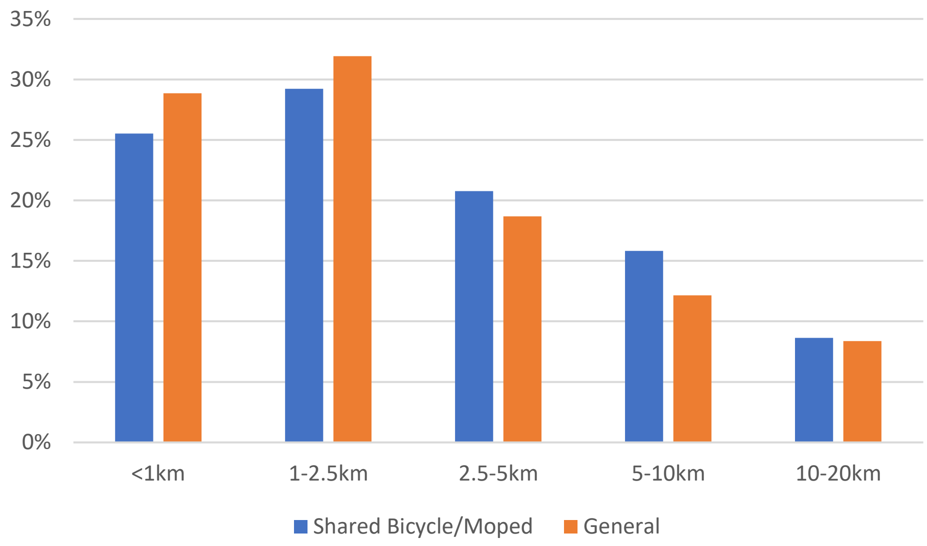

Figure 40 - Percentage of total number of trips per motive for expected shared bicycle/moped trips and NVP trips in general

10. Trip characteristics of different user groups of shared mobility

The multiple probability function determined in the ordered logit model is used to determine the likelihood a NVP user falls within one of the user groups, being frequent, non-frequent and no user. All users from the NVP between July 2022 and June 2023 that made trips originating and ending within the study area, are assessed based on this likelihood function. The different user groups are determined based on a weighting. Every user has a certain probability of belonging to a certain user group based on an adjusted regression equation depicted in Appendix F, Table 13. This probability is the respective weight per user for every user group. Every trip characteristic of the trips made by all users are thus combined based on the individually assigned weights. The trip distances, motives and modes of transport per user group are analysed to see whether there are differences in general travel behaviour between these groups. This chapter aims to answer the final research question being: *what are the general trip characteristics of the identified user groups of shared mobility in the studied metropolitan areas?*

10.1. Trip characteristics shared car user groups

In Figure 41, the shares of the total number of trips per mode of transport are shown per shared car user group. From this figure it can be seen that the user groups have a similar modal split, however there are some differences. For example, a non-user uses their car more often compared to the other user groups, whilst using Public Transport (PT) less often, which is consistent with the findings of Chapter 6 stating that car owners are less likely to use shared cars. Furthermore, non-frequent users generally use the bicycle and public transport more often, and the car less. Frequent users are similar in car and bicycle use compared to the no-user but make more use of public transport.

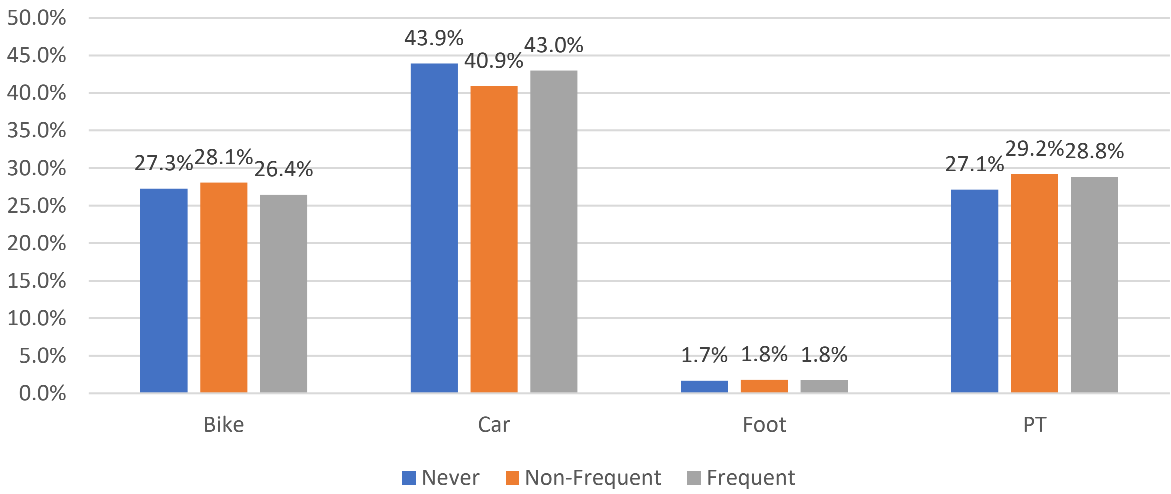

Figure 41 - Percentage of total number of trips per mode of transport per shared car user group

In Figure 42, the proportions per trip motive are depicted per user group. From this figure, it can be seen that no-users travel more for work purposes and less for shopping purposes than the other frequency groups. The non-frequent and frequent user groups have similar patterns for trip motives besides for recreational trips, which are conducted more often by frequent users. This corresponds with Figure 34, which showed that shared car user travel more for recreational and work purpose.

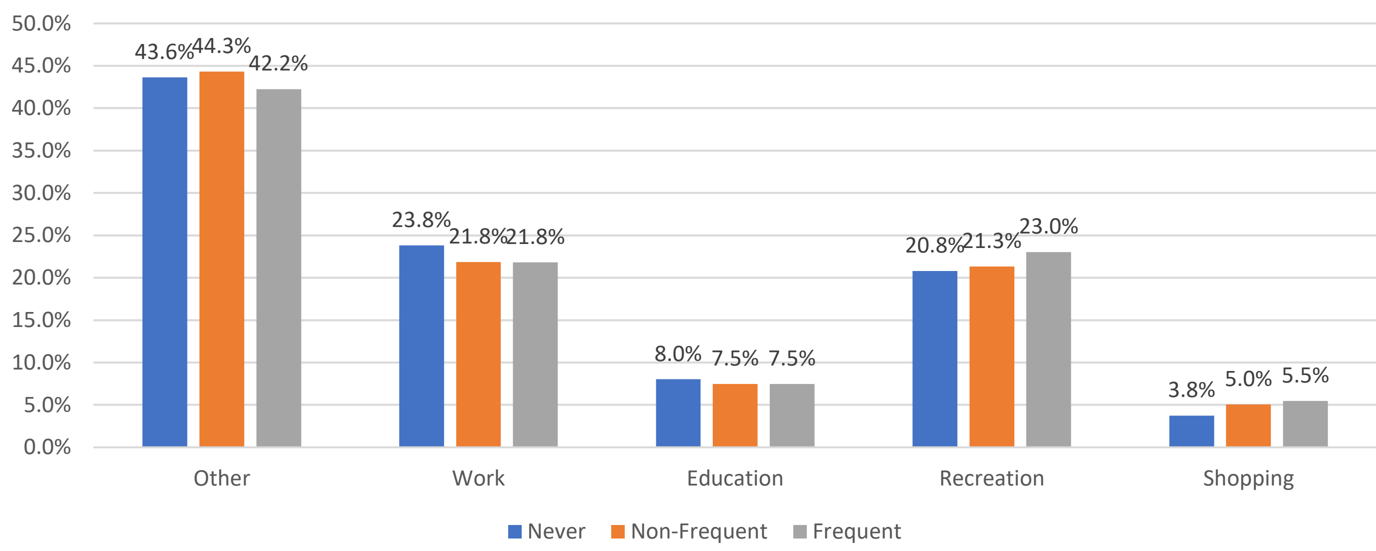

Figure 42 - Percentage of total number of trips per motive per shared car user group

In Figure 43, the percentage of the total trips is shown per distance category for all user groups. This shows that there is limited to no difference between all groups for travel distances.

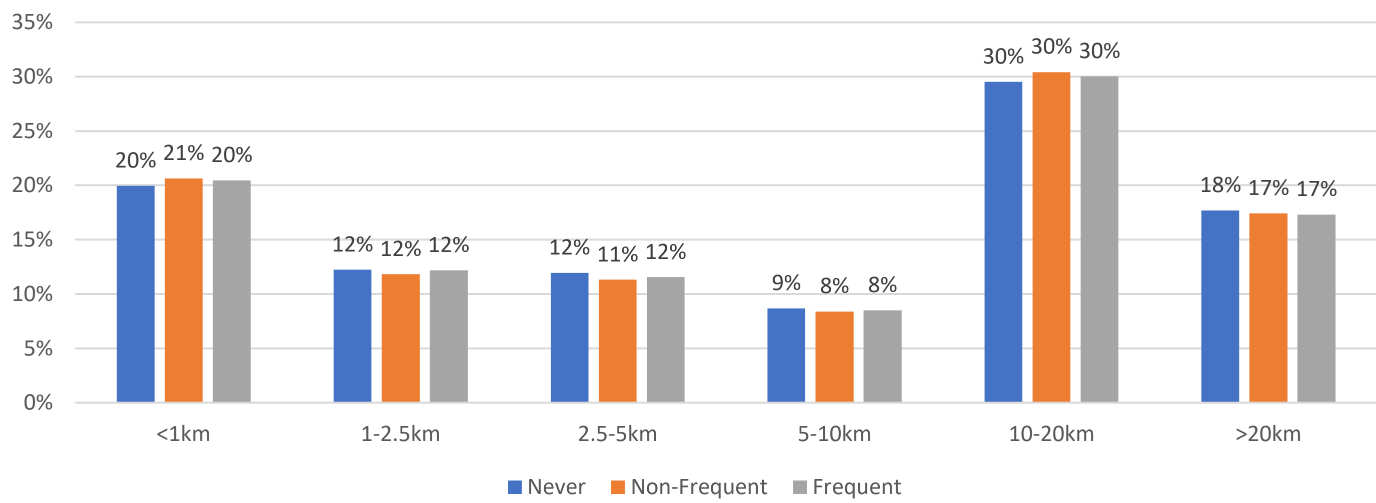

Figure 43 - Percentage of total number of trips per distance category per shared car user group

10.2. Trip characteristics shared bicycle user groups

In Figure 44, the shares per mode of transport are depicted for the different shared bicycle user groups. No-users are more likely to travel by bicycle than the other modes, which is interesting, but could mean that they prefer their own vehicle over shared bicycles. Non-frequent users travel more by public transport, which could also be the reason for using shared bicycles, for example an OV-fiets in combination with their train trip. Frequent users use cars more often than the other user groups, which is not in line with expectations from literature (Fishman, Washington, & Haworth, 2014). A possible explanation for this is that frequent shared bicycle users use the shared bicycle at certain trips that could also be done by bus or tram.

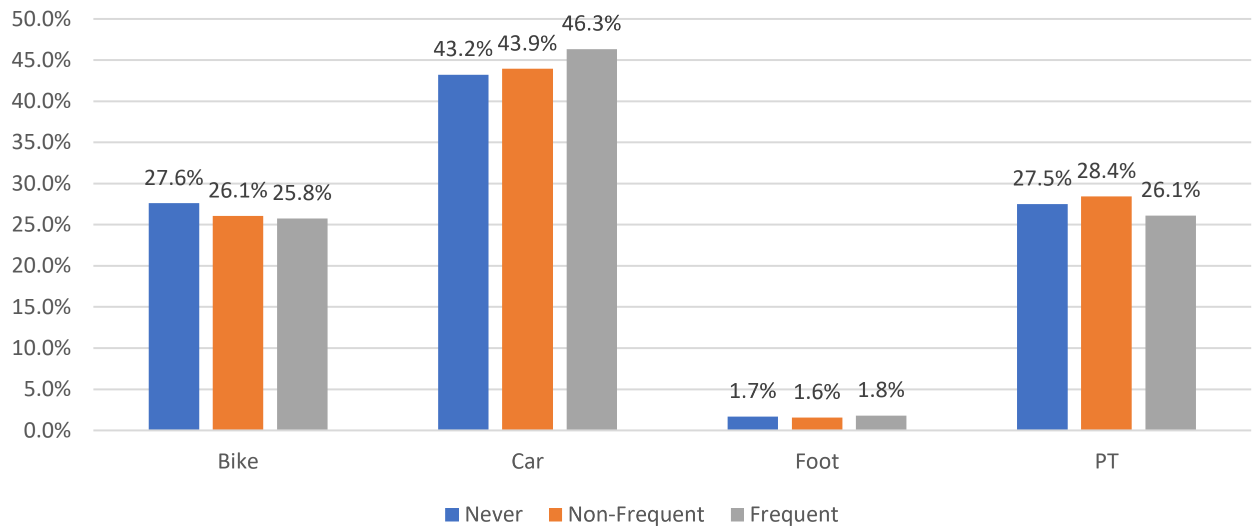

Figure 44 - Percentage of total number of trips per mode of transport per shared bicycle user group

In Figure 45, the proportions are shown per trip motive for all the user groups. From this it can be concluded that never users travel more often for business purposes, whilst frequent users travel more for recreational purposes. Non-frequent users have more shopping trips. From these findings it can be said that it is more likely that recreational, and to a lesser degree shopping trips, are replaced by shared bicycles than business trips. These findings are not in line with Figure 39, which showed shared bicycle/moped users travelling for business more than cyclists in general. Shared bicycle users travelling for recreational purpose more is however in line with those findings.

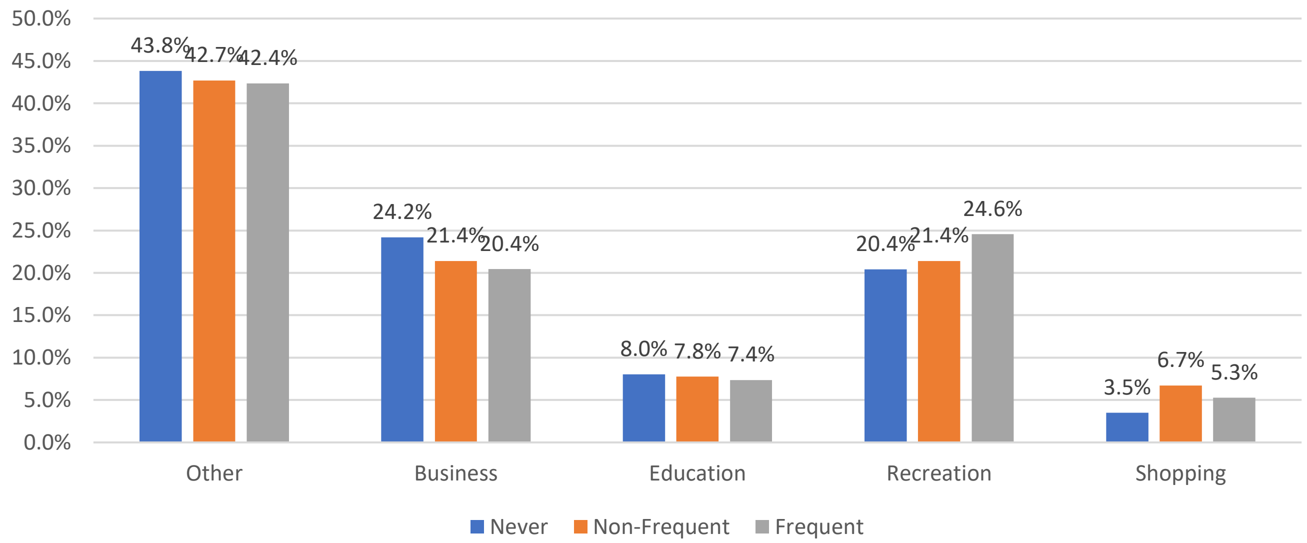

Figure 45 - Percentage of total number of trips per motive per shared bicycle user group

In Figure 46, the percentages of the total number of trips per distance category are shown for each user group. The differences between the user groups are, similar to shared car user groups, not that high. However, there are some distinctions, such as that frequent shared bicycle users undertake trips between 1 and 2.5 kilometres more often than the other groups, whilst they also undertake less trips between 10 and 20 kilometres. This can be linked to a higher share of recreational trips for this user group, which have in general less trips of 10-20 kilometres and more trips of 1 – 2.5 kilometres, as can be seen in Appendix K, Figure 60.

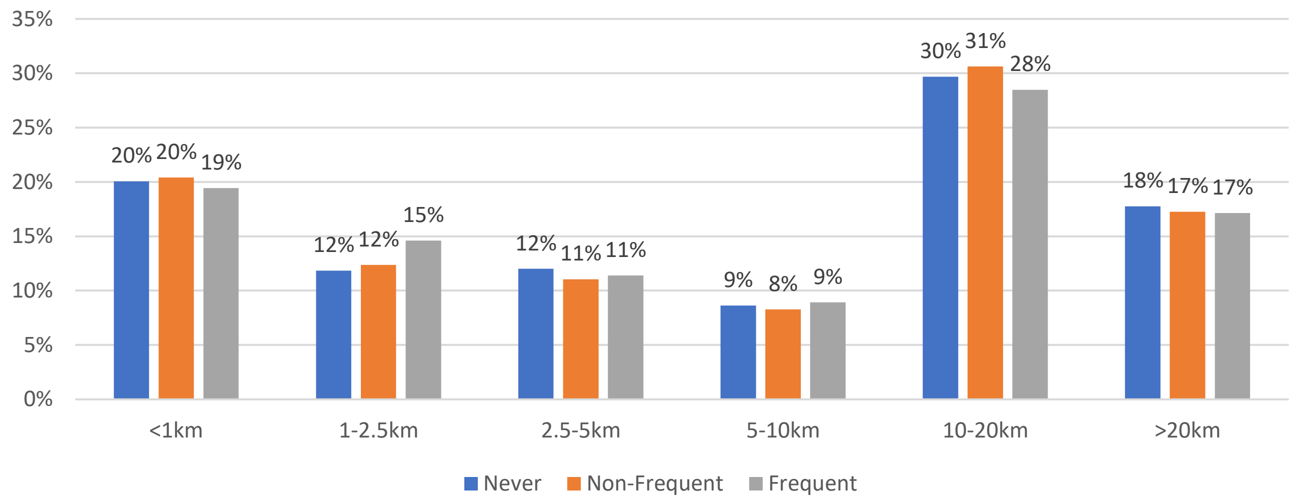

Figure 46 - Percentage of total number of trips per distance category per shared bicycle user group

10.3. Trip characteristics shared moped user groups

In Figure 47, the proportion of the total number of trips per mode of transport is shown for each of the shared moped user groups. The differences between the different user groups are small, especially between the no and non-frequent user groups. What can be seen is that frequent users use public transport more often and use the car less frequent. This could indicate that these users use shared mopeds in combination with public transport as was also found in the spatial analysis in section 8.3.2.2.

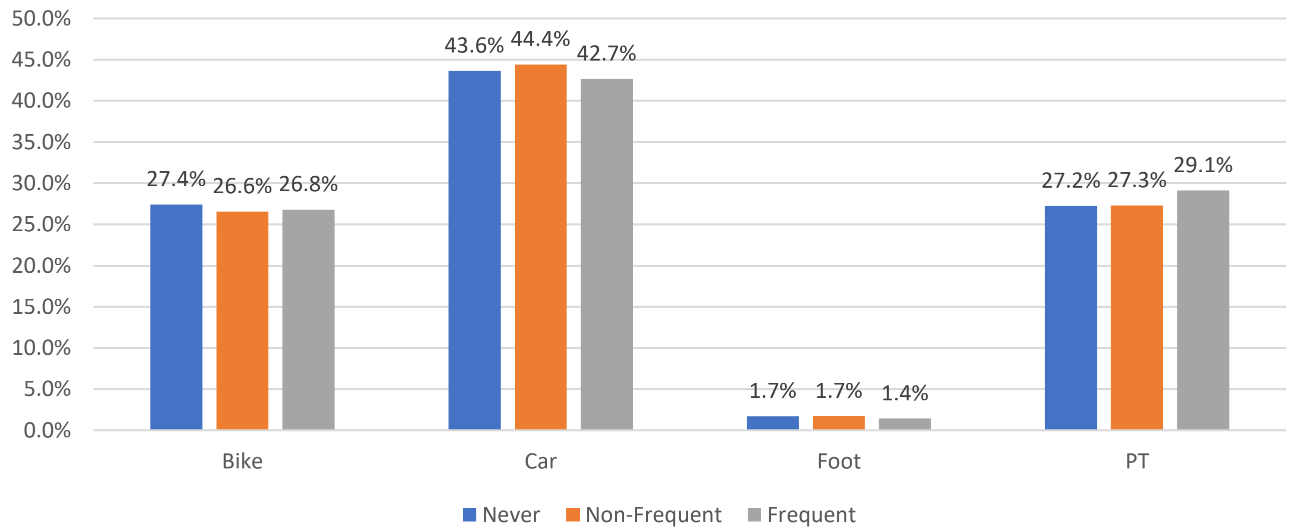

Figure 47 - Percentage of total number of trips per mode of transport per shared moped user group

In Figure 48, the shares of trips are depicted per motive for all of the different user groups. This shows a pattern similar to the shared bicycle user groups, as the never group undertakes more trips for work purposes compared to the other groups. However, non-frequent shared moped users conduct more trips for recreational purposes than the other groups, and frequent users make more shopping trips. This is the opposite of what was found for shared bicycle users.

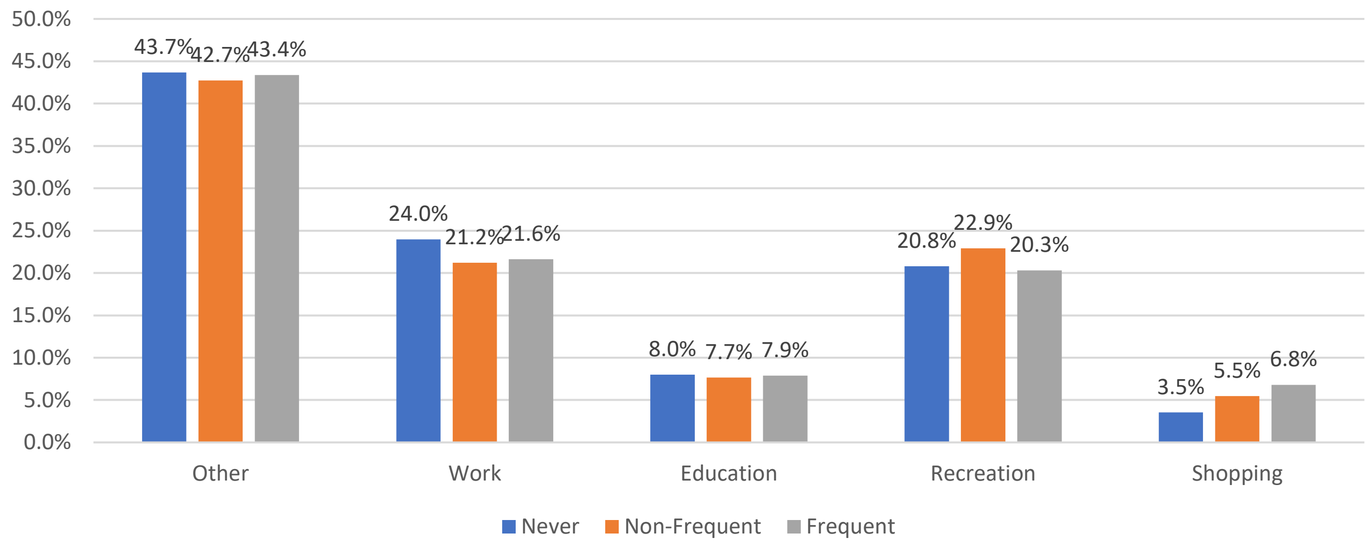

Figure 48 - Percentage of total number of trips per motive per shared moped user group

In Figure 49, the percentages per distance category are shown for each of the user groups. This again shows that the trip distance does not vary much between the different user groups, which shows that although trip distance can affect the use of shared mopeds, as shown in section 4.2, trip distance is not affecting the frequency of use from general travel behaviour.

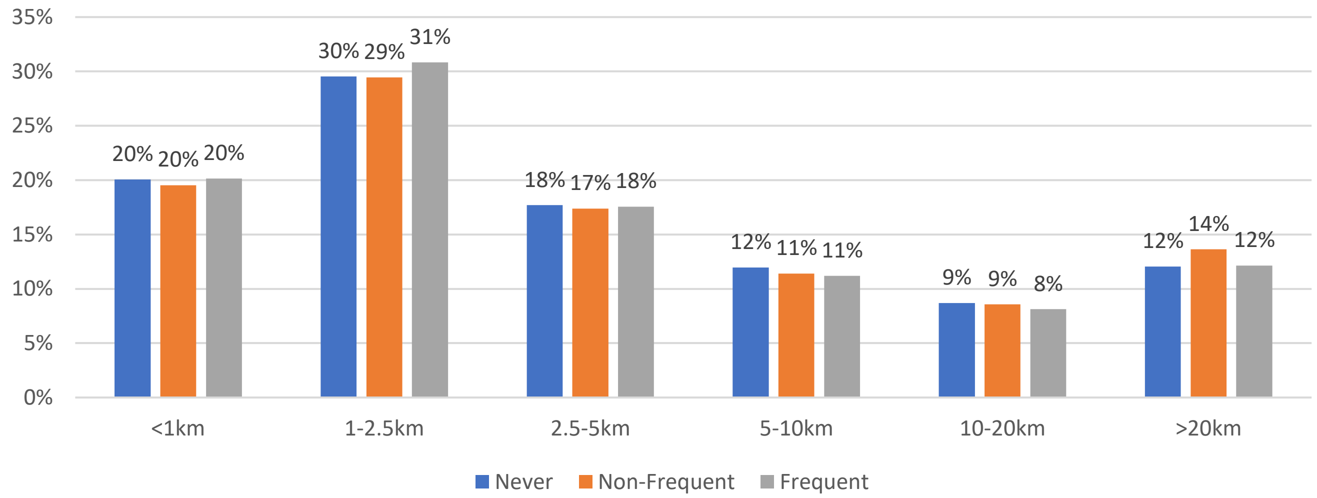

Figure 49 - Percentage of total number of trips per distance category per shared moped user group

11. Discussion

The three parts of this research have been discussed in their corresponding sections above. There are however some linkages between the parts that are not yet discussed. A link to practice and the used methodology are also discussed in this chapter. Finally, the limitations of the research are discussed.

11.1. Linkages between user characteristics, locational effects and travel behaviour

In this research, three different analyses have been conducted, which were about the user characteristics, locational effects and travel behaviour. During these analyses, contradicting and complementary findings were done, which are discussed in this section.

Firstly, respondents with children were deemed to have a higher probability of being a shared mobility user. However, areas with higher percentages of households with children were found to have a negative effect on the use and availability of shared mobility. This contradiction can be explained by the small number of respondents indicating that they had children (177 against 535). Within the survey the people with children that did use shared mobility were overrepresented compared to the actual distribution in Rotterdam-The Hague.

The contradiction can also be explained by a possible correlation with other variables. A significant correlation with other variables was not found in this research, but it can still be argued that this factor is in some way correlated with age and car ownership. People that are older than 30 are more likely to have a child than younger age groups, which could lead to correlation (NJi, 2023). Also, people that get children are more likely to own a car (PBL, 2020).

Both the personal and the spatial study show that low/middle education levels are linked to a lower probability of using shared mobility. Combined with the fact that higher average WOZ values and increased digital skills increase the use of shared mobility, governmental bodies should be warned that shared mobility is not inclusive for all inhabitants of the Netherlands. As it is an aim of the Dutch government to increase the inclusivity of shared mobility, governments should take an active role into steering shared mobility providers to adjust their services towards a more inclusive mode of transport (Ideate, 2023).

Car owners were found to be less likely of being a shared car user according to the survey. This could also be seen in the travel behaviour analysis as no-users of shared cars were more likely to use a car whilst travelling compared to the other user groups. Also, respondents answered that they preferred to use their own personal vehicle and are hesitant to use shared cars as it could not satisfy their travel demands. This shows again that initiatives to limit the use of private vehicles, such as limiting parking spots in neighbourhoods can lead to more shared car use (as found in Section 4.5).

Different parts of this study highlight the fact that increasing shared car availability would be an effective measure for private and public bodies to increase the use of this mode. It was one of the important reasons for not using shared cars, something that could also be seen in the spatial study. A

Land use was deemed to be an important predictor for the use of shared mopeds/bicycles as forest, commercial and recreational land use all increased the use. This could also be seen in the trip characteristics, where shopping trips were found to be made more frequently with shared moped/bicycle trips compared to cycling trips in general. However, trips with a recreational purpose are less frequent. Reasons for this difference can be that for the land use component only the origin of the trip is studied, whilst for the travel motives the destination is more important.

This research shows that age is an important predictor in the use of shared modes. People over 45 years old (and especially those over 65 years old) were found to have a lower probability of using shared modes, which corresponds to the effect, of more people from these age groups in an area, on the use and availability of shared mobility. The possible link to some of the other variables like households with children and digital skills also increases the importance of age.

Similar to previous studies increased digital skills was found to have a positive effect on the use of shared mobility. As data is limited on the digital skills levels per area, it was not possible to include this variable in the spatial analysis, which could be something that is of interest for further research. Digital skills could also not be included in the trip characteristics analysis, as NVP users are assumed to have high digital skills since their trip data is gathered via their smartphone. Therefore, it will be difficult to include digital skills within the NVP for future research, however in assisted ODIN surveys it could be of interest in the future to include a question about digital skills.

Shared mobility is often used in combination with public transport (Jorritsma, Witte, González, & Hamersma, 2021). This could also be concluded from the spatial analysis, however, it could have been interesting to also link the use of shared modes to the use of public transport in the conducted survey. In this research an existing survey is used, which was not tailor made to this research. Adding a question about the combination of both modes and conducting a survey solely based on a shared mobility user could have yielded some different results.

11.2. Link to practice

This research has provided insights in the use, locations of use and users of shared mobility. This is of added value to not only the academic world, but also shared mobility providers and governmental bodies. Governmental bodies can use this research when setting up new mobility policies, including the use of shared mobility. Findings of this study aid in identifying reasons for increased use and in identifying locations that are more suited for the use of shared modes. Shared mobility was also found to be not inclusive to all people. This is something especially governmental bodies need to be concerned about and take appropriate measures, like for example aid to increase digital skills or subsidies to decrease the costs of using shared mobility.

The characteristics of a shared mobility user can be of interest to the shared mobility provider for advertisement purposes. Furthermore, the reasons for not using shared mobility can be used to improve their services to increase the use of their modes. By identifying the effect of built environment and demographics, this research can help shared mobility providers to identify possible new cities or areas to provide shared modes to. Finally, this research has shown that the current availability of shared cars is holding the use of this mode back and therefore shared mobility providers (in cooperation with governmental bodies) need to increase the number of shared cars in the studied cities.

11.3. Limitations

As indicated in the previous sections, this research has limitations. This part of the discussion gives an overview of possibilities that could improve further research.

11.3.1. Small sample size of users

A limitation to this research was the small sample size of shared mobility users. This made it difficult to accurately assess the user characteristics, and exceptions in the data can skew the results towards a bias. It also limited the results of why people use shared mobility.

11.3.2. Different sample group per research part

It is difficult to transfer the results of the different research parts to each other. The fact that different sample groups and trips are assessed in the spatial analysis, the survey and the analysis of the travel behaviour has made it difficult to link, verify and validate the different results. It also led to assumptions in determining the likelihood of trips being made by shared mobility, which in turn could have impacted the results of especially the final parts of the research. Preferably, the Kantar panel, which is used to gather the trip data for the NVP, would have also been used for distributing the survey and determining whether a specific trip was made by shared mobility.

11.3.3. Bias in survey responses

In Section 6.2.1 the socio-demographic characteristics of the survey respondents were compared with the population of Rotterdam and The Hague. From this comparison a bias towards middle income and highly educated people was found in the survey compared to the study area population. Literature suggests that adding weights to the response to account for the bias can increase the representativeness and validity of the results. This was tried for the regression model studying the characteristics of shared car users. Adding weights to the survey responses did not lead to different results, which, together with the late timing in the research to add this, led to it not being implemented in this research. However, it is advised that further research does add weights to the survey responses to account for a possible bias.

11.3.4. Inconsistency of study areas

As the research has had multiple study areas for different parts of the research, locational differences could have affected the outcome of this research. As the user characteristics have only been defined for respondents from Rotterdam and the Hague, it could have been that by transferring those results to Amsterdam and Utrecht some important locational differences have been neglected or assumed to also occur in these new areas. For the spatial analysis for mopeds/bicycles has only been trained on data from Rotterdam and The Hague, which showed some differences with the other metropolitan areas in the analysis for shared cars. However, adding Amsterdam and Utrecht also increased the number of studied trips in the NVP and thus reduces the possible overdispersion of some NVP users on the findings.

11.3.5. Use of the NVP

The trip data of the NVP has also brought some limitations along. Firstly, the trip data of the NVP consists of trips from a small number of users (approximately 5000 people in the study area). Therefore, often trips of the same user were selected in Chapter 9 and 10, as most neighbourhoods and PC5 areas only had a few unique users. Increasing the number of unique members in the NVP could therefore increase the validity of this research by decreasing the individual importance of a user.

Furthermore, this research is subject to the assumptions and assignment methods used by Mobidot and Goudappel. As these did not include shared mobility as a possible mode, the identified trips that had a high likelihood of being made with shared modes could not be verified. Also, the possible mistakes in assigning the trip motive or mode could possibly have an effect on the results of this research.

11.3.6. Use (multinomial) logistic regression model

Different logistic regression models are used to assess the characteristics of users of shared mobility and the frequency of use. However, at the end of this research other types of regression models were identified that could also be used for this analysis. Models such as nested logit and latent class models can for example be used as well as logistic regression. As these models yield a different approach in modelling the influence of independent variables, for example by giving a more important place to car ownership, could lead to a higher accuracy in the coefficients of the different variables.

12. Conclusion

After discussing the results of the different parts of this research, it is possible to answer the research questions and reflect on the research goal. Furthermore, recommendations for future research are presented.

12.1. User characteristics

The first research question was:

What are characteristics of users of shared mobility in the Rotterdam – The Hague area?

Through the regression models based on the survey outcomes, it became clear that shared mobility users are often highly educated young adults. The non-ownership of cars and the possession of a driver's license also characterise shared car and moped users. Living in a household with a child will also increase the probability of using shared mopeds and bicycles. Furthermore, a higher digital skills level increases the chance of using any of the studied shared modes.

Even though there were limited amounts of frequent users, clear distinctions between the different shared mobility user groups were observed. Where the probability of being a frequent user of shared mopeds decreases per older age group, for shared bicycle and car users only specific age groups make a significant difference between user groups. Furthermore, gender only impacts shared moped frequency groups, with males being more likely to be a frequent user. Having a driving license was only found to impact shared car user groups as it increased the odds of being a non-frequent user significantly, whilst also influencing the frequent user groups, but less severe. The effect of having children differs between modes, whereas having one child leads to a higher chance of being a frequent shared car or bicycle user, it increased the chance of being a non-frequent shared moped user, just as having more than 2 children did. Low education levels were seen as a predictor for especially non-users for all modes, similar to people with a middle education level, which had a large effect on the frequency groups of shared bicycles. Finally, a higher level of digital skills increased the probability of being a frequent user of shared bicycles and mopeds, it also had a positive (albeit smaller) effect on being a non-frequent user compared to no-users.

12.2. Reasons for (not) using shared mobility

The second research question was:

What are reasons for people to (not) use shared mobility modes?

A main reason for using shared mobility could be seen, which was that these modes increase the flexibility of travelling. Besides added flexibility, higher accessibility was indicated as a main reason for using shared mobility modes. For shared cars and mopeds also ‘shorter travel times’ was seen as a reason for using these modes, which could indicate other slower modes of transport being replaced. Shared cars and bicycles were also deemed to be easy to use, indicating that this might need to be improved for shared mopeds.

Private ownership of vehicles is the main barrier for the use of shared mobility. More than 60% of the respondents gave this reason for not using shared mobility. Respondents also found shared mobility to be too expensive. Therefore, lowering the costs for using these modes could increase the use of shared mobility, however this is not specifically studied in this research. Shared mobility was also deemed to not satisfy the travel demands of the respondents, leading to people not using it. This indicates that certain people are not planning to use shared mobility under any circumstances.

A limited availability of shared cars, derived from the fact that respondents indicated 'needing to walk too far' as a main reason, also led to people not using this mode. Therefore, providers and municipalities need to work on increasing the availability, such that more people potentially use shared cars. Reasons people do not use shared mopeds are people perceiving it to be too dangerous and because they do not know how to use it. Extra safety precautions and guidance in use can therefore be of added value to increase the use.

12.3. Effect of built environment and demographics

The third research question was:

What is the effect of built environment factors and demographics on the use of shared mobility modes?

There are different built environment and demographic variables effecting the use of shared cars and shared bicycles/mopeds. Older people have a negative relation on the use of both shared mode groups. However, for shared mopeds/bicycles, more age groups (45 – 64 and 65 and older) were found to be a significant negative predictor (only 65 years and older). A higher percentage of males or people in households with children also have a negative effect on the use of shared cars, bicycles and mopeds. Strong urbanization (shared cars) and high population density (shared bicycle/moped) are also positively associated with the use of shared mobility. Areas with a high percentage of people with low or middle Education level are associated with less shared car usage. Lower average WOZ values decrease the use of shared mopeds and bicycles. This shows that currently shared mobility modes are not seen as an inclusive mode.

A more diverse land use increases the availability and thus the use of shared cars. Also, forest, commercial and recreational land use increase the use of shared bicycles and mopeds. Shared bicycles and mopeds are also used more at areas with more public transport services, which indicates a direct link between the use of public transport in combination with these shared modes.

12.4. Trip characteristics shared mobility trips

The fourth research question was:

What are the trip characteristics of trips that have a high likelihood to be made by shared mobility in the studied metropolitan areas based on the built environment factors and demographics of the originating area, and the characteristics of the user?

Shared car trips were found to be work and recreational trips more often than general car trips. Shopping trips were less likely to be done by shared cars. Trips likely made by shared cars are also more often trips longer than 10 kilometres compared to car trips in general. However, it was difficult to determine the trip characteristics of shared mobility trips since the potential shared mobility trips were based on multiple datasets and assumptions, instead of trips that are known to be made by shared mobility.

Trips likely made by shared bicycle and moped were determined in two different ways. Firstly, bike trips that would most likely be made with shared bike or moped were determined based on current bicycle trips. This led to shared bicycle and moped trips to have a larger share of trips between 2.5 and 10 kilometres compared to bicycle trips in general. Also work and shopping trips are more frequent for shared bicycle/mopeds trips. Recreational and educational trips are less likely to be shared bicycle/moped trips. A second way to determine trips that could have been made by or are most likely to be replaced by shared bike/moped was to exclude trips with large distances (>20 kilometres) and than study the trip characteristics, which led to walking and public transport trips likely to be replaced by shared bicycles or mopeds. Also, medium distance (2.5 till 10 kilometres) trips or trips for work were seen to have a higher likelihood of being made by shared bicycle/moped compared to the other distances and motives.

12.5. Travel behaviour user groups

The fifth research question was:

What are the general trip characteristics of the identified user groups of shared mobility in the studied metropolitan areas?

No large differences were found in the travel behaviour and trip characteristics of the different user groups for all the different shared modes. Trip distances did not differ between the user groups for any of the shared modes, whilst there were some small differences between trip motives and used modes. Shared bicycle and moped non-users were found to travel more often by bicycle and for work. Shared bicycle non-frequent users and frequent shared moped users travelled more often by public transport and for shopping purposes. Frequent shared bicycle users and non-frequent shared moped users travelled more by car and for recreational purposes. The no user of shared cars was found to travel more by car and for work purposes. Frequent shared car users travelled more often by public transport and for shopping and recreational purposes.

12.6. Reflection to research goal and recommendations

The aim of this research was to identify the where, why and by whom shared mobility is used. This has been achieved by answering the different research questions. However, determining the reasons for using shared mobility and the trip characteristics was difficult to do with the used method and available data. Therefore, a good overview of which variables can have an impact on the users and use of shared mobility is provided, but the linkage between parts had its limitations. The results are also difficult to transfer to other areas in the Netherlands, because of large differences in demographics and land use.

Governmental bodies and shared mobility providers are advised to use this research, as they can learn from the findings in multiple ways. Firstly, shared mobility is not found to be inclusive, something the government aimed it would be. Secondly, reasons for not using shared mobility can help the providers to improve their modes. Furthermore, providers and governmental bodies can learn from the effects of built environment and demographics on the use of shared mobility, to increase the use. Increasing the availability of especially shared cars would help as well.

For further research, it is recommended that the same group of people is studied for all different analyses conducted in this research. Furthermore, a closer cooperation with the distributors of shared mobility vehicles could have been beneficial as it can be of interest to compare the findings of the spatial analysis with current strategies of these distributors. Also trip data of shared cars could then be used in the spatial analysis instead of using only the availability locations of shared cars.

In this research, also only the origin of a trip is taken into account in determining the trips with a high likelihood of being made by shared mobility, whilst the mode choice for a specific trip also depends on the destination. Incorporating the destination requires a more complex approach with an optimization model to distribute the trips across the different areas. This might lead to more accurate results. Furthermore, the study of actual shared mobility trips could give an even better understanding of the trip characteristics of shared mobility trips. This data is unfortunately not easy to obtain. In an ideal situation trip made with shared modes are registered in the NVP, so further research should investigate these possibilities or more cooperation with the shared mobility providers. An increase in unique users in the NVP can lead to an increased validity by decreasing the individual importance of a user. Therefore, it is recommended that more people are recruited to participate in the NVP.

It is also recommended that a more detailed study is conducted into which regression models are used in the spatial analysis or analysis into the user characteristics. Other models can be a better fit in uncovering the patterns in user characteristics than the logistic regression models now used and should therefore be studied in more detail.

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Appendix A: Flyer

Figure 50 - Flyer for distributing survey

Appendix B: Smarthubs survey

In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:

Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.

Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.

Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.

Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat.

Hoe vaak reist u met de onderstaande vervoermiddelen?
*

Kies het toepasselijke antwoord voor elk onderdeel:

	4 of meer dagen per week	1-3 dagen per week	1-3 dagen per maand	1-11 dagen per jaar	Nooit
Taxi of andere soortgelijke diensten, bijv. Uber	○	○	○	○	○
Bus, tram, metro	○	○	○	○	○
Trein	○	○	○	○	○
Deelfiets/Deel-e-fiets	○	○	○	○	○
Deelscooter	○	○	○	○	○
Deelauto als bestuurder of passagier	○	○	○	○	○

Figure 51 - Frequency of shared mobility question

Wat zijn de belangrijkste **redenen** waarom je het afgelopen jaar met een **deelauto** hebt gereisd? Selecteer alles wat van toepassing is: *

Beantwoord deze vraag alleen als aan de volgende voorwaarden is voldaan:
Antwoord ONGELIJK 'Nooit' bij vraag ' [Sharedmodes]' (In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat. Hoe vaak reist u met de onderstaande vervoermiddelen? (Deelauto als bestuurder of passagier))

Meerdere antwoorden mogelijk
Kies alle voor u geldende mogelijkheden:

- ☐ Ik kan meer plekke bereiken
- ☐ Voertuigen zijn makkelijk te gebruiken
- ☐ Er zijn veel voertuigen beschikbaar
- ☐ Het is goedkoop
- ☐ Het maakt reizen flexibeler
- ☐ Het zorgt voor een kortere reisduur
- ☐ Overige:

Figure 52 - Question about reasoning for using shared car

Wat zijn de belangrijkste **redenen** waarom je het afgelopen jaar met een **deelscooter** hebt gereisd? Selecteer alles wat van toepassing is: *

Beantwoord deze vraag alleen als aan de volgende voorwaarden is voldaan:
Antwoord ONGELIJK 'Nooit' bij vraag ' [Sharedmodes]' (In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat. Hoe vaak reist u met de onderstaande vervoermiddelen? (Deelscooter))

Meerdere antwoorden mogelijk
Kies alle voor u geldende mogelijkheden:

- ☐ Ik kan meer plekken bereiken
- ☐ Apps zijn makkelijk te gebruiken
- ☐ Er zijn veel voertuigen beschikbaar
- ☐ Het is goedkoop
- ☐ Het maakt reizen flexibeler
- ☐ Het zorgt voor een kortere reisduur
- ☐ Overige:

Figure 53 - Question about reasoning for using shared mopeds

Wat zijn de belangrijkste **redenen** waarom je het afgelopen jaar met een **deelfiets/e-fiets** hebt gereisd? Selecteer alles wat van toepassing is: *

Beantwoord deze vraag alleen als aan de volgende voorwaarden is voldaan:
Antwoord ONGELIJK 'Nooit' bij vraag ' [Sharedmodes]' (In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat. Hoe vaak reist u met de onderstaande vervoermiddelen? (Deelfiets/Deel-e-fiets))

Meerdere antwoorden mogelijk
Kies alle voor u geldende mogelijkheden:

- ☐ Ik kan meer plekken bereiken
- ☐ Voertuigen zijn makkelijk te gebruiken
- ☐ Er zijn veel voertuigen beschikbaar
- ☐ Het is goedkoop
- ☐ Het maakt reizen flexibeler
- ☐ Het zorgt voor een kortere reisduur
- ☐ Overige:

Figure 54 - Question about reasoning for using shared bicycle

Wat zijn de belangrijkste **redenen** waarom je het afgelopen jaar nooit met een **deelauto** hebt gereisd? Selecteer alles wat van toepassing is: *

Beantwoord deze vraag alleen als aan de volgende voorwaarden is voldaan:
Antwoord was 'Nooit' bij vraag ' [Sharedmodes]' (In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat. Hoe vaak reist u met de onderstaande vervoermiddelen? (Deelauto als bestuurder of passagier))

Meerdere antwoorden mogelijk
Kies alle voor u geldende mogelijkheden:

- ☐ Nog nooit van gehoord
- ☐ Het is te duur
- ☐ Ik moet te ver lopen om een voertuig te bereiken
- ☐ Ik vind het te gevaarlijk
- ☐ Ik vertrouw het gebruik van deelvoertuigen niet
- ☐ Ik weet niet hoe ik dit voertuig moet gebruiken
- ☐ Ik heb niet het gevoel dat dit voertuig aan al mijn reisbehoeften kan voldoen
- ☐ Ik heb het in het verleden geprobeerd en ik was teleurgesteld over de ervaring
- ☐ Overige:

Figure 55 - Question about reasoning for not using shared car

Wat zijn de belangrijkste **redenen** waarom je het afgelopen jaar nooit met een **deelscooter** hebt gereisd? Selecteer alles wat van toepassing is: *

Beantwoord deze vraag alleen als aan de volgende voorwaarden is voldaan:
Antwoord was 'Nooit' bij vraag ' [Sharedmodes]' (In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat. Hoe vaak reist u met de onderstaande vervoermiddelen? (Deelscooter))

Meerdere antwoorden mogelijk
Kies alle voor u geldende mogelijkheden:

- [ ] Nog nooit van gehoord
- [ ] Het is te duur
- [ ] Ik moet te ver lopen om een voertuig te bereiken
- [ ] Ik vind het te gevaarlijk
- [ ] Ik vertrouw het gebruik van deelvoertuigen niet
- [ ] Ik weet niet hoe ik dit voertuig moet gebruiken
- [ ] Ik heb niet het gevoel dat dit voertuig aan al mijn reisbehoeften kan voldoen
- [ ] Ik heb het in het verleden geprobeerd en ik was teleurgesteld over de ervaring
- [ ] Overige:

Figure 56 - Question about reasoning for not using shared mopeds

Wat zijn de belangrijkste **redenen** waarom je het afgelopen jaar nooit met een **deelfiets/e-fiets** hebt gereisd? Selecteer alles wat van toepassing is: *

Beantwoord deze vraag alleen als aan de volgende voorwaarden is voldaan:
Antwoord was 'Nooit' bij vraag ' [Sharedmodes]' (In de rest van de enquête zullen enkele vragen betrekking hebben op GEDEELDE vervoerwijzen:Deelfiets/e-fiets: biedt gebruikers toegang tot fietsen op verschillende ophaal- en inleverlocaties. Fietsen zijn beschikbaar via een mobiele app, een klantenkaart of een automaat.Deelauto: meestal aangeboden op speciale locaties. Gebruikers moeten in het bezit zijn van een rijbewijs. Betalen gaat vaak via een mobiele app, een online rekening op een website of bij een automaat.Deelscooter: geeft toegang tot scooters op verschillende locaties. Meestal hebben mensen toegang tot een scooter via een mobiele app.Deelbakfiets/e-fiets: biedt gebruikers toegang tot bakfietsen op verschillende ophaal- en inleverlocaties. Bakfietsen zijn verkrijgbaar via een mobiele app, een klantenkaart of automaat. Hoe vaak reist u met de onderstaande vervoermiddelen? (Deelfiets/Deel-e-fiets))

Meerdere antwoorden mogelijk
Kies alle voor u geldende mogelijkheden:

- [ ] Nog nooit van gehoord
- [ ] Het is te duur
- [ ] Ik moet te ver lopen om een voertuig te bereiken
- [ ] Ik vind het te gevaarlijk
- [ ] Ik vertrouw het gebruik van deelvoertuigen niet
- [ ] Ik weet niet hoe ik dit voertuig moet gebruiken
- [ ] Ik heb niet het gevoel dat dit voertuig aan al mijn reisbehoeften kan voldoen
- [ ] Ik heb het in het verleden geprobeerd en ik was teleurgesteld over de ervaring
- [ ] Overige:

Figure 57 - Question about reasoning for not using shared bicycle

Appendix C: Characteristics respondents survey

Table 10 - Characteristics survey respondents

Variable	Explanation
Gender	Male or female
Age group	Age below 25 years old 25 – 39 years old 40 – 54 years old 55 – 64 years old 65 – 74 years old Older than 74 years old
Education	Low: Secondary Vocational Education, Senior High School and Compulsory Education or less Middle: High school graduate High: University undergraduate degree and MSc/MA/Phd or other equal level
Occupation	In retirement Employed (working full/part time) Working in household or other unpaid activity Self-employed (working full/part time) Student Unable to work Unemployed Other
Income level	Low: Up to 1600 euros per month Middle: 1601 till 4800 euros per month High: more than 4800 euros per month
Number of adults in household	0, 1, 2 and 2 or more
Number of children in household	0, 1, 2 and 2 or more
Number of cars in household	0, 1, 2
Household with children	Yes or no
At least one car in household	Yes or no
Digital skills	Level 0/1: Respondent is not using a mobile phone with internet connection (level 0) or respondent is using a mobile phone with internet connection, but is not using applications for planning trips (level 1) Level 2: Respondent is using a mobile phone, and is using applications for planning trips (either for their own vehicle or PT) Level 3: Respondent is using a mobile phone, and is using applications for planning trips (either for their own vehicle or PT), and is using applications to buy tickets/seat reservations for PT, and is using applications to transfer money

Appendix D: Cramer's V score

Table 11 - Cramer's V score

	Education group	**Number of children**	**Driving license**	**Age Group**	**Gender**	**Income level**	**Number of adults**	**Number of cars**	**Occupation**	**Digital skills**
Educationgroup	1.00	0.08	0.21	0.29	0.01	0.28	0.08	0.07	0.31	0.20
Number of children	0.08	1.00	0.11	0.23	0.09	0.16	0.21	0.19	0.19	0.11
Driving license	0.21	0.11	1.00	0.18	0.06	0.20	0.12	0.41	0.24	0.23
Age Group	0.29	0.23	0.18	1.00	0.17	0.23	0.23	0.15	0.49	0.24
Gender	0.01	0.09	0.06	0.17	1.00	0.19	0.12	0.04	0.23	0.02
Income level	0.28	0.16	0.20	0.23	0.19	1.00	0.31	0.21	0.38	0.18
Number of adults	0.08	0.21	0.12	0.23	0.12	0.31	1.00	0.28	0.26	0.09
Number of cars	0.07	0.19	0.41	0.15	0.04	0.21	0.28	1.00	0.18	0.12
Occupation	0.31	0.19	0.24	0.49	0.23	0.38	0.26	0.18	1.00	0.27
Digital skills	0.20	0.11	0.23	0.24	0.02	0.18	0.09	0.12	0.27	1.00

Appendix E: Logistic regression results NVP

Table 12 - Logistic regression NVP

	Shared car	Shared bicycle	Shared moped
(Intercept)	0.09 (0.21)	**-0.34*** (0.16)	0.12 (0.18)
No driving license	**-1.13**** (0.37)		**-1.24**$^{\cdot}$ (0.74)
Car ownership	**-1.16***** (0.22)		
Age below 25	-0.50 (0.37)	0.11 (0.33)	**1.16**** (0.37)
Age of 40 – 54	**-0.59*** (0.26)	**-0.76**** (0.24)	**-1.29***** (0.24)
Age of 55 – 64	**-1.31**** (0.44)	**-0.90*** (0.37)	**-2.47***** (0.46)
Age of 65 – 74	**-1.07**** (0.36)	**-2.14***** (0.54)	**-4.55***** (1.02)
Age above 74 years	-16.12 (613.46)	**-1.51*** (0.76)	**-2.52**** (0.77)
Low education	**-0.67*** (0.29)	**-0.98***** (0.26)	**-0.64*** (0.26)
Middle education	-0.29 (0.32)	**-1.79***** (0.40)	**-0.77*** (0.35)
Household with children		**0.38**$^{\cdot}$ (0.23)	
Male			**0.54*** (0.21)
AIC	609.05	653.35	598.06
BIC	654.72	694.04	642.16
Log Likelihood	-294.53	-317.68	-289.03
Deviance	589.05	635.35	578.06
Num. obs.	711	679	608

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Appendix F: Multinomial Logistic regression results NVP

Table 13 – Multinomial Logistic regression model NVP

	Shared car	Shared bicycle	Shared moped
Non-Frequent			
Intercept	-0.18 (0.24)	**-0.97***** (0.22)	**-1.18***** (0.27)
Low education	**-1.12**** (0.41)	**-0.88**** (0.32)	**-0.89*** (0.39)
Middle education	-0.54 (0.42)	**-1.46**** (0.46)	**-1.19*** (0.55)
Household with children	-0.01 (0.33)	-0.02 (0.28)	**0.84**** (0.31)
No driving license	**-1.23**** (0.48)		0.23 (0.78)
Age below 25	-0.76 (0.49)	0.24 (0.38)	0.67 (0.54)
Age of 40 – 54	**-0.81*** (0.33)	**-0.66*** (0.30)	**-1.10**** (0.34)
Age of 55 – 64	**-2.04**** (0.76)	**-1.10*** (0.47)	**-2.08**** (0.76)
Age of 65 – 74	**-0.84*** (0.43)	**-3.18**** (1.03)	**-2.96**** (1.04)
Age above 74 years	-14.60 (645.12)	**-1.86**$^{\cdot}$ (1.05)	-0.80 (0.82)
Car available	**-1.24***** (0.28)		
Male		0.32 (0.24)	0.28 (0.30)
Frequent			
Intercept	**-1.34***** (0.32)	**-1.24***** (0.25)	-0.29 (0.21)
Low education	-0.24 (0.38)	**-1.13**** (0.37)	**-0.53**$^{\cdot}$ (0.31)
Middle education	-0.01 (0.44)	**-2.42**** (0.75)	-0.59 (0.40)
Household with children	**0.77*** (0.36)	**0.87**** (0.30)	-0.15 (0.27)
No driving license	**-1.03**$^{\cdot}$ (0.53)		**-18.28***** (0.00)
Age below 25	0.02 (0.52)	-0.08 (0.50)	**1.30***** (0.39)
Age of 40 – 54	-0.38 (0.37)	**-0.91**** (0.35)	**-1.47***** (0.29)
Age of 55 – 64	-0.45 (0.56)	-0.64 (0.52)	**-2.59***** (0.55)

Age of 65 – 74	**-1.27**$^{\cdot}$ (0.66)	**-1.33*** (0.64)	**-20.07***** (0.00)
Age above 74 years	**-15.28***** (0.00)	-1.05 (1.06)	-15.79 (601.00)
Car available	**-1.23***** (0.35)		
Male		-0.18 (0.28)	**0.65**** (0.24)
AIC	788.90	881.76	845.33
BIC	889.36	972.17	942.35
Log Likelihood	-372.45	-420.88	-400.66
Deviance	744.90	841.76	801.33
Num. obs.	711	679	608

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Appendix G: Demographic variables

Table 14 - Demographic variables negative binomial regression

Variable	Explanation
OAD	Address density (per km^2)
STED	Level of urbanization 1 >= 2 500 addresses per km^2 2: 1 500 - 2 500 addresses per km^2 3: 1 000 - 1 500 addresses per km^2 4: 500 - 1 000 addresses per km^2 5: < 500 addresses per km^2
BEV_DICHTH	Population density
P_00_14_JR	Percentage of people younger than 15
P_15_24_JR	Percentage of people between 15 and 24
P_25_44_JR	Percentage of people between 25 and 44
P_45_64_JR	Percentage of people between 45 and 64
P_65_EO_JR	Percentage of people older than 64
P_EENP_HH	Percentage of one person households
P_HH_M_K	Percentage of households with children
P_HH_Z_K	Percentage of households without children
GEM_HH_GR	Average household size
WOZ	Average WOZ value (x 1000 euro)
P_ARB_WN	Percentage of employed workers
P_ARB_ZS	Percentage of self-employed workers
P_LAAGINKP	Percentage of the national 40% households with the lowest income
P_HOOGINKP	Percentage of the national 20% households with the highest income
Man	Percentage of man
HH	Number of households
Opl_hg	Percentage of people with high education
Opl_md	Percentage of people with middle education
Opl_lg	Percentage of people with low education
Auto	Number of cars (per km^2)
Motor	Number of motorcycles (per km^2)
Aantal_inw	Number of people (per km^2)
Aantal_won	Number of houses (per km^2)
Laag	Percentage of people with a median income that falls within 0-20%, 0-40% and 20-40% of the median income of the entire population
Midden	Percentage of people with a median income that falls within 20-60%, 40-60% and 40-80% of the median income of the entire population
Hoog	Percentage of people with a median income that falls within 60-80%, 60-100% and 80-100% of the median income of the entire population

Appendix H: Correlation independent variables shared car

Table 15 - Pearson correlation independent variables shared car

	OAD	STED	BEV_DICHTH	P_00_14_JR	P_15_24_JR	P_25_44_JR	P_45_64_JR	P_65_EO_JR	P_EENP_HH	P_HH_M_K	P_HH_Z_K	GEM_HH_GR	P_N_W_AL	P_WEST_AL	man	P_ARB_PP
OAD	1.00	-0.68	0.79	-0.33	0.02	0.62	-0.36	-0.26	0.63	-0.53	-0.41	-0.58	0.37	0.66	0.03	-0.14
STED	-0.68	1.00	-0.60	0.14	0.02	-0.47	0.40	0.16	-0.53	0.38	0.47	0.49	-0.48	-0.45	0.14	0.28
BEV_DICHTH	0.79	-0.60	1.00	-0.15	0.01	0.54	-0.30	-0.32	0.49	-0.34	-0.46	-0.44	0.44	0.46	-0.06	-0.14
P_00_14_JR	-0.33	0.14	-0.15	1.00	-0.17	-0.11	-0.03	-0.37	-0.61	0.82	-0.18	0.75	0.10	-0.36	-0.07	0.29
P_15_24_JR	0.02	0.02	0.01	-0.17	1.00	0.07	-0.14	-0.38	0.18	-0.05	-0.28	-0.05	0.14	0.09	0.24	-0.05
P_25_44_JR	0.62	-0.47	0.54	-0.11	0.07	1.00	-0.68	-0.62	0.57	-0.41	-0.50	-0.49	0.43	0.51	0.26	0.18
P_45_64_JR	-0.36	0.40	-0.30	-0.03	-0.14	-0.68	1.00	0.17	-0.53	0.38	0.47	0.42	-0.39	-0.33	0.10	0.13
P_65_EO_JR	-0.26	0.16	-0.32	-0.37	-0.38	-0.62	0.17	1.00	0.00	-0.27	0.49	-0.15	-0.35	-0.18	-0.44	-0.44
P_EENP_HH	0.63	-0.53	0.49	-0.61	0.18	0.57	-0.53	0.00	1.00	-0.89	-0.55	-0.94	0.40	0.59	-0.03	-0.42
P_HH_M_K	-0.53	0.38	-0.34	0.82	-0.05	-0.41	0.38	-0.27	-0.89	1.00	0.11	0.96	-0.13	-0.53	0.01	0.40
P_HH_Z_K	-0.41	0.47	-0.46	-0.18	-0.28	-0.50	0.47	0.49	-0.55	0.11	1.00	0.30	-0.63	-0.32	0.03	0.18
GEM_HH_GR	-0.58	0.49	-0.44	0.75	-0.05	-0.49	0.42	-0.15	-0.94	0.96	0.30	1.00	-0.27	-0.57	0.05	0.44
P_N_W_AL	0.37	-0.48	0.44	0.10	0.14	0.43	-0.39	-0.35	0.40	-0.13	-0.63	-0.27	1.00	0.19	0.02	-0.47
P_WEST_AL	0.66	-0.45	0.46	-0.36	0.09	0.51	-0.33	-0.18	0.59	-0.53	-0.32	-0.57	0.19	1.00	0.13	-0.15
man	0.03	0.14	-0.06	-0.07	0.24	0.26	0.10	-0.44	-0.03	0.01	0.03	0.05	0.02	0.13	1.00	0.29
P_ARB_PP	-0.14	0.28	-0.14	0.29	-0.05	0.18	0.13	-0.44	-0.42	0.40	0.18	0.44	-0.47	-0.15	0.29	1.00
P_ARB_WN	0.02	-0.38	0.19	0.07	0.02	0.26	-0.28	-0.15	0.09	0.02	-0.22	-0.12	0.32	-0.17	-0.16	-0.14
P_ARB_ZS	-0.02	0.38	-0.19	-0.07	-0.02	-0.26	0.28	0.15	-0.09	-0.02	0.22	0.12	-0.32	0.17	0.16	0.14
P_LAAGINKP	0.08	-0.13	0.17	-0.14	0.35	-0.05	-0.18	0.08	0.37	-0.22	-0.40	-0.28	0.55	-0.12	-0.13	-0.68
P_HOOGINKP	0.01	0.14	-0.13	0.21	-0.14	-0.05	0.17	-0.12	-0.34	0.25	0.28	0.33	-0.45	0.24	0.11	0.52
opl_hg	0.48	-0.24	0.27	-0.20	0.10	0.42	-0.20	-0.26	0.30	-0.31	-0.08	-0.27	-0.13	0.60	0.15	0.26
opl_md	-0.39	0.30	-0.27	-0.09	0.17	-0.18	0.25	0.00	-0.21	0.15	0.19	0.13	-0.08	-0.40	0.15	0.03
opl_lg	-0.15	0.02	0.00	0.05	-0.02	-0.09	0.08	0.03	-0.01	0.08	-0.13	0.02	0.42	-0.34	0.02	-0.37
WOZ	0.06	0.22	-0.12	0.10	-0.03	-0.18	0.22	0.01	-0.19	0.13	0.19	0.23	-0.33	0.29	0.07	0.23
auto	-0.19	0.17	-0.23	-0.06	0.01	-0.06	0.06	0.06	-0.10	0.03	0.17	0.07	-0.15	-0.05	0.10	0.07
motor	-0.40	0.56	-0.43	-0.07	-0.04	-0.31	0.44	0.10	-0.37	0.19	0.45	0.28	-0.48	-0.31	0.23	0.33
ovhaltes	0.44	-0.29	0.32	-0.23	0.01	0.35	-0.23	-0.10	0.37	-0.33	-0.19	-0.35	0.21	0.35	0.04	-0.09
agricultuur	-0.37	0.64	-0.44	0.01	0.09	-0.26	0.27	0.06	-0.29	0.18	0.29	0.30	-0.32	-0.28	0.20	0.28
bos	-0.19	0.28	-0.26	-0.02	-0.02	-0.20	0.14	0.16	-0.09	0.02	0.16	0.08	-0.15	-0.01	-0.01	-0.08
commercieel	0.26	-0.23	0.02	-0.32	0.11	0.38	-0.33	-0.06	0.43	-0.43	-0.16	-0.41	0.12	0.32	0.17	-0.03
industrie	-0.09	0.07	-0.10	0.26	-0.07	0.22	-0.24	-0.20	-0.12	0.17	-0.05	0.15	0.08	-0.05	0.06	0.22
recreatie	-0.13	-0.04	-0.24	0.05	-0.01	-0.09	-0.01	0.08	-0.06	0.06	0.02	0.04	0.08	-0.05	-0.06	-0.12
LandUseMix	-0.24	0.20	-0.39	0.07	-0.04	-0.07	-0.07	0.10	-0.05	0.03	0.05	0.04	-0.01	-0.06	-0.04	-0.02

Table 16 - Pearson correlation independent variables shared car

	P_ARB_WN	P_ARB_ZS	P_LAAGINKP	P_HOOGINKP	opl_hg	opl_md	opl_lg	WOZ	auto	motor	ovhaltes	agricultuur	bos	commercieel	industrie	recreatie
OAD	0.02	-0.02	0.08	0.01	0.48	-0.39	-0.15	0.06	-0.19	-0.40	0.44	-0.37	-0.19	0.26	-0.09	-0.13
STED	-0.38	0.38	-0.13	0.14	-0.24	0.30	0.02	0.22	0.17	0.56	-0.29	0.64	0.28	-0.23	0.07	-0.04
BEV_DICHTH	0.19	-0.19	0.17	-0.13	0.27	-0.27	0.00	-0.12	-0.23	-0.43	0.32	-0.44	-0.26	0.02	-0.10	-0.24
P_00_14_JR	0.07	-0.07	-0.14	0.21	-0.20	-0.09	0.05	0.10	-0.06	-0.07	-0.23	0.01	-0.02	-0.32	0.26	0.05
P_15_24_JR	0.02	-0.02	0.35	-0.14	0.10	0.17	-0.02	-0.03	0.01	-0.04	0.01	0.09	-0.02	0.11	-0.07	-0.01
P_25_44_JR	0.26	-0.26	-0.05	-0.05	0.42	-0.18	-0.09	-0.18	-0.06	-0.31	0.35	-0.26	-0.20	0.38	0.22	-0.09
P_45_64_JR	-0.28	0.28	-0.18	0.17	-0.20	0.25	0.08	0.22	0.06	0.44	-0.23	0.27	0.14	-0.33	-0.24	-0.01
P_65_EO_JR	-0.15	0.15	0.08	-0.12	-0.26	0.00	0.03	0.01	0.06	0.10	-0.10	0.06	0.16	-0.06	-0.20	0.08
P_EENP_HH	0.09	-0.09	0.37	-0.34	0.30	-0.21	-0.01	-0.19	-0.10	-0.37	0.37	-0.29	-0.09	0.43	-0.12	-0.06
P_HH_M_K	0.02	-0.02	-0.22	0.25	-0.31	0.15	0.08	0.13	0.03	0.19	-0.33	0.18	0.02	-0.43	0.17	0.06
P_HH_Z_K	-0.22	0.22	-0.40	0.28	-0.08	0.19	-0.13	0.19	0.17	0.45	-0.19	0.29	0.16	-0.16	-0.05	0.02
GEM_HH_GR	-0.12	0.12	-0.28	0.33	-0.27	0.13	0.02	0.23	0.07	0.28	-0.35	0.30	0.08	-0.41	0.15	0.04
P_N_W_AL	0.32	-0.32	0.55	-0.45	-0.13	-0.08	0.42	-0.33	-0.15	-0.48	0.21	-0.32	-0.15	0.12	0.08	0.08
P_WEST_AL	-0.17	0.17	-0.12	0.24	0.60	-0.40	-0.34	0.29	-0.05	-0.31	0.35	-0.28	-0.01	0.32	-0.05	-0.05
man	-0.16	0.16	-0.13	0.11	0.15	0.15	0.02	0.07	0.10	0.23	0.04	0.20	-0.01	0.17	0.06	-0.06
P_ARB_PP	-0.14	0.14	-0.68	0.52	0.26	0.03	-0.37	0.23	0.07	0.33	-0.09	0.28	-0.08	-0.03	0.22	-0.12
P_ARB_WN	1.00	-1.00	0.16	-0.42	-0.29	0.28	0.26	-0.72	-0.08	-0.30	0.04	-0.50	-0.27	0.03	0.09	0.13
P_ARB_ZS	-1.00	1.00	-0.16	0.42	0.29	-0.28	-0.26	0.72	0.08	0.30	-0.04	0.50	0.27	-0.03	-0.09	-0.13
P_LAAGINKP	0.16	-0.16	1.00	-0.82	-0.50	0.22	0.63	-0.42	-0.10	-0.16	0.05	-0.03	-0.05	0.00	-0.20	0.03
P_HOOGINKP	-0.42	0.42	-0.82	1.00	0.66	-0.47	-0.72	0.72	0.06	0.05	-0.04	0.06	0.13	-0.04	0.15	-0.04
opl_hg	-0.29	0.29	-0.50	0.66	1.00	-0.65	-0.77	0.51	-0.01	-0.17	0.20	-0.15	0.05	0.22	0.10	-0.10
opl_md	0.28	-0.28	0.22	-0.47	-0.65	1.00	0.36	-0.47	0.07	0.37	-0.13	0.24	-0.07	-0.08	-0.01	0.05
opl_lg	0.26	-0.26	0.63	-0.72	-0.77	0.36	1.00	-0.49	-0.03	0.02	-0.05	0.05	-0.06	-0.08	-0.09	0.05
WOZ	-0.72	0.72	-0.42	0.72	0.51	-0.47	-0.49	1.00	0.04	0.09	-0.03	0.23	0.24	-0.07	0.01	-0.10
auto	-0.08	0.08	-0.10	0.06	-0.01	0.07	-0.03	0.04	1.00	0.19	-0.09	0.11	0.07	0.07	0.00	-0.02
motor	-0.30	0.30	-0.16	0.05	-0.17	0.37	0.02	0.09	0.19	1.00	-0.20	0.50	0.12	-0.08	-0.05	-0.06
ovhaltes	0.04	-0.04	0.05	-0.04	0.20	-0.13	-0.05	-0.03	-0.09	-0.20	1.00	-0.20	-0.11	0.23	-0.05	-0.12
agricultuur	-0.50	0.50	-0.03	0.06	-0.15	0.24	0.05	0.23	0.11	0.50	-0.20	1.00	0.12	-0.17	0.01	-0.15
bos	-0.27	0.27	-0.05	0.13	0.05	-0.07	-0.06	0.24	0.07	0.12	-0.11	0.12	1.00	-0.07	-0.02	-0.03
commercieel	0.03	-0.03	0.00	-0.04	0.22	-0.08	-0.08	-0.07	0.07	-0.08	0.23	-0.17	-0.07	1.00	0.00	-0.15
industrie	0.09	-0.09	-0.20	0.15	0.10	-0.01	-0.09	0.01	0.00	-0.05	-0.05	0.01	-0.02	0.00	1.00	-0.04
recreatie	0.13	-0.13	0.03	-0.04	-0.10	0.05	0.05	-0.10	-0.02	-0.06	-0.12	-0.15	-0.03	-0.15	-0.04	1.00
LandUseMix	0.00	0.00	-0.06	0.07	-0.03	0.02	-0.04	0.02	0.03	0.04	-0.09	0.07	0.27	0.23	0.24	0.43

Appendix I: Correlation independent variables shared moped/bicycle

Table 17 - Pearson correlation independent variables shared moped/bicycle

	aantal_inw	aantal_won	land_use_mix	haltes	stations	ov	man	hh	agricultuur	bos	commercieel	industrie	recreatie	woningen	sted	oad
aantal_inw	1.00	0.89	0.11	0.11	0.08	0.11	0.04	0.18	0.00	-0.06	-0.05	0.01	0.00	0.03	0.01	-0.06
aantal_won	0.89	1.00	0.13	0.15	0.08	0.15	-0.03	-0.17	-0.04	-0.05	0.04	-0.02	0.00	-0.03	-0.09	-0.01
land_use_mix	0.11	0.13	1.00	0.32	0.10	0.32	0.00	0.01	0.26	0.21	0.26	0.25	0.53	-0.66	0.29	-0.36
haltes	0.11	0.15	0.32	1.00	0.36	1.00	0.09	-0.08	0.07	0.11	0.24	0.08	0.14	-0.41	0.11	-0.13
stations	0.08	0.08	0.10	0.36	1.00	0.40	0.09	-0.04	-0.01	-0.01	0.10	0.04	-0.01	-0.13	0.02	-0.02
ov	0.11	0.15	0.32	1.00	0.40	1.00	0.09	-0.08	0.07	0.11	0.24	0.08	0.14	-0.41	0.11	-0.13
man	0.04	-0.03	0.00	0.09	0.09	0.09	1.00	-0.04	0.02	-0.02	0.18	0.05	-0.07	-0.14	0.01	0.10
hh	0.18	-0.17	0.01	-0.08	-0.04	-0.08	-0.04	1.00	0.17	0.04	-0.32	0.11	0.03	0.18	0.32	-0.26
agricultuur	0.00	-0.04	0.26	0.07	-0.01	0.07	0.02	0.17	1.00	0.10	-0.05	0.12	0.03	-0.28	0.52	-0.27
bos	-0.06	-0.05	0.21	0.11	-0.01	0.11	-0.02	0.04	0.10	1.00	-0.05	0.00	0.02	-0.25	0.26	-0.19
commercieel	-0.05	0.04	0.26	0.24	0.10	0.24	0.18	-0.32	-0.05	-0.05	1.00	0.03	-0.12	-0.63	-0.08	0.13
industrie	0.01	-0.02	0.25	0.08	0.04	0.08	0.05	0.11	0.12	0.00	0.03	1.00	0.01	-0.21	0.14	-0.12
recreatie	0.00	0.00	0.53	0.14	-0.01	0.14	-0.07	0.03	0.03	0.02	-0.12	0.01	1.00	-0.42	0.16	-0.30
woningen	0.03	-0.03	-0.66	-0.41	-0.13	-0.41	-0.14	0.18	-0.28	-0.25	-0.63	-0.21	-0.42	1.00	-0.28	0.23
sted	0.01	-0.09	0.29	0.11	0.02	0.11	0.01	0.32	0.52	0.26	-0.08	0.14	0.16	-0.28	1.00	-0.61
oad	-0.06	-0.01	-0.36	-0.13	-0.02	-0.13	0.10	-0.26	-0.27	-0.19	0.13	-0.12	-0.30	0.23	-0.61	1.00
p_00_14_jr	0.19	-0.09	-0.06	-0.13	-0.05	-0.13	-0.04	0.80	0.01	-0.04	-0.34	0.09	-0.02	0.32	0.12	-0.12
p_15_24_jr	0.08	0.02	-0.10	0.01	0.05	0.02	0.35	-0.09	-0.03	-0.08	0.17	-0.03	-0.13	-0.02	-0.09	0.20
p_25_44_jr	0.02	0.09	-0.16	-0.02	0.06	-0.02	0.38	-0.31	-0.15	-0.17	0.26	0.04	-0.20	-0.03	-0.30	0.43
p_45_64_jr	-0.03	-0.12	0.06	-0.01	-0.05	-0.01	-0.06	0.38	0.16	0.14	-0.21	-0.06	0.09	0.05	0.27	-0.27
p_65_eo_jr	-0.15	0.02	0.21	0.08	-0.04	0.08	-0.50	-0.28	0.06	0.16	-0.05	-0.03	0.23	-0.15	0.12	-0.30
p_west_al	-0.13	-0.02	-0.05	0.05	0.02	0.05	0.19	-0.32	-0.14	0.04	0.22	-0.08	-0.09	-0.07	-0.16	0.21
p_n_w_al	0.12	0.02	-0.22	-0.11	0.00	-0.11	0.08	0.16	-0.18	-0.17	-0.05	-0.05	-0.14	0.24	-0.29	0.40
p_eenp_hh	-0.15	0.15	-0.07	0.05	0.04	0.05	0.07	-0.93	-0.21	-0.08	0.30	-0.11	-0.08	-0.10	-0.38	0.36
p_hh_z_k	-0.07	-0.05	0.22	0.14	0.02	0.13	-0.06	0.09	0.24	0.18	0.05	0.05	0.16	-0.30	0.33	-0.34
p_hh_m_k	0.22	-0.11	-0.02	-0.13	-0.05	-0.13	-0.06	0.95	0.11	0.00	-0.36	0.09	0.01	0.26	0.25	-0.23
woz	-0.10	-0.18	0.16	0.12	0.00	0.12	-0.03	0.35	0.16	0.24	0.00	0.08	0.10	-0.19	0.37	-0.32
laag	0.04	0.08	-0.16	-0.12	-0.04	-0.11	0.00	-0.20	-0.13	-0.10	-0.01	-0.08	-0.12	0.18	-0.26	0.27
midden	-0.02	0.01	0.03	0.06	0.06	0.06	0.02	-0.12	-0.01	-0.02	0.00	-0.01	0.02	-0.03	-0.04	0.04
hoog	-0.02	-0.11	0.16	0.07	-0.02	0.07	-0.02	0.37	0.17	0.15	0.01	0.10	0.12	-0.18	0.36	-0.37

Table 18 - Pearson correlation independent variables shared moped/bicycle

	p_00_14_jr	p_15_24_jr	p_25_44_jr	p_45_64_jr	p_65_eo_jr	p_west_al	p_n_w_al	p_eenp_hh	p_hh_z_k	p_hh_m_k	woz	laag	midden	hoog
aantal_inw	0.19	0.08	0.02	-0.03	-0.15	-0.13	0.12	-0.15	-0.07	0.22	-0.10	0.04	-0.02	-0.02
aantal_won	-0.09	0.02	0.09	-0.12	0.02	-0.02	0.02	0.15	-0.05	-0.11	-0.18	0.08	0.01	-0.11
land_use_mix	-0.06	-0.10	-0.16	0.06	0.21	-0.05	-0.22	-0.07	0.22	-0.02	0.16	-0.16	0.03	0.16
haltes	-0.13	0.01	-0.02	-0.01	0.08	0.05	-0.11	0.05	0.14	-0.13	0.12	-0.12	0.06	0.07
stations	-0.05	0.05	0.06	-0.05	-0.04	0.02	0.00	0.04	0.02	-0.05	0.00	-0.04	0.06	-0.02
ov	-0.13	0.02	-0.02	-0.01	0.08	0.05	-0.11	0.05	0.13	-0.13	0.12	-0.11	0.06	0.07
man	-0.04	0.35	0.38	-0.06	-0.50	0.19	0.08	0.07	-0.06	-0.06	-0.03	0.00	0.02	-0.02
hh	0.80	-0.09	-0.31	0.38	-0.28	-0.32	0.16	-0.93	0.09	0.95	0.35	-0.20	-0.12	0.37
agricultuur	0.01	-0.03	-0.15	0.16	0.06	-0.14	-0.18	-0.21	0.24	0.11	0.16	-0.13	-0.01	0.17
bos	-0.04	-0.08	-0.17	0.14	0.16	0.04	-0.17	-0.08	0.18	0.00	0.24	-0.10	-0.02	0.15
commercieel	-0.34	0.17	0.26	-0.21	-0.05	0.22	-0.05	0.30	0.05	-0.36	0.00	-0.01	0.00	0.01
industrie	0.09	-0.03	0.04	-0.06	-0.03	-0.08	-0.05	-0.11	0.05	0.09	0.08	-0.08	-0.01	0.10
recreatie	-0.02	-0.13	-0.20	0.09	0.23	-0.09	-0.14	-0.08	0.16	0.01	0.10	-0.12	0.02	0.12
woningen	0.32	-0.02	-0.03	0.05	-0.15	-0.07	0.24	-0.10	-0.30	0.26	-0.19	0.18	-0.03	-0.18
sted	0.12	-0.09	-0.30	0.27	0.12	-0.16	-0.29	-0.38	0.33	0.25	0.37	-0.26	-0.04	0.36
oad	-0.12	0.20	0.43	-0.27	-0.30	0.21	0.40	0.36	-0.34	-0.23	-0.32	0.27	0.04	-0.37
p_00_14_jr	1.00	-0.14	-0.08	0.10	-0.42	-0.23	0.33	-0.68	-0.25	0.86	0.13	0.04	-0.17	0.15
p_15_24_jr	-0.14	1.00	0.16	-0.39	-0.47	0.09	0.23	0.22	-0.33	-0.08	-0.12	0.27	-0.11	-0.20
p_25_44_jr	-0.08	0.16	1.00	-0.58	-0.65	0.30	0.17	0.33	-0.22	-0.26	-0.34	0.04	0.22	-0.30
p_45_64_jr	0.10	-0.39	-0.58	1.00	0.18	-0.19	-0.21	-0.47	0.34	0.34	0.33	-0.25	-0.03	0.34
p_65_eo_jr	-0.42	-0.47	-0.65	0.18	1.00	-0.11	-0.36	0.17	0.35	-0.35	0.14	-0.09	-0.02	0.12
p_west_al	-0.23	0.09	0.30	-0.19	-0.11	1.00	-0.31	0.28	0.10	-0.35	0.18	-0.20	0.09	0.14
p_n_w_al	0.33	0.23	0.17	-0.21	-0.36	-0.31	1.00	0.05	-0.65	0.27	-0.52	0.62	-0.25	-0.46
p_eenp_hh	-0.68	0.22	0.33	-0.47	0.17	0.28	0.05	1.00	-0.37	-0.87	-0.41	0.35	0.04	-0.47
p_hh_z_k	-0.25	-0.33	-0.22	0.34	0.35	0.10	-0.65	-0.37	1.00	-0.10	0.49	-0.61	0.20	0.51
p_hh_m_k	0.86	-0.08	-0.26	0.34	-0.35	-0.35	0.27	-0.87	-0.10	1.00	0.19	-0.06	-0.15	0.25
woz	0.13	-0.12	-0.34	0.33	0.14	0.18	-0.52	-0.41	0.49	0.19	1.00	-0.51	-0.07	0.70
laag	0.04	0.27	0.04	-0.25	-0.09	-0.20	0.62	0.35	-0.61	-0.06	-0.51	1.00	-0.64	-0.48
midden	-0.17	-0.11	0.22	-0.03	-0.02	0.09	-0.25	0.04	0.20	-0.15	-0.07	-0.64	1.00	-0.37
hoog	0.15	-0.20	-0.30	0.34	0.12	0.14	-0.46	-0.47	0.51	0.25	0.70	-0.48	-0.37	1.00

Appendix J: Regression results shared mopeds/bicycles destination

Table 19 - Regression results shared moped/bicycle destination

	Full	Den Haag	Rotterdam
(Intercept)	-0.85 (0.84)	**-3.69**** (1.25)	**-2.18**$^{\cdot}$ (1.19)
Address density	**0.55***** (0.06)	**0.84***** (0.09)	**0.58***** (0.08)
Percentage of people with the age between 45 and 64 years old	**-0.03***** (0.01)	**-0.03***** (0.01)	**-0.03***** (0.01)
Percentage of people older than 64 years old	**-0.04***** (0.00)	**-0.03***** (0.00)	**-0.05***** (0.01)
Percentage of households with children	**-0.04***** (0.00)	**-0.04***** (0.00)	**-0.03***** (0.00)
Percentage of males	**-0.02*** (0.01)	**-0.02*** (0.01)	-0.01 (0.01)
Average WOZ-value	**1.11***** (0.06)	**1.12***** (0.08)	**1.26***** (0.09)
Number of transit stops per m^2	**1.54***** (0.21)	**2.01***** (0.29)	**1.30***** (0.30)
Percentage of forest land use	**0.02***** (0.00)	**0.02***** (0.00)	0.01 (0.01)
Percentage of commercial land use	**0.02***** (0.00)	**0.01***** (0.00)	**0.02***** (0.00)
Percentage of recreational land use	**0.01***** (0.00)	**0.01***** (0.00)	**0.01**** (0.00)
AIC	25834.27	12261.82	13507.16
BIC	25899.87	12318.66	13564.87
Log Likelihood	-12905.13	-6118.91	-6741.58
Deviance	2081.57	980.63	1090.80
Num. obs.	1749	843	906

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Appendix K: Descriptive statistics NVP trips

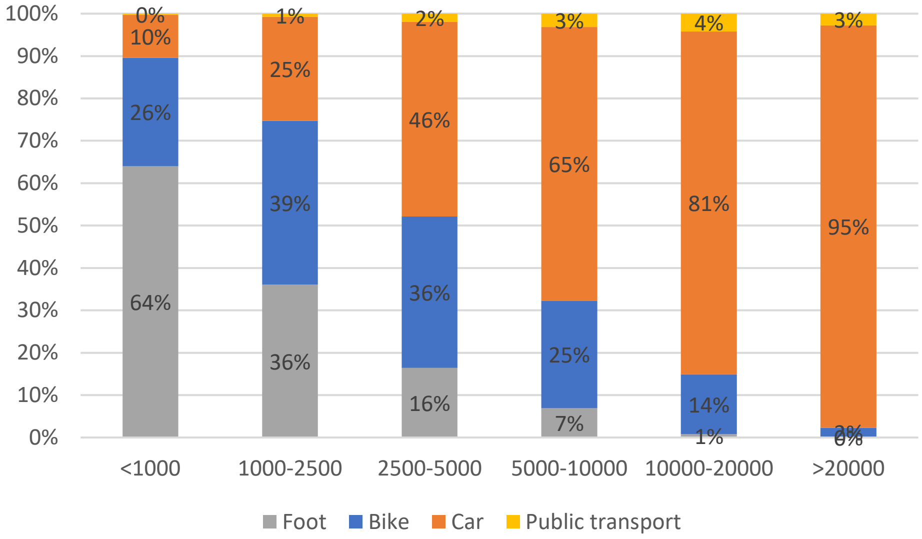

Figure 58 - Percentage of total trips per distance category per mode of transport

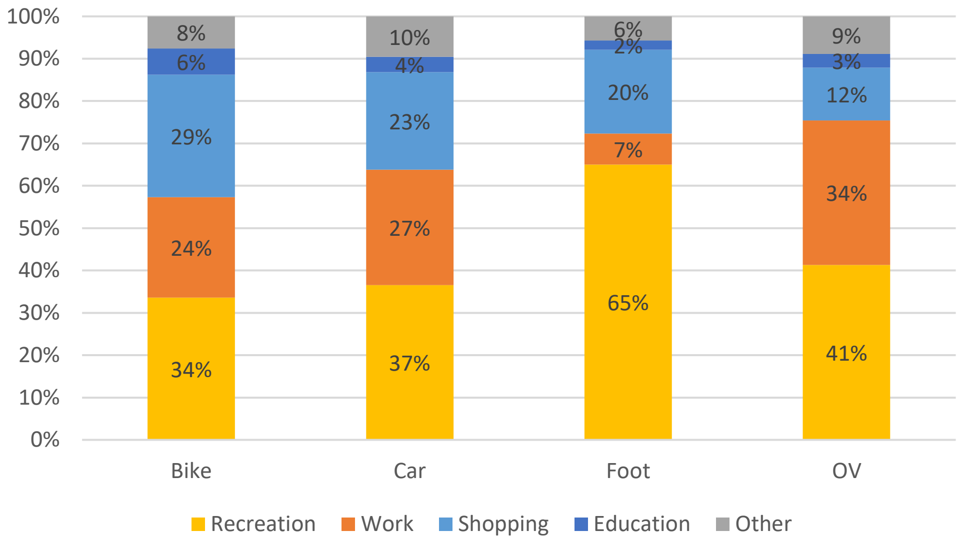

Figure 59 - Percentage of total trips per mode per trip motive

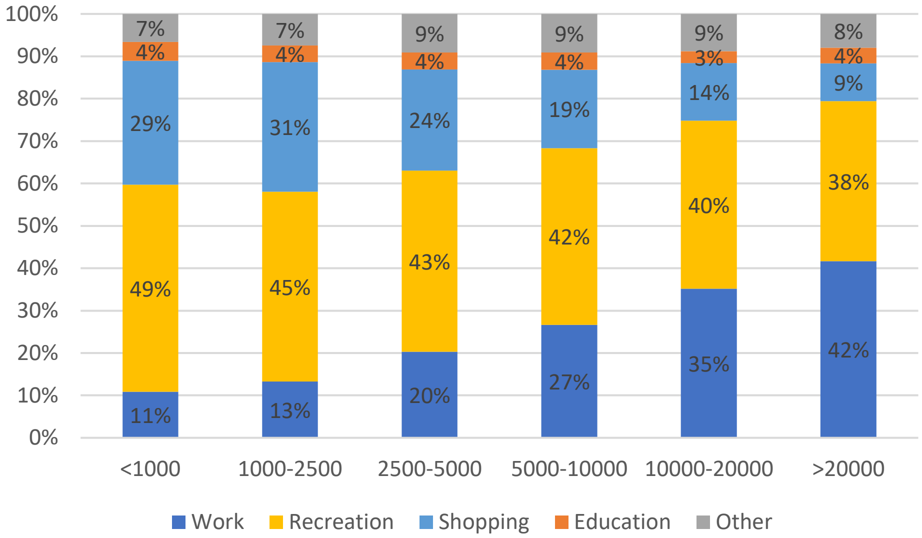

Figure 60 - Percentage of total trips per distance category per trip motive

Appendix L: Logistic regression results shared car with weighted responses

Table 20 - Logistic regression results weighted responses shared car

	Shared car
(Intercept)	0.28 (0.25)
No driving license	**-1.25***** (0.34)
Number of cars	**-0.71***** (0.17)
Age below 25	**-0.74*** (0.30)
Age of 40 – 54	**-0.63*** (0.30)
Age of 55 – 64	**-1.69***** (0.43)
Age of 65 and older	**-1.29***** (0.35)
Low education	**-0.59*** (0.29)
Middle education	-0.26 (0.27)
Male	**-0.50*** (0.22)
AIC	585.62
BIC	631.29
Log Likelihood	-282.81
Deviance	582.18
McFadden R^2	0.160
Num. obs.	711

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Appendix M: Independent variables shared cars per city

Figure 61 - Percentage of people older than 65 per neighbourhood in Amsterdam

Figure 62 - Percentage of households with children per neighbourhood in Amsterdam

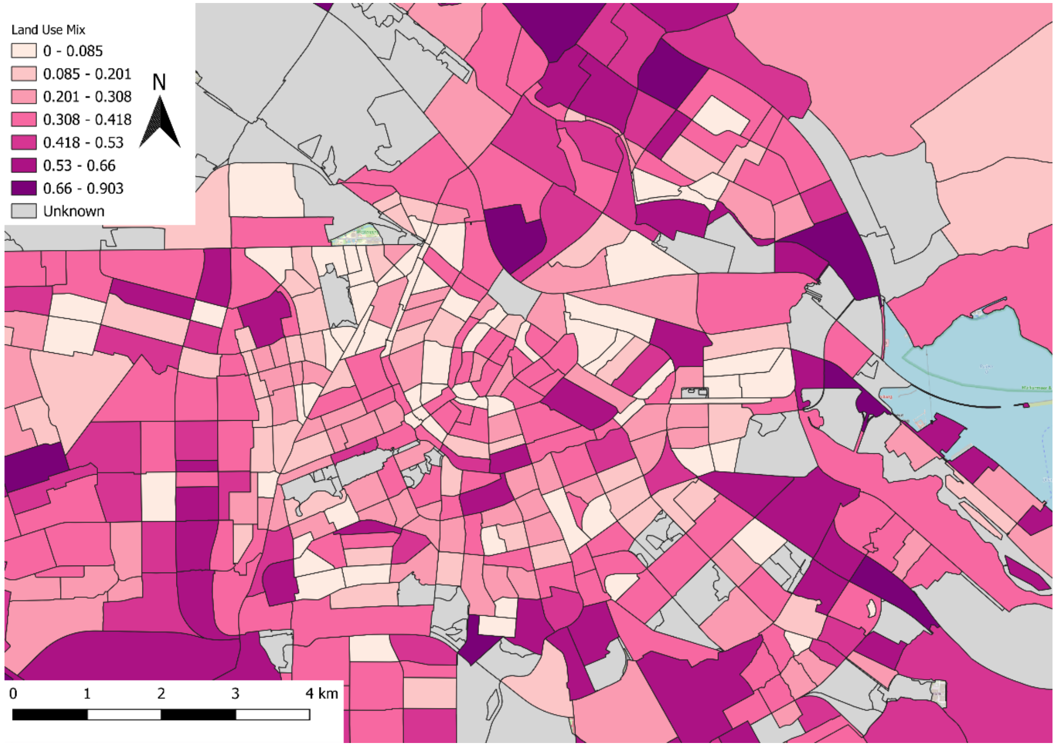

Figure 63 – Land Use Mix per neighbourhood in Amsterdam

Figure 64 - Percentage of males per neighbourhood in Amsterdam

Figure 65 - Percentage of people with middle education level per neighbourhood in Amsterdam

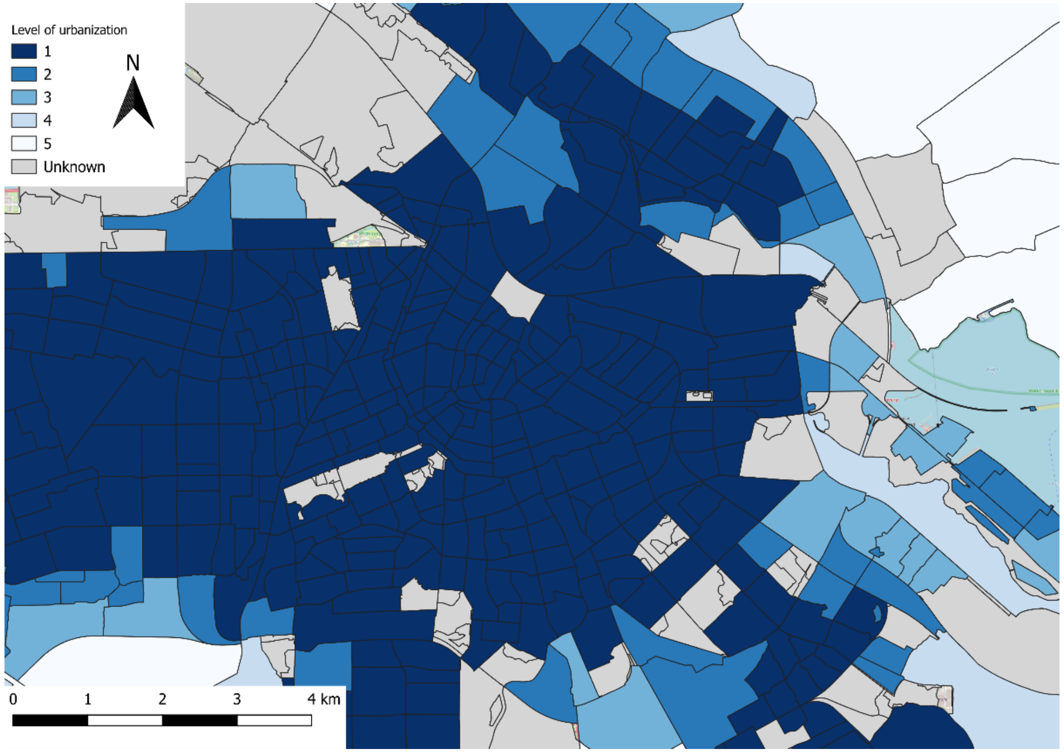

Figure 66 – Level of urbanization per neighbourhood in Amsterdam

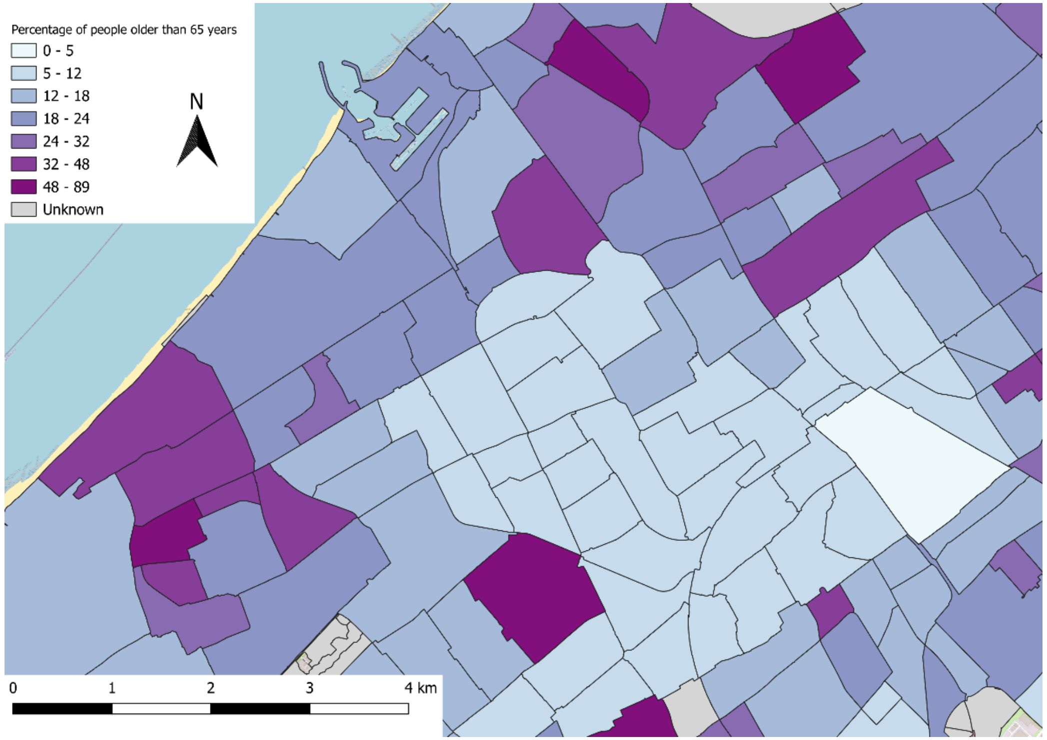

Figure 67 - Percentage of people older than 65 per neighbourhood in The Hague

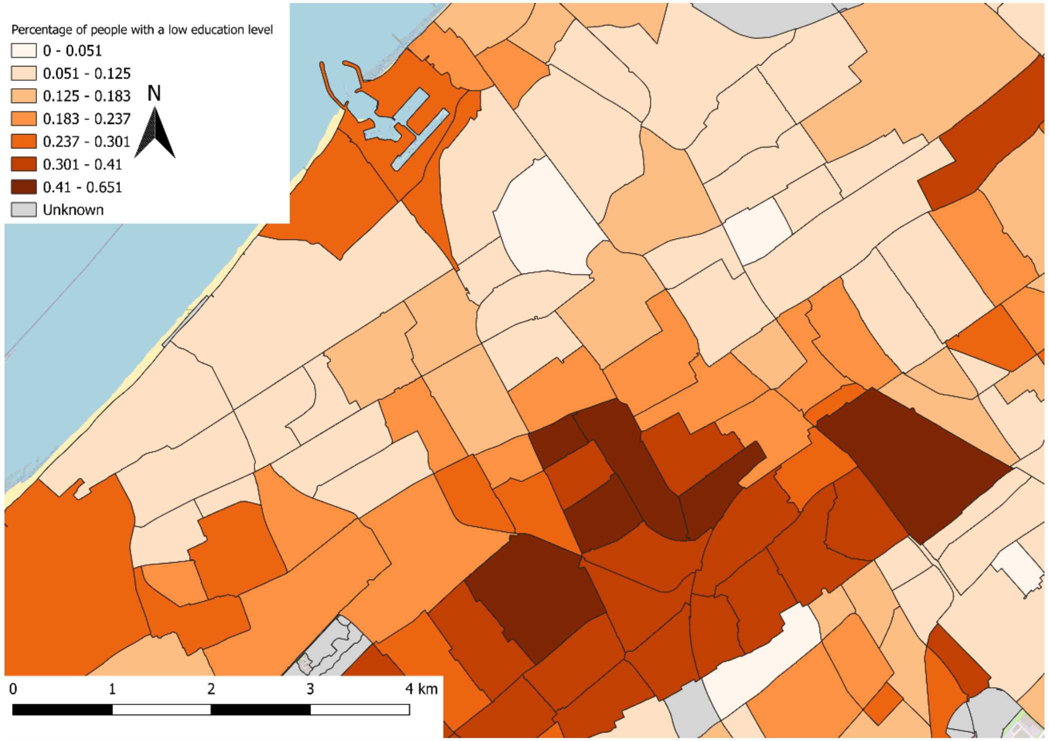

Figure 68 - Percentage of people with low education level per neighbourhood in The Hague

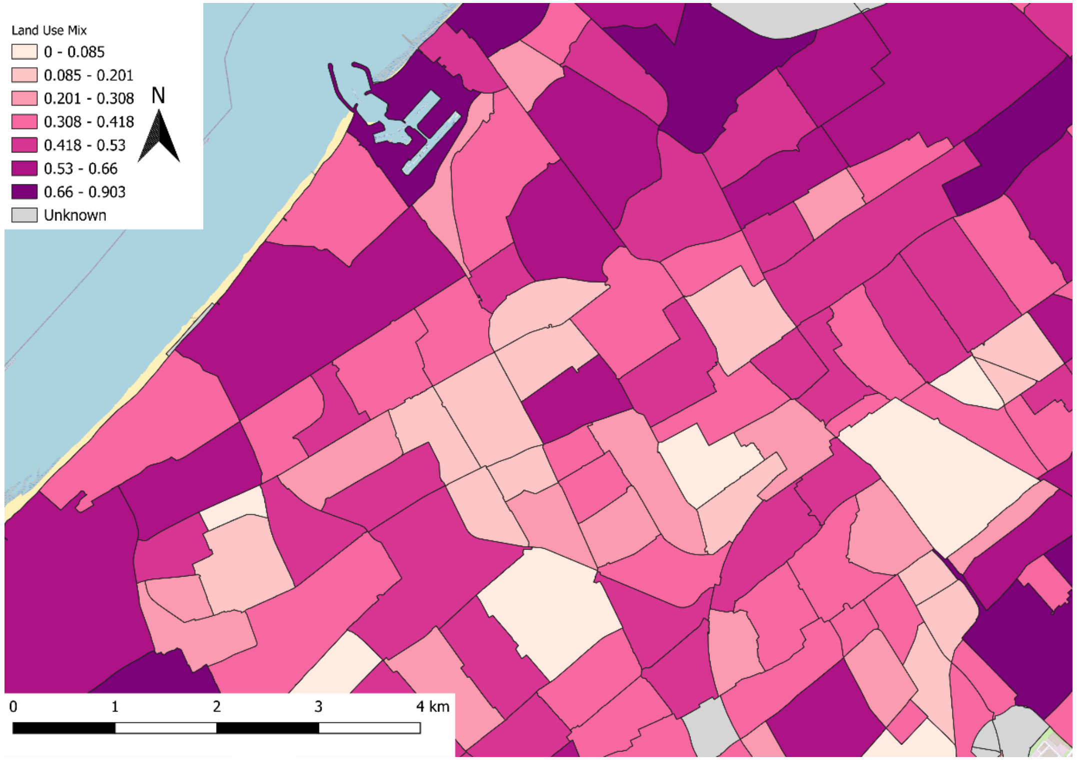

Figure 69 – Land Use Mix per neighbourhood in The Hague

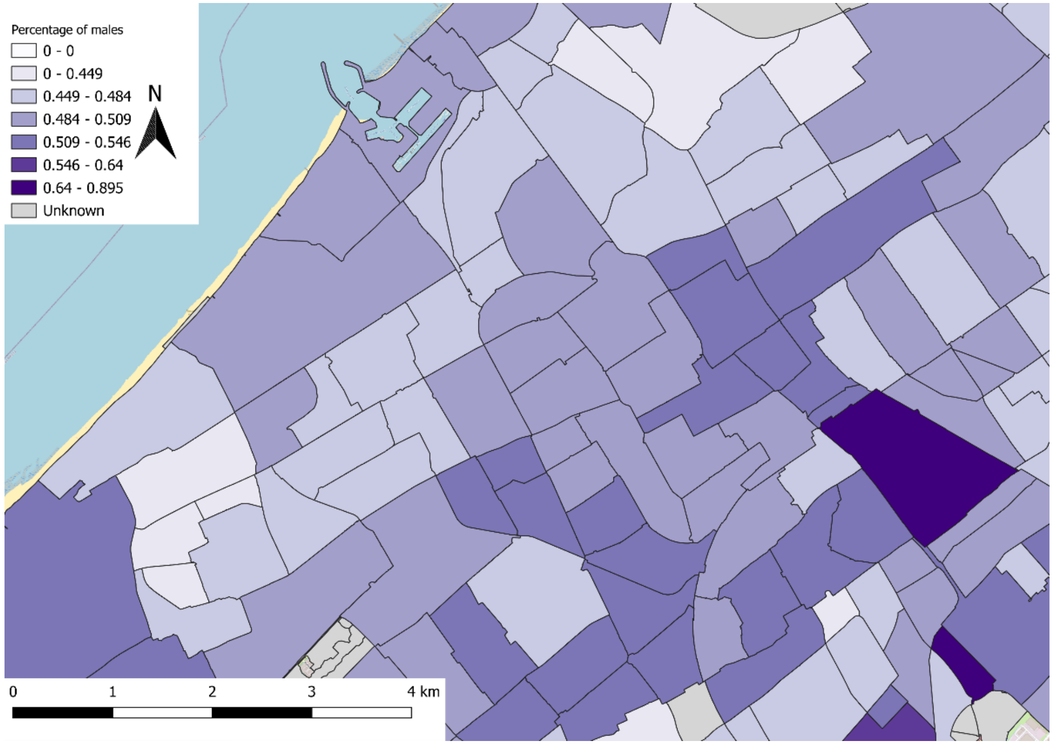

Figure 70 - Percentage of males per neighbourhood in The Hague

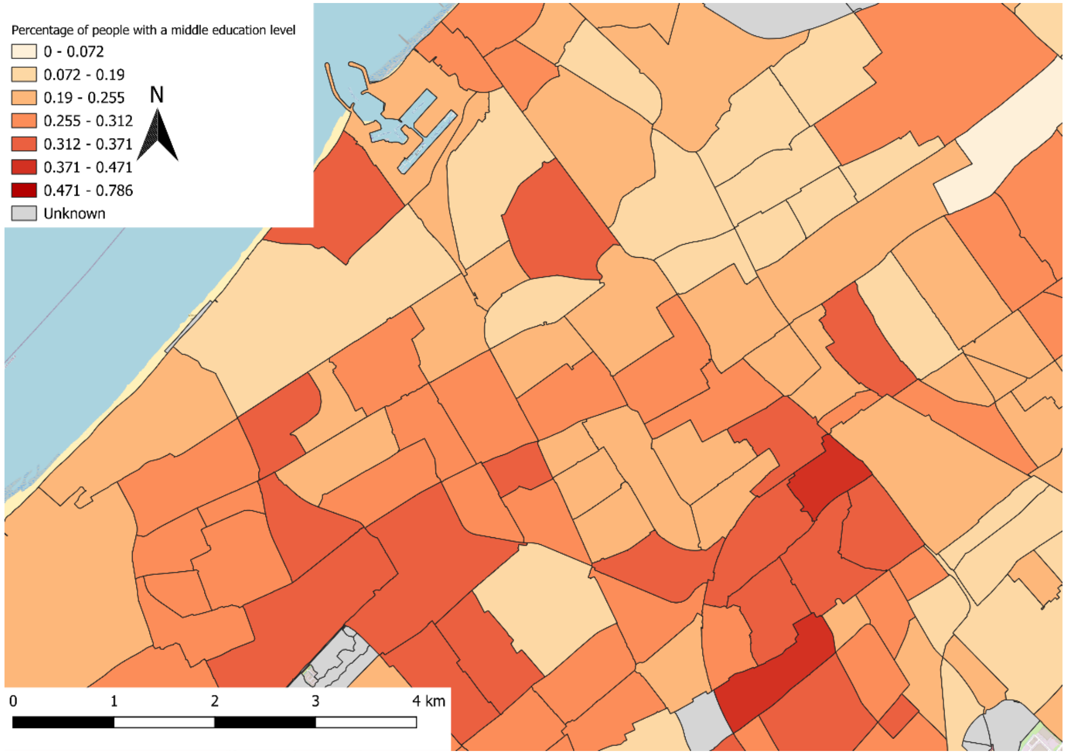

Figure 71 - Percentage of people with a middle education level per neighbourhood in The Hague

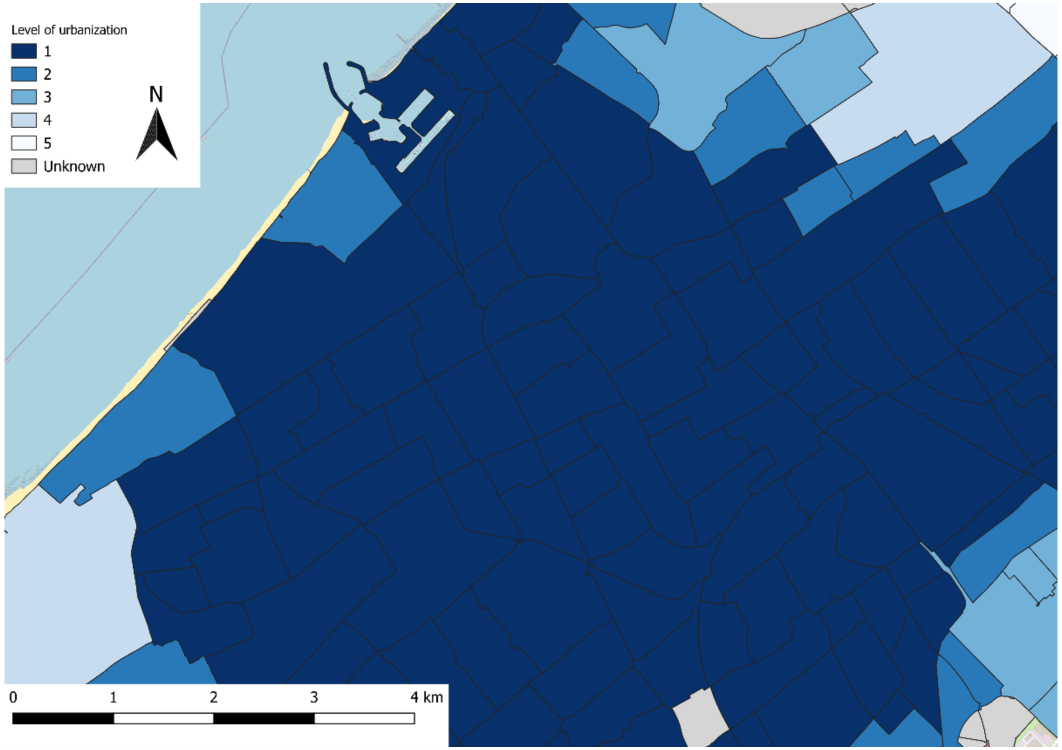

Figure 72 – Level of urbanization per neighbourhood in The Hague

Figure 73 - Percentage of people with low education level per neighbourhood in Rotterdam

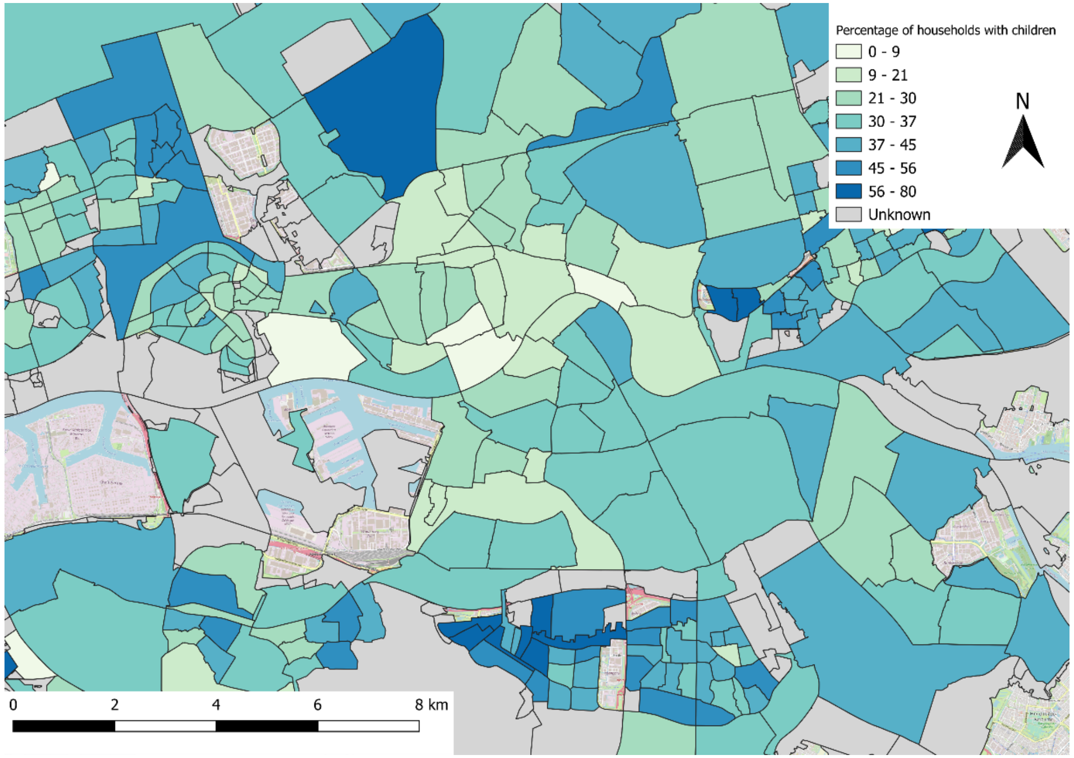

Figure 74 - Percentage of households with children per neighbourhood in Rotterdam

Figure 75 – Land Use Mix per neighbourhood in Rotterdam

Figure 76 - Percentage of males per neighbourhood in Rotterdam

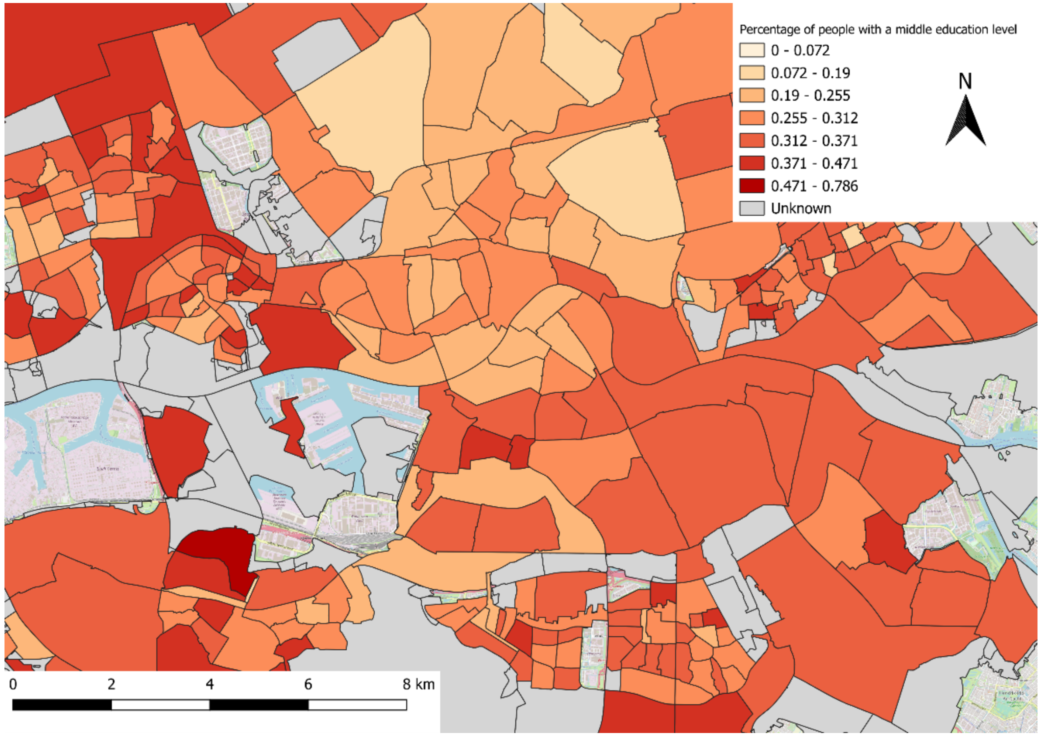

Figure 77 - Percentage of people with middle education level per neighbourhood in Rotterdam

Figure 78 – Level of urbanization per neighbourhood in Rotterdam

Figure 79 - Percentage of people older than 65 per neighbourhood in Utrecht

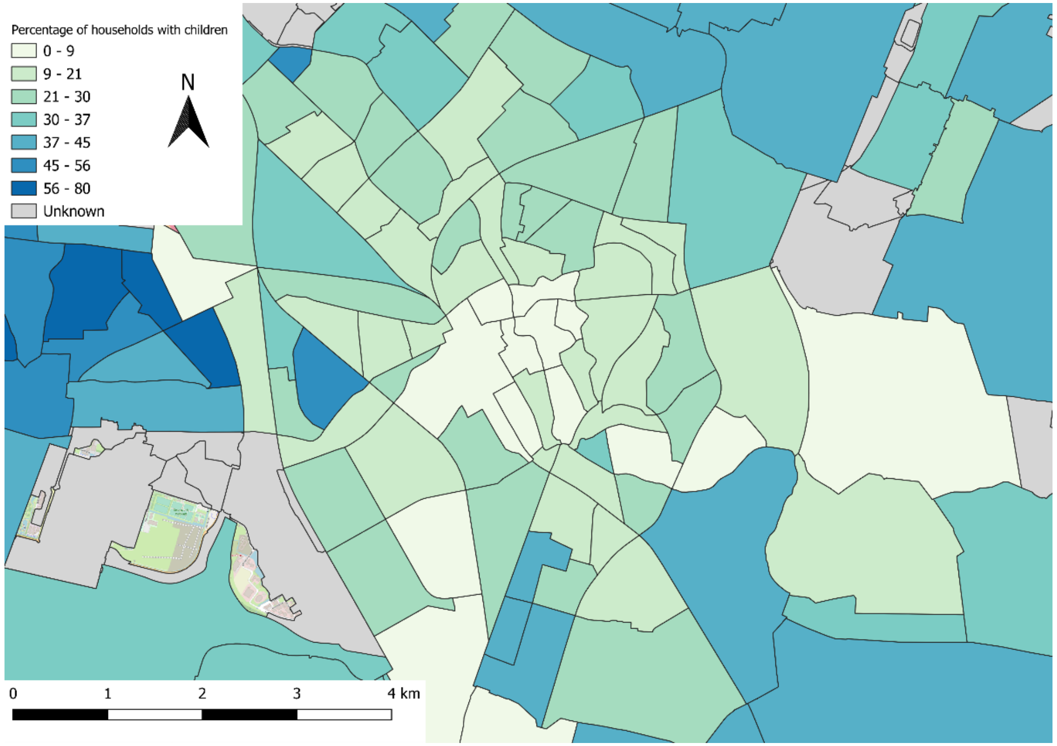

Figure 80 - Percentage of households with children per neighbourhood in Utrecht

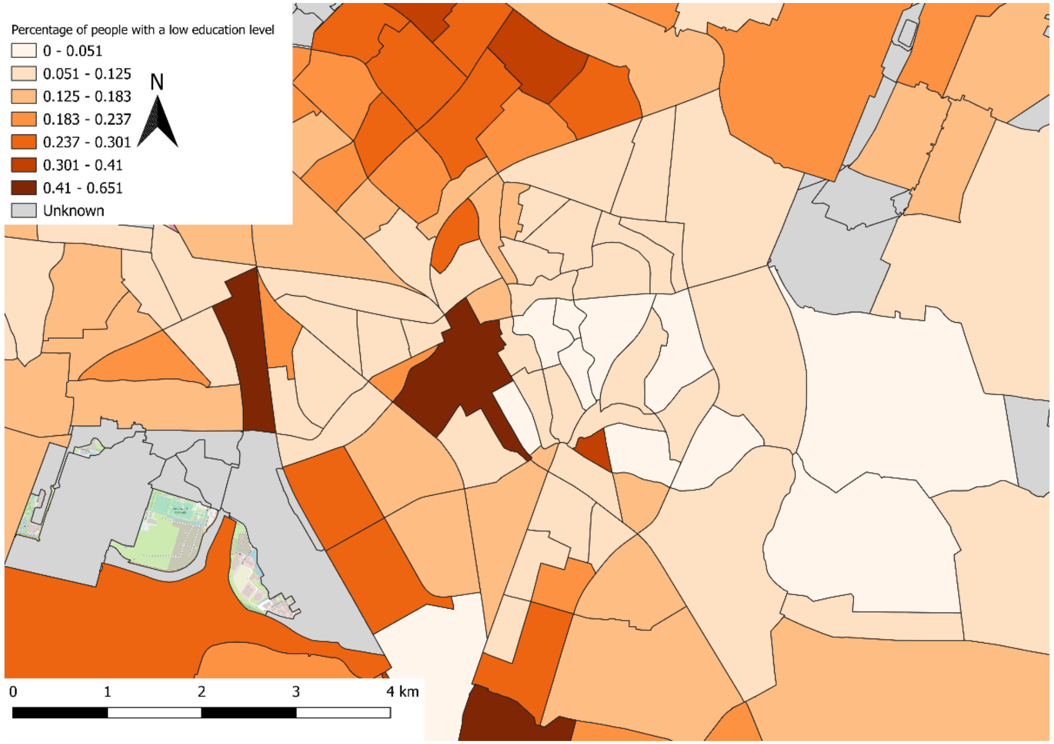

Figure 81 - Percentage of people with middle education level per neighbourhood in Utrecht

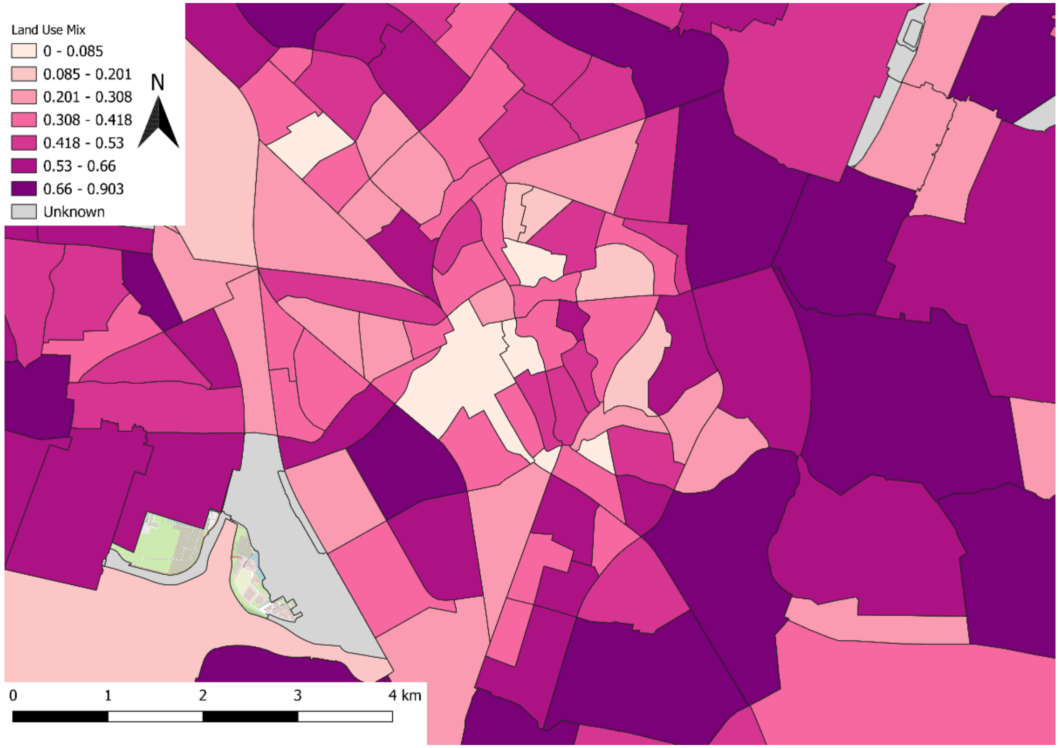

Figure 82 – Land Use Mix per neighbourhood in Utrecht

Figure 83 - Percentage of males per neighbourhood in Utrecht

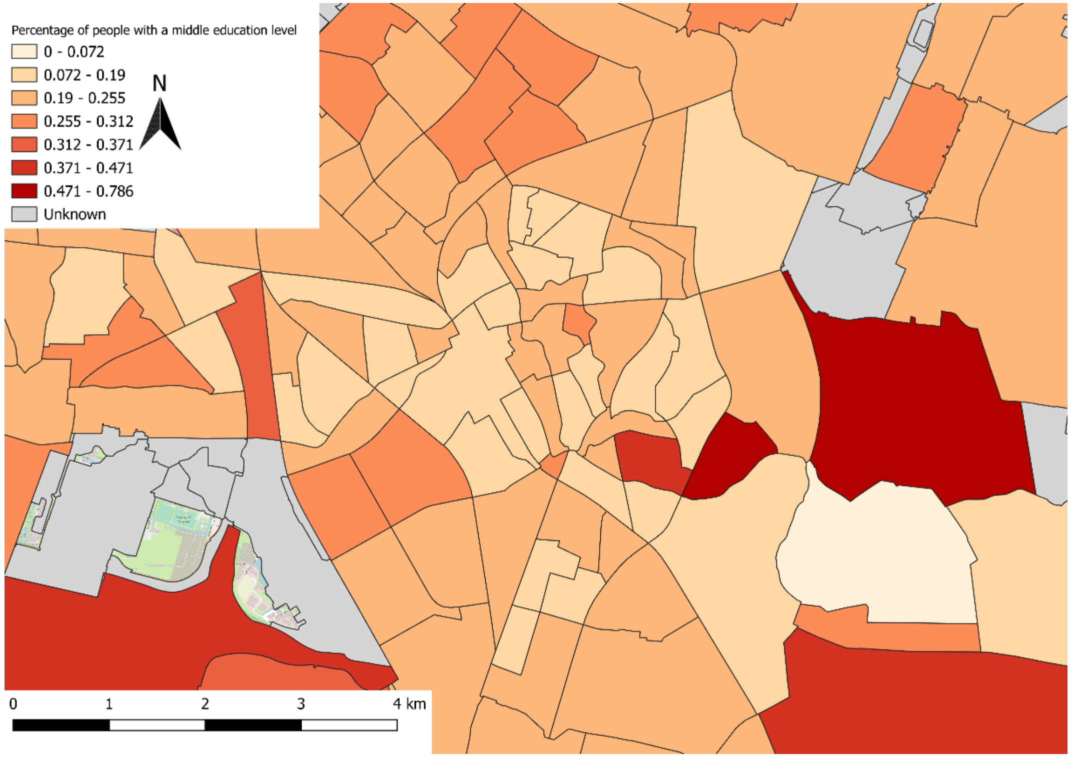

Figure 84 - Percentage of people with a middle education level per neighbourhood in Utrecht

Appendix N: Independent variables shared bicycle/moped per city

Figure 85 - Percentage of people older than 65 per PC5 area in Amsterdam

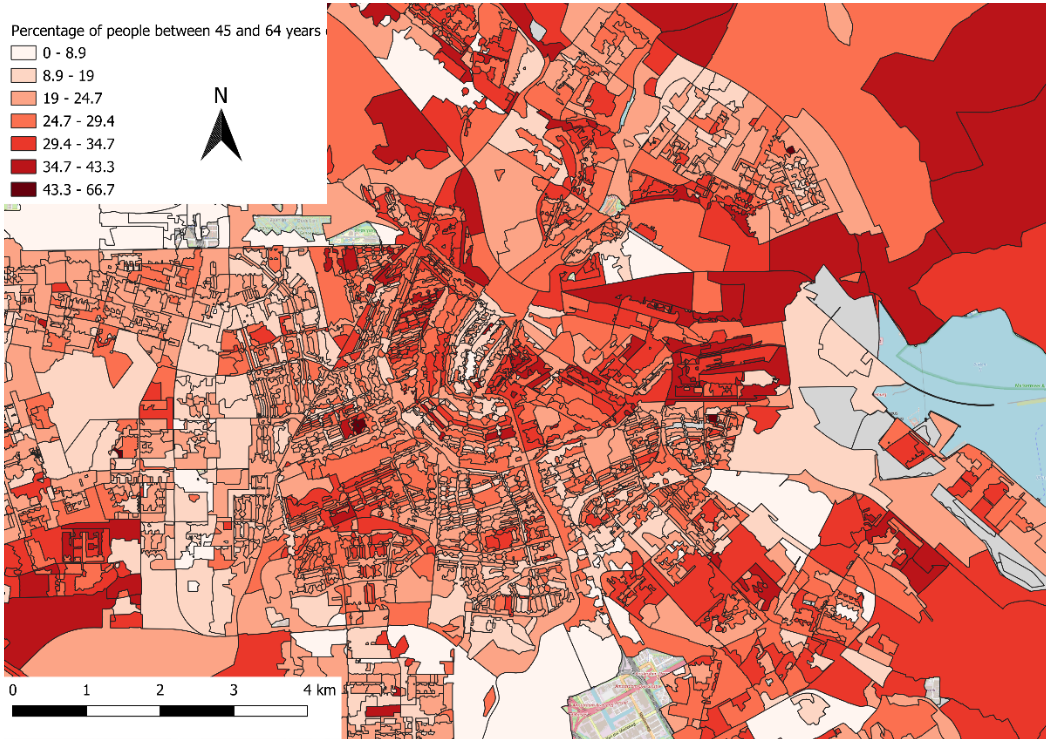

Figure 86 - Percentage of people between 45 and 65 years old per PC5 area in Amsterdam

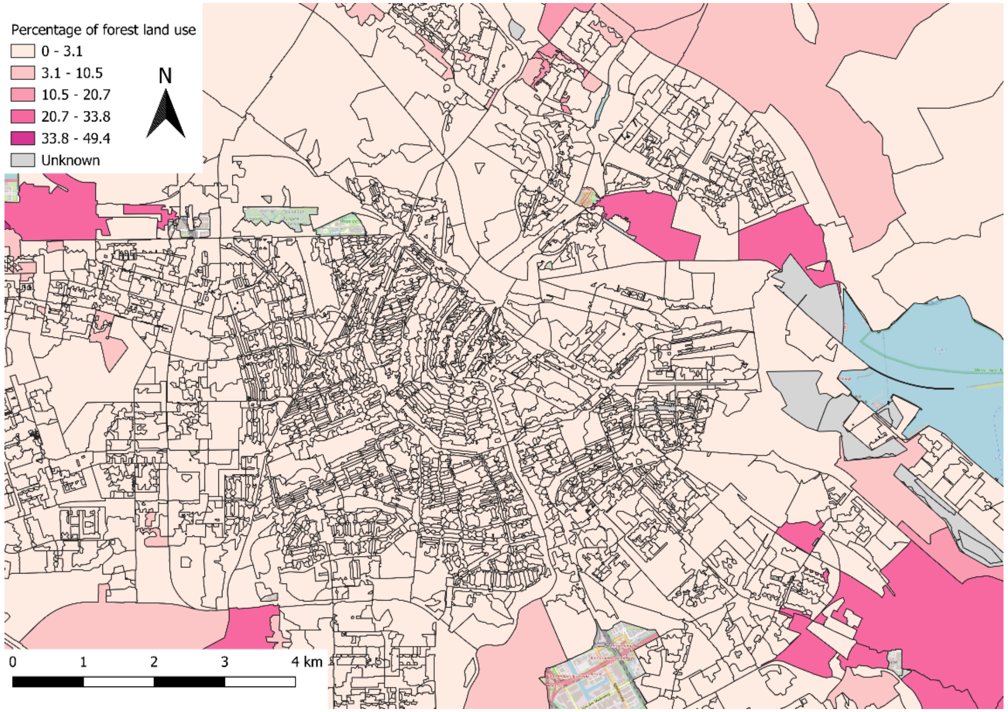

Figure 87 – Percentage of forest land use per PC5 area in Amsterdam

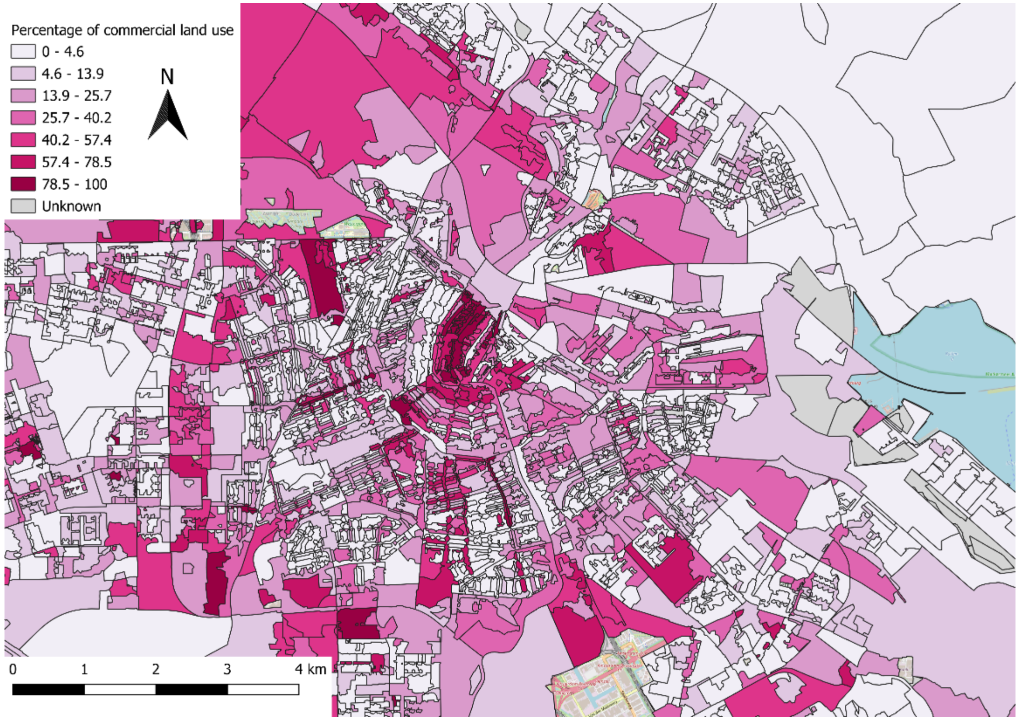

Figure 88 - Percentage of commercial land use per PC5 area in Amsterdam

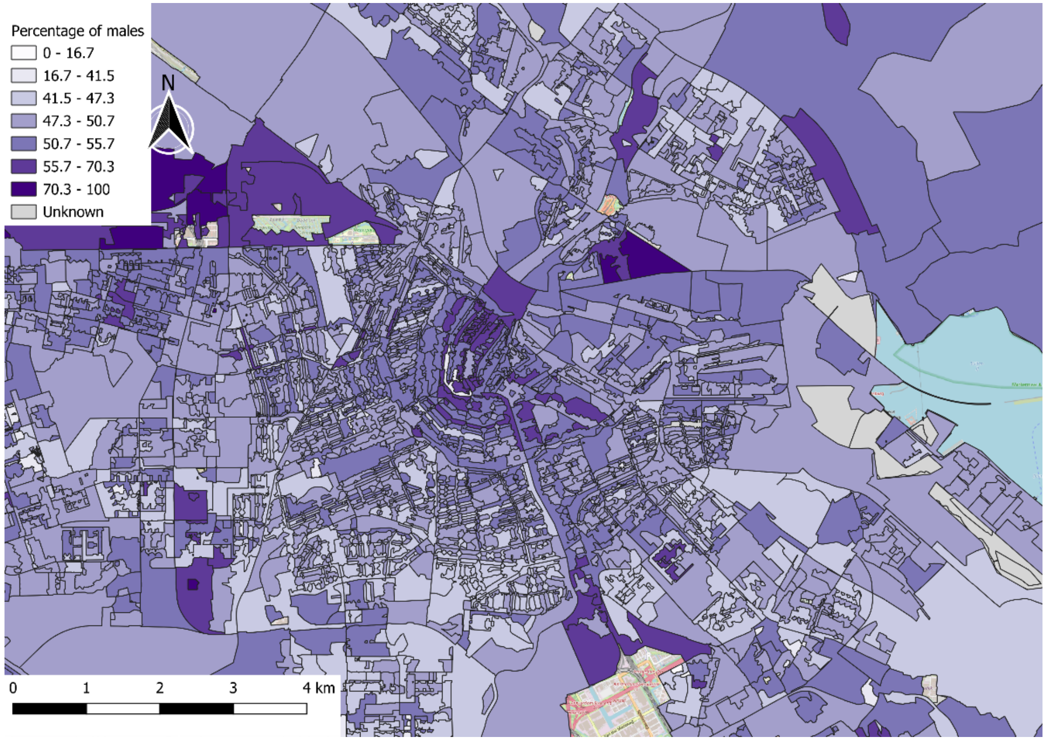

Figure 89 - Percentage of males per PC5 area in Amsterdam

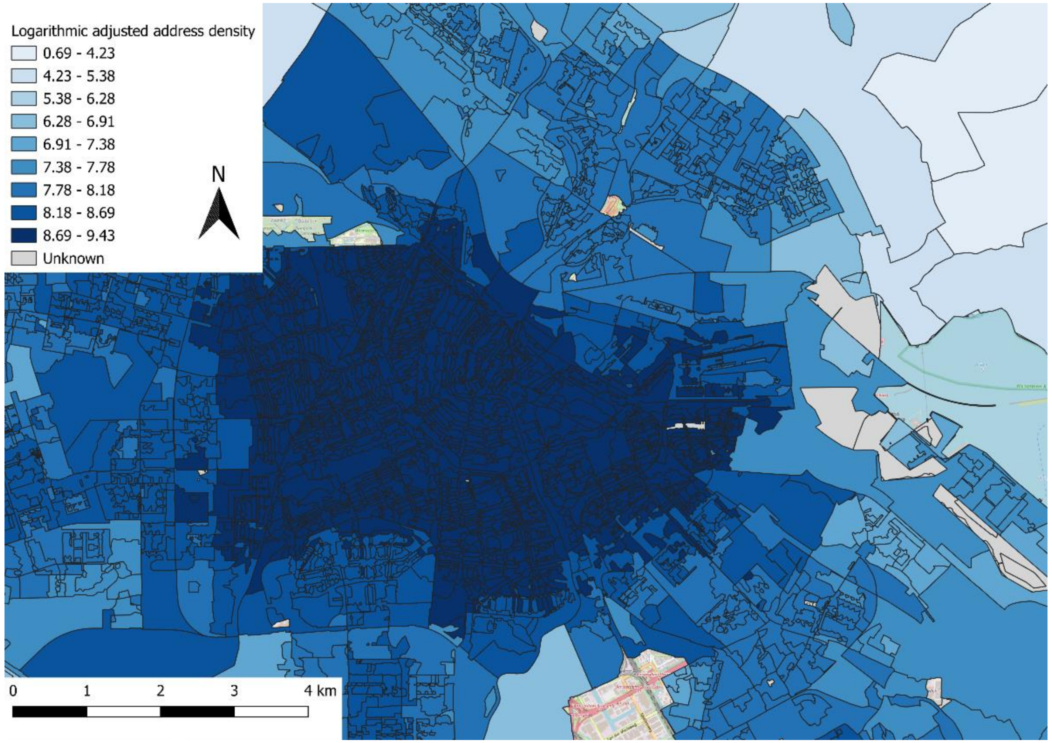

Figure 90 – Logarithmic adjusted address density per PC5 area in Amsterdam

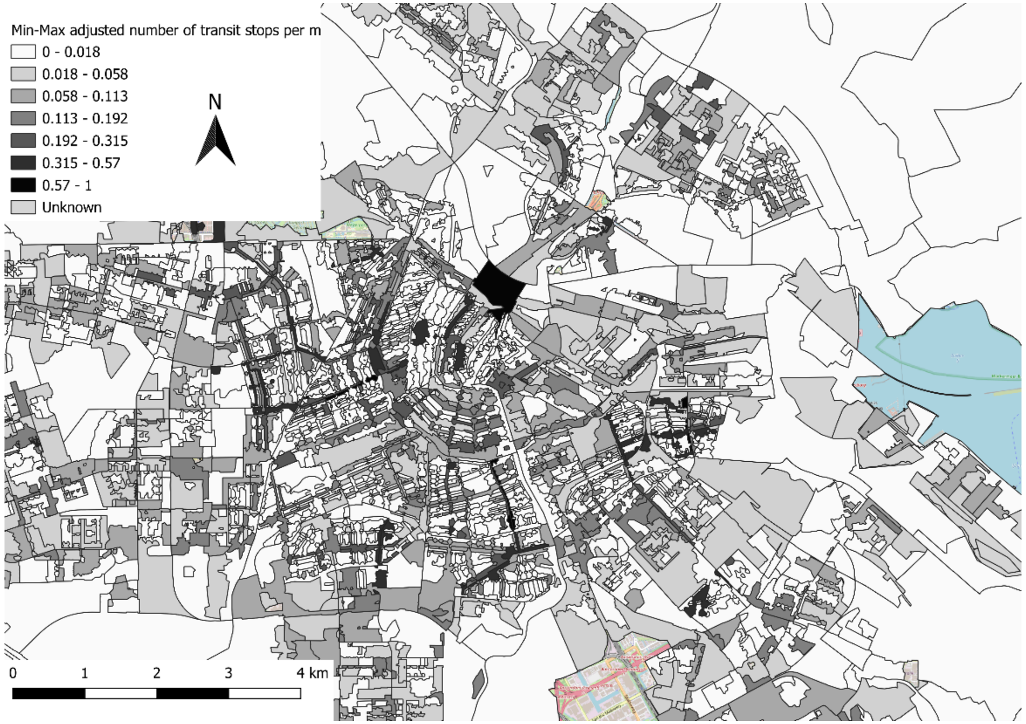

Figure 91 – Min-Max adjusted number of transit stops per m² per PC5 area in Amsterdam

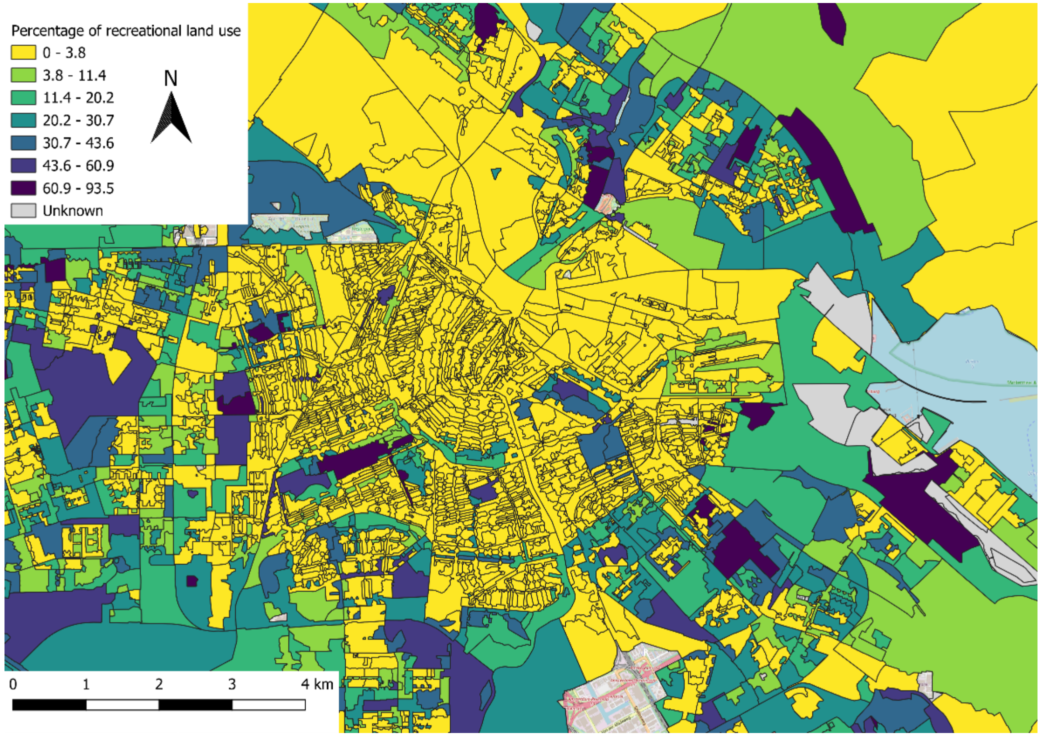

Figure 92 – Percentage of recreational land use per PC5 area in Amsterdam

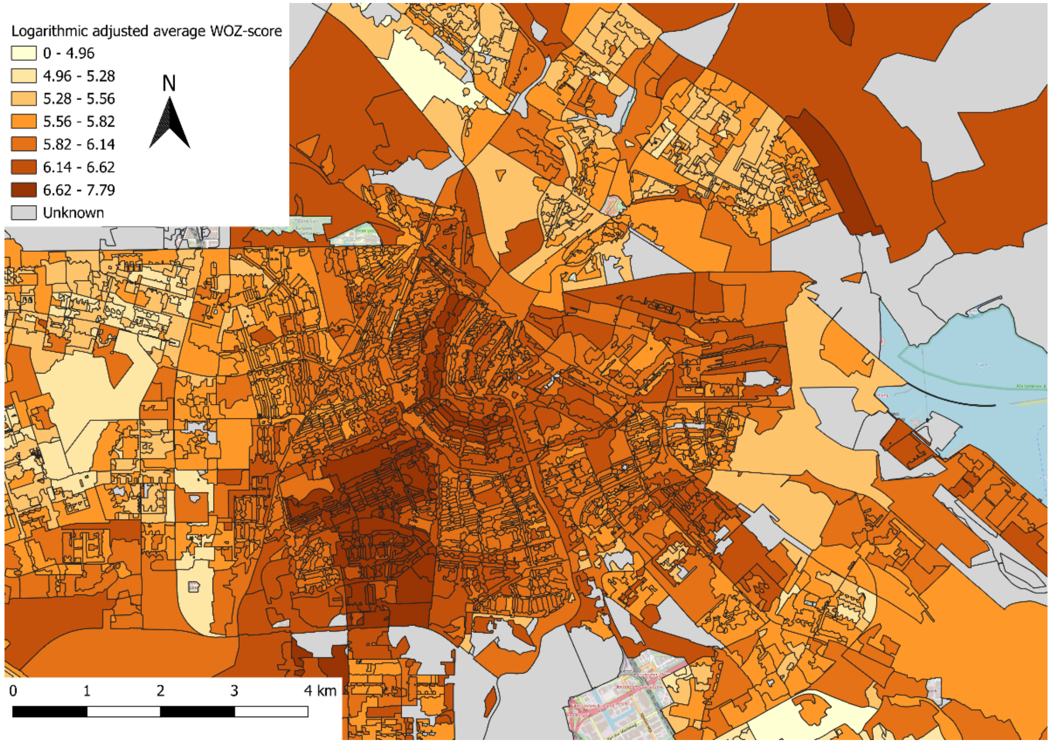

Figure 93 – Logarithmic adjusted average WOZ-score per PC5 area in Amsterdam

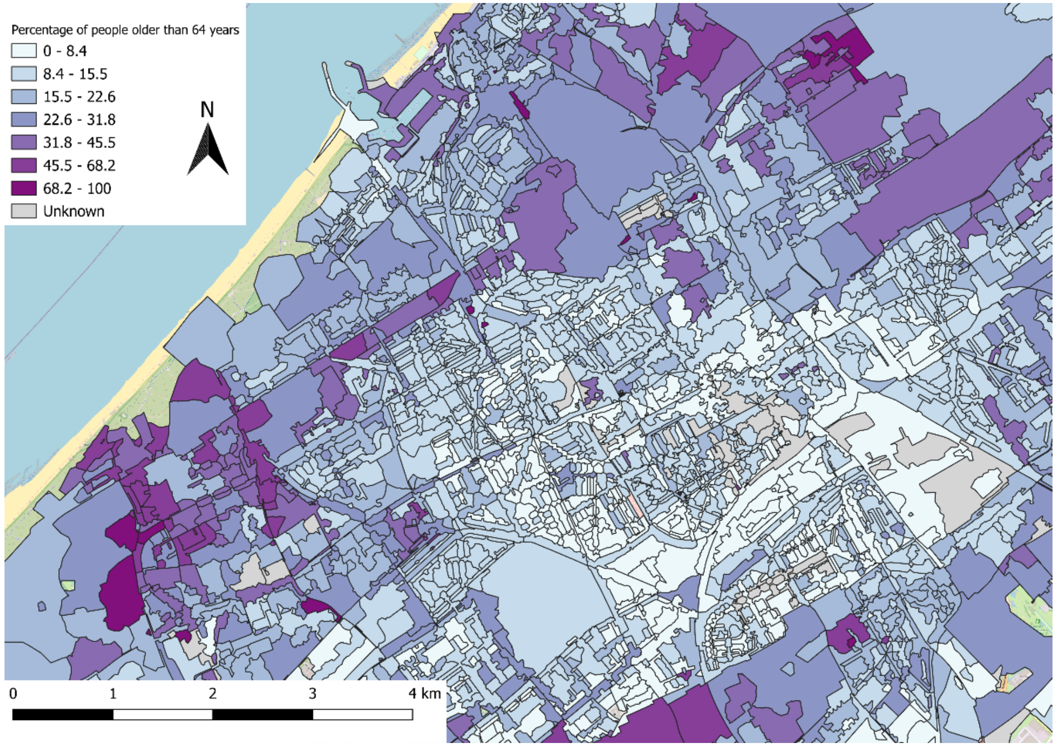

Figure 94 – Percentage of people older than 64 years per PC5 area in The Hague

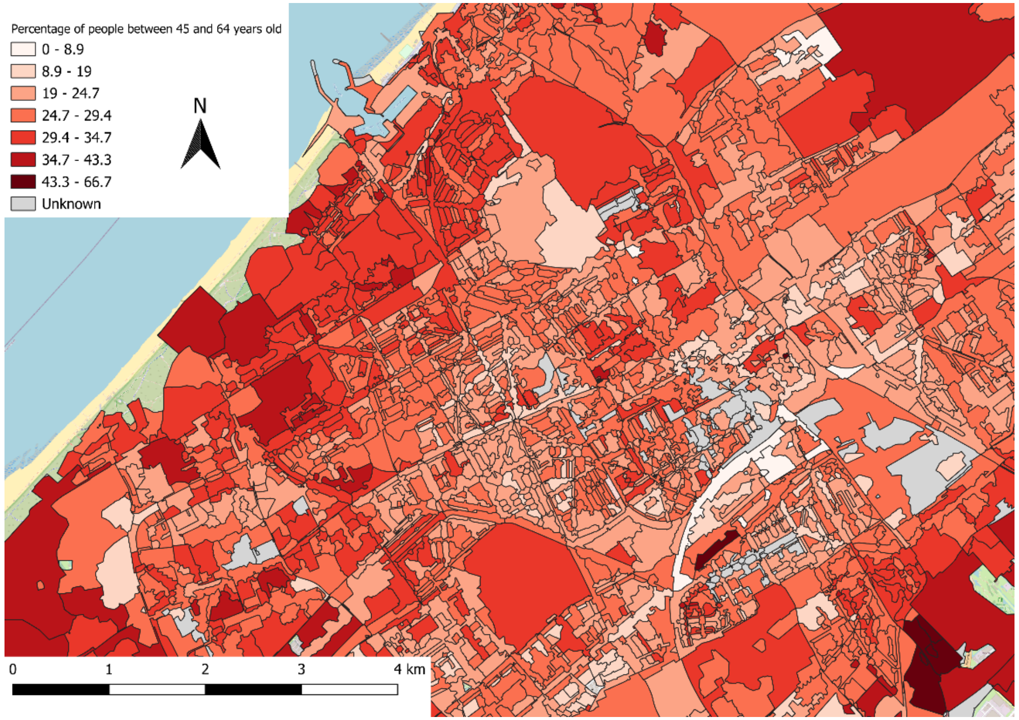

Figure 95 - Percentage of people between 45 and 64 years old per PC5 area in The Hague

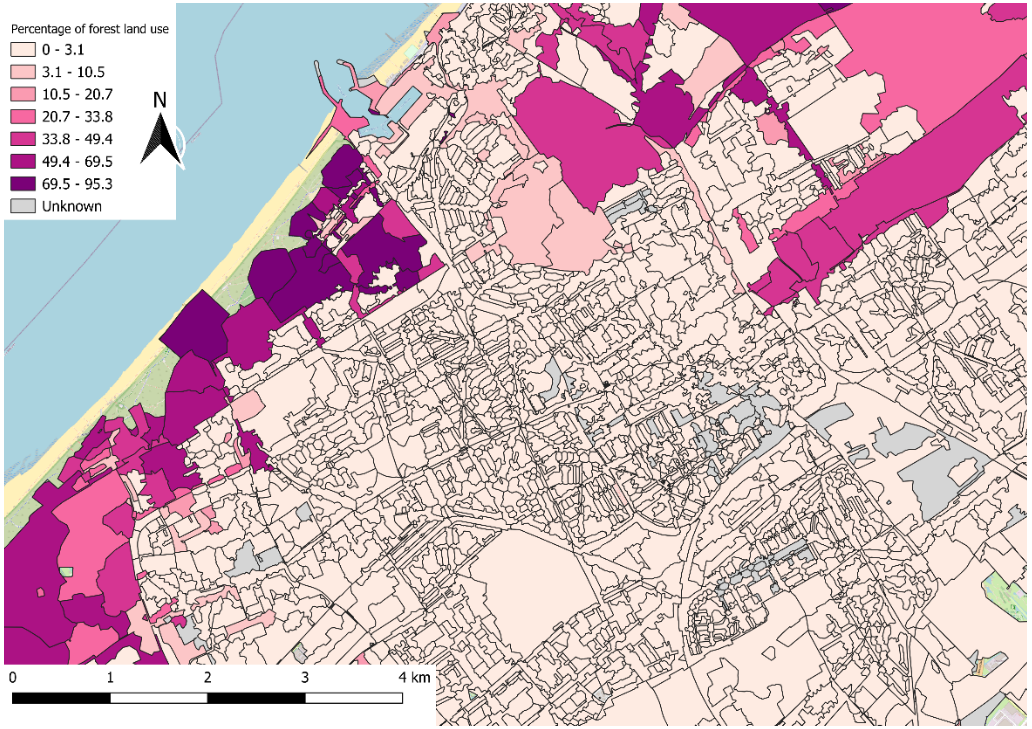

Figure 96 - Percentage of forest land use per PC5 area in The Hague

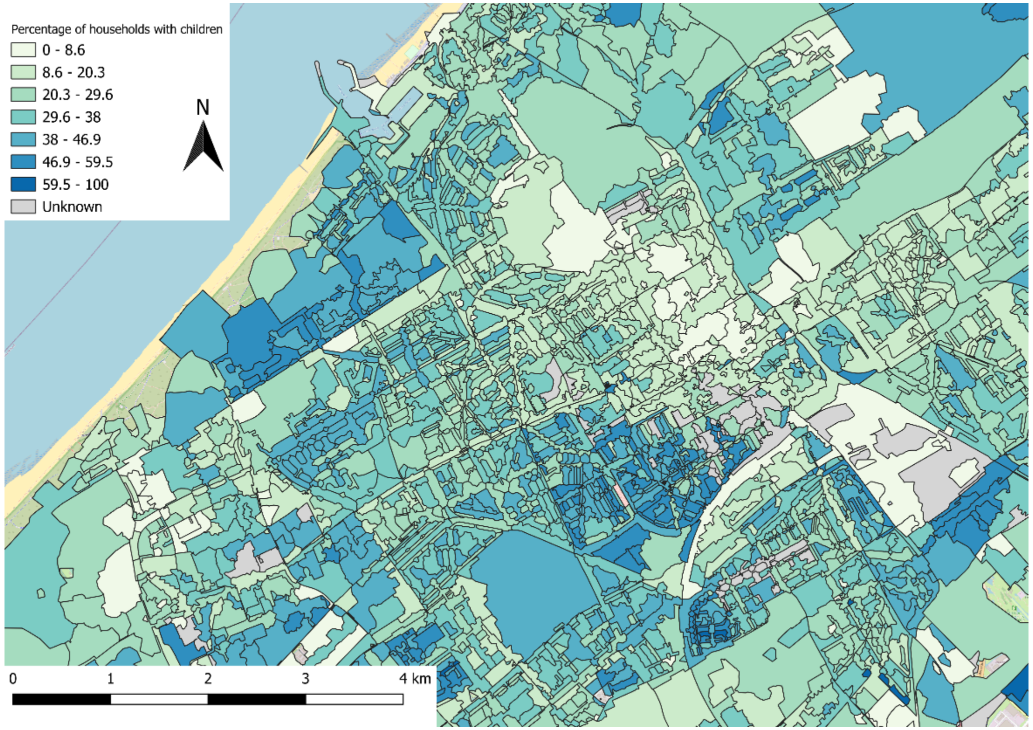

Figure 97 – Percentage of households with children per Pc5 area in The Hague

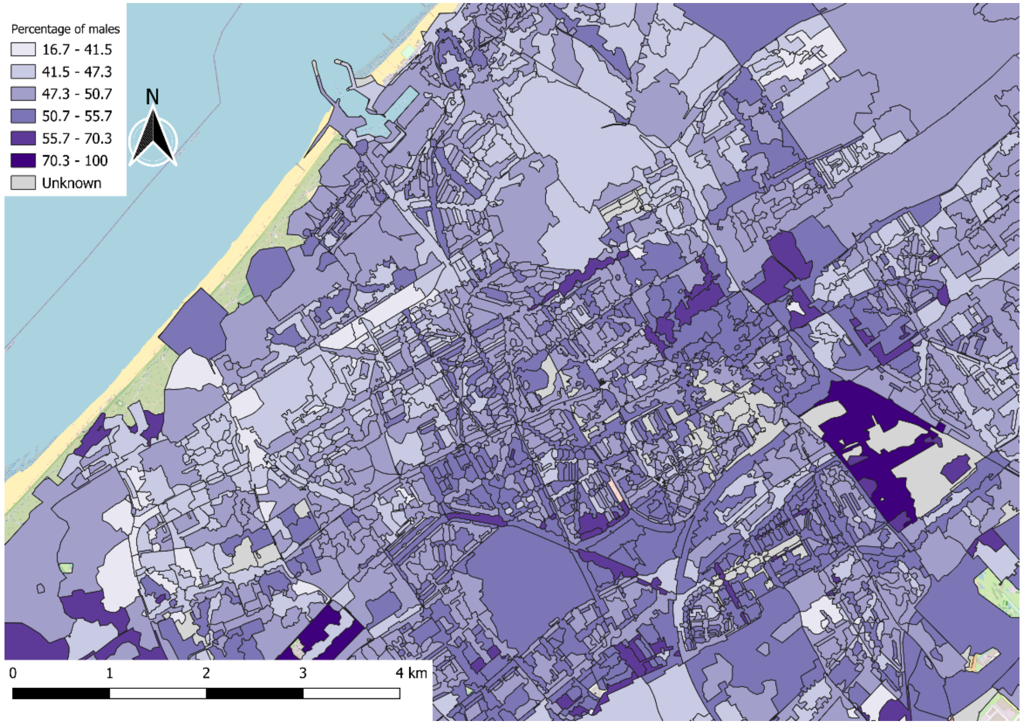

Figure 98 - Percentage of males per PC5 area in The Hague

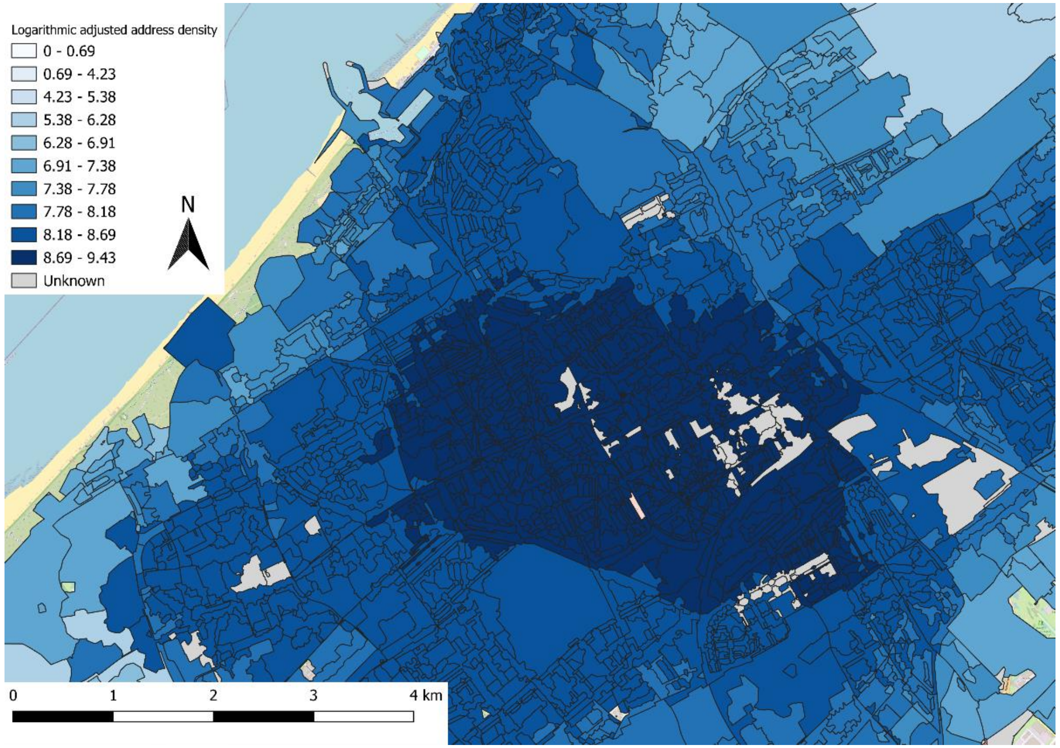

Figure 99 – Logarithmic adjusted address density per PC5 area in The Hague

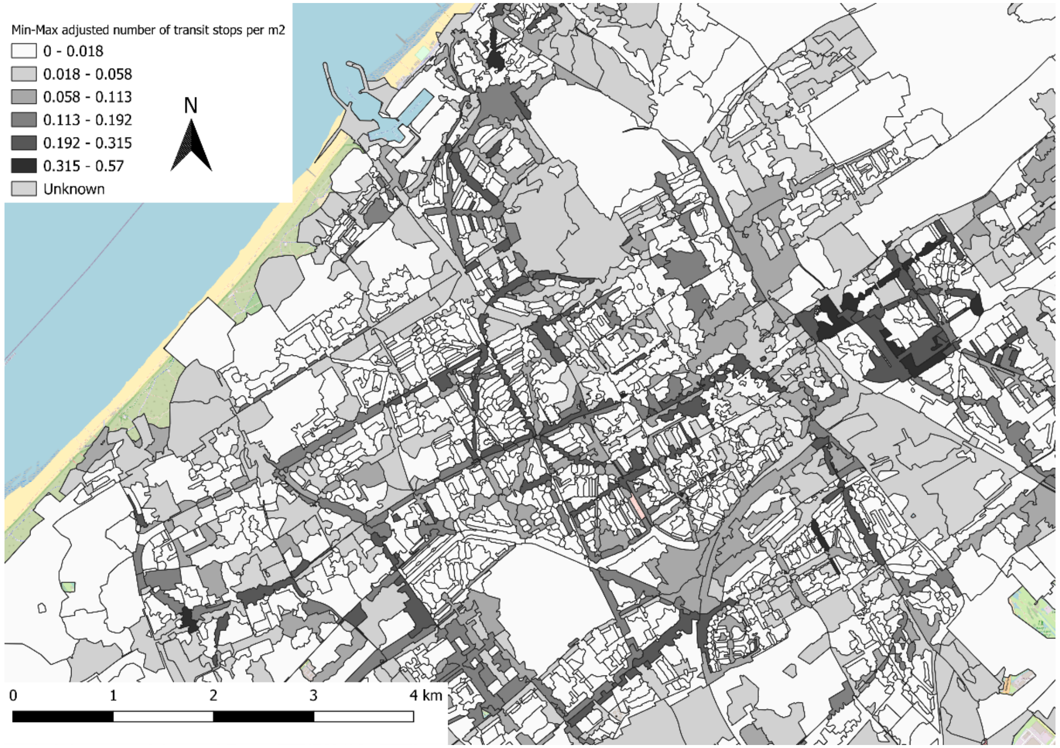

Figure 100 – Min-Max adjusted number of transit stops per m^2 per PC5 area in The Hague

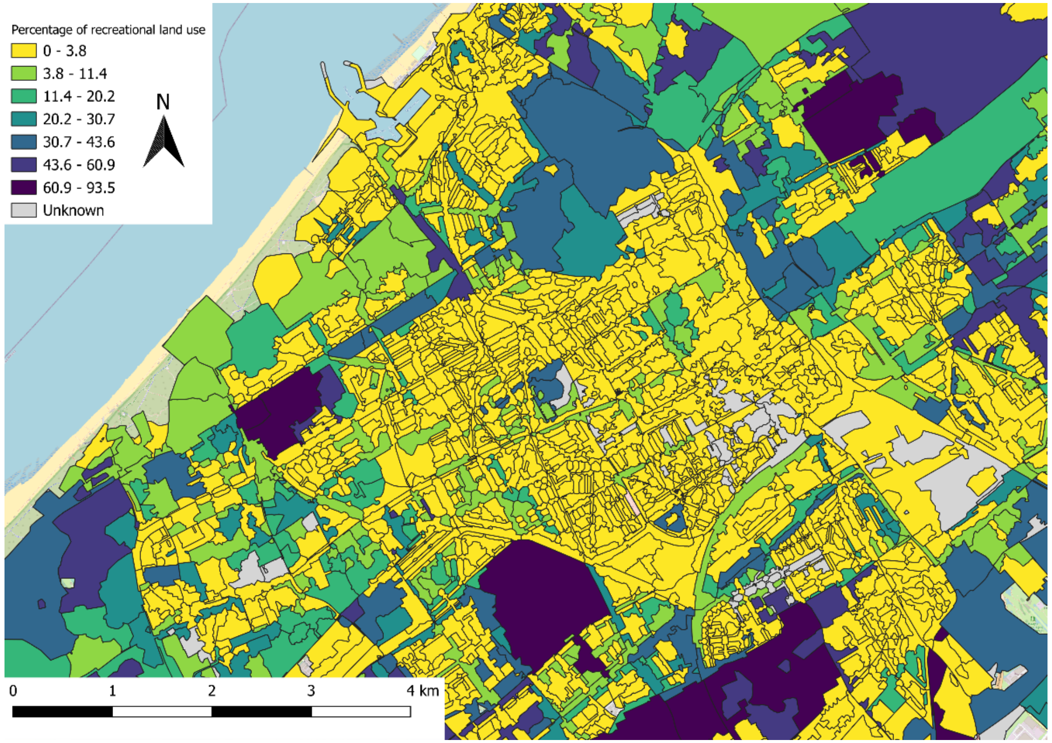

Figure 101 – Percentage of recreational land use per PC5 area in The Hague

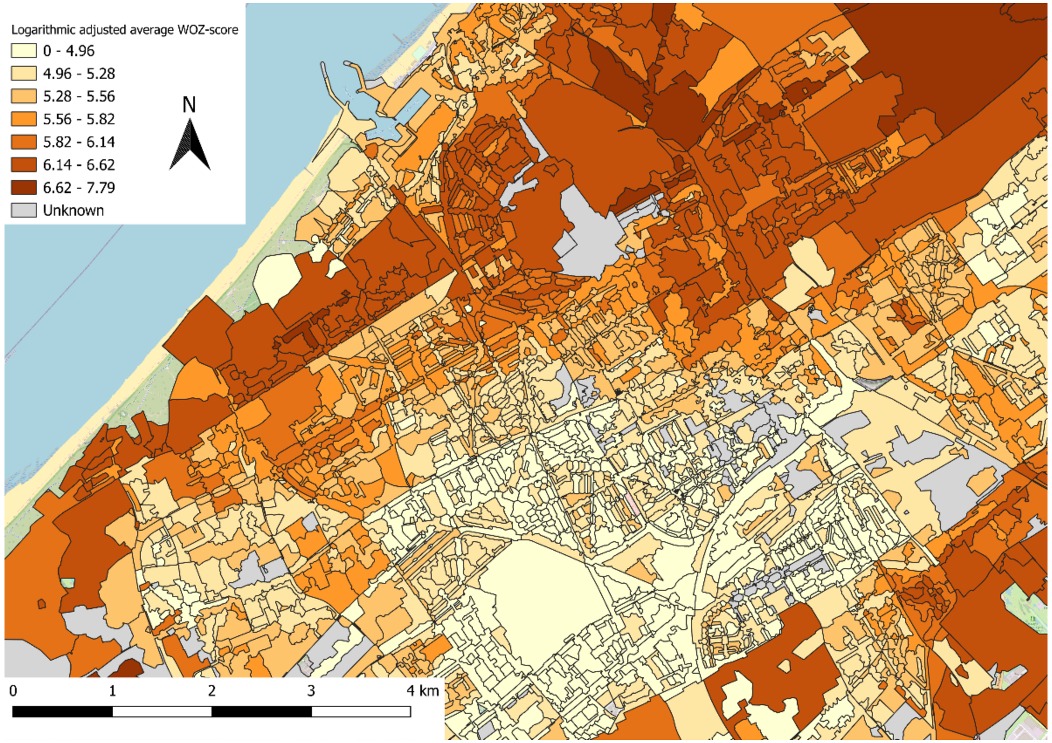

Figure 102 – Logarithmic adjusted average WOZ-score per PC5 area in The Hague

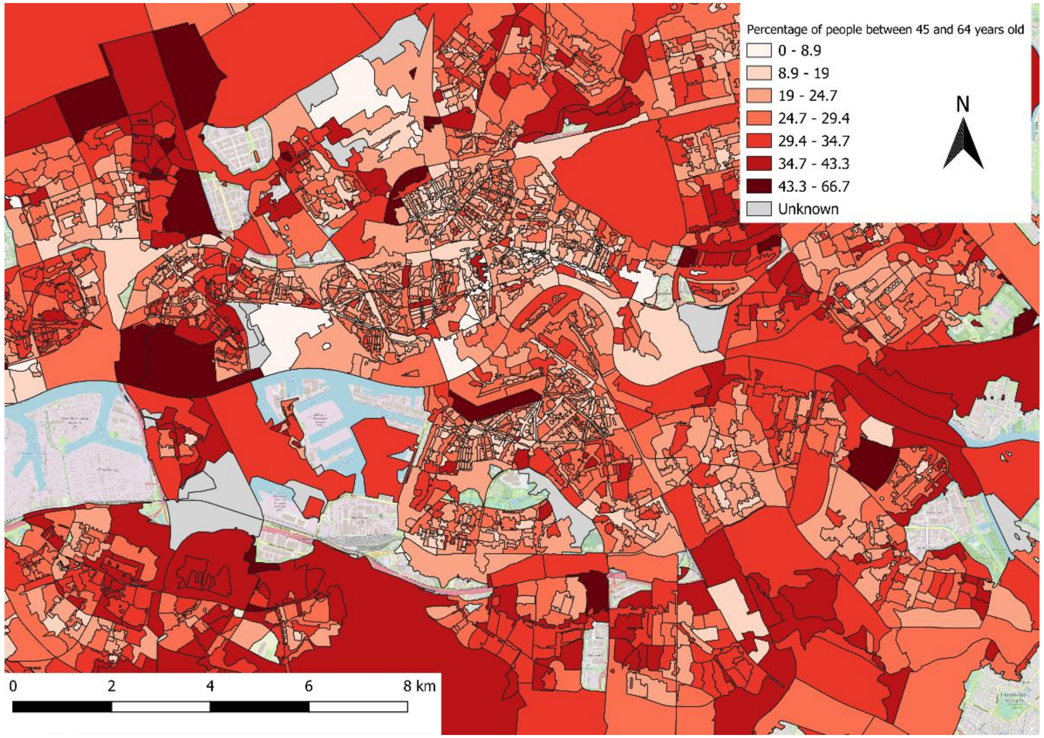

Figure 103 - Percentage of people between 45 and 64 years old per PC5 area in Rotterdam

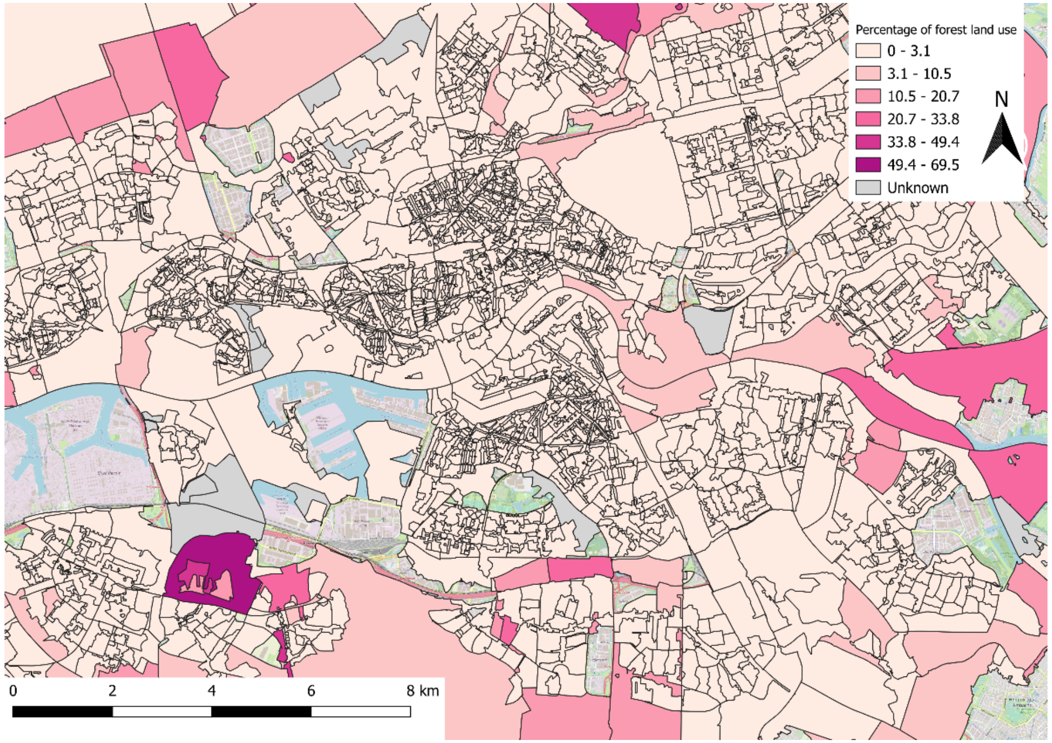

Figure 104 - Percentage of forest land use per PC5 area in Rotterdam

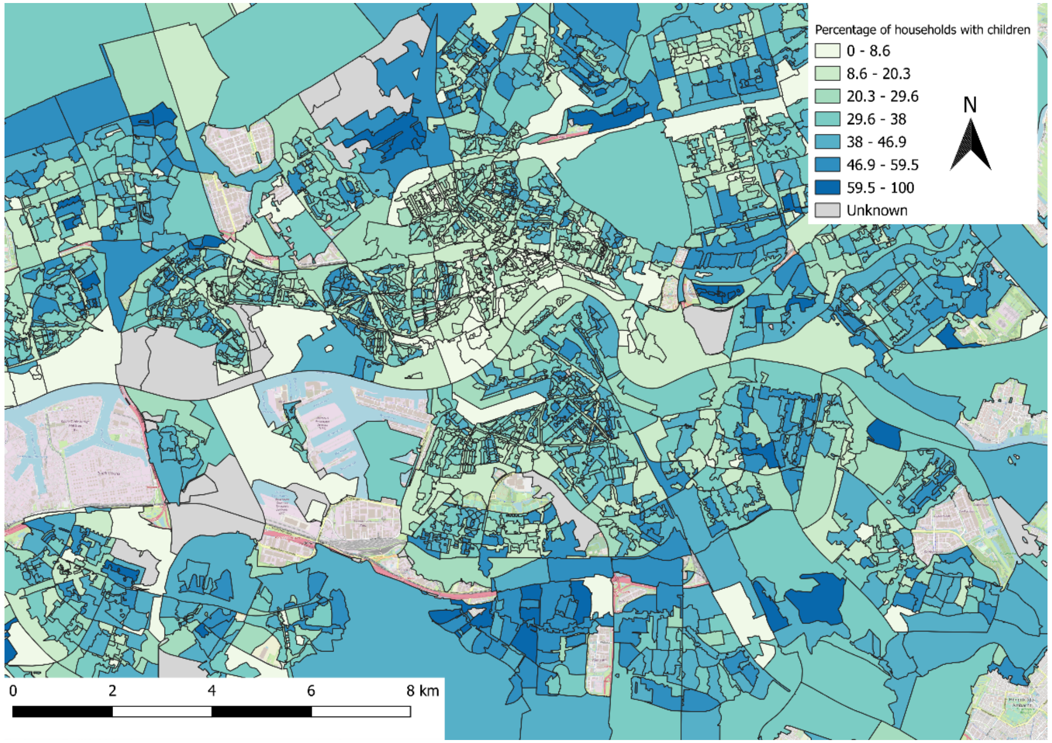

Figure 105 – Percentage of households with children per PC5 area in Rotterdam

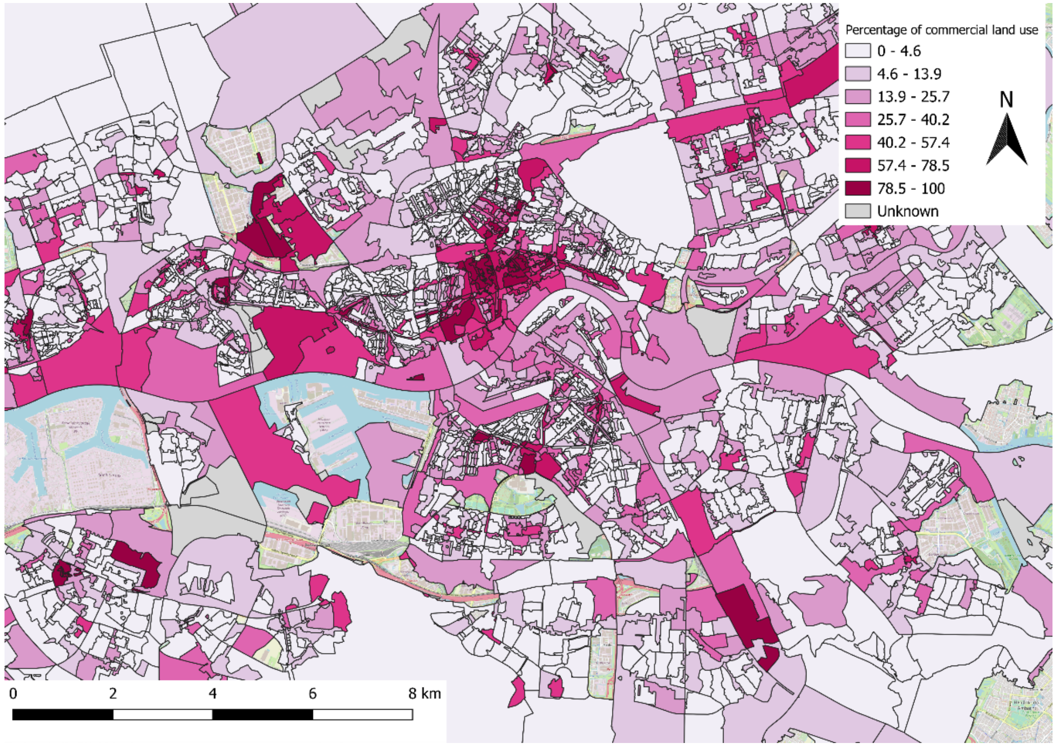

Figure 106 - Percentage of commercial land use per PC5 area in Rotterdam

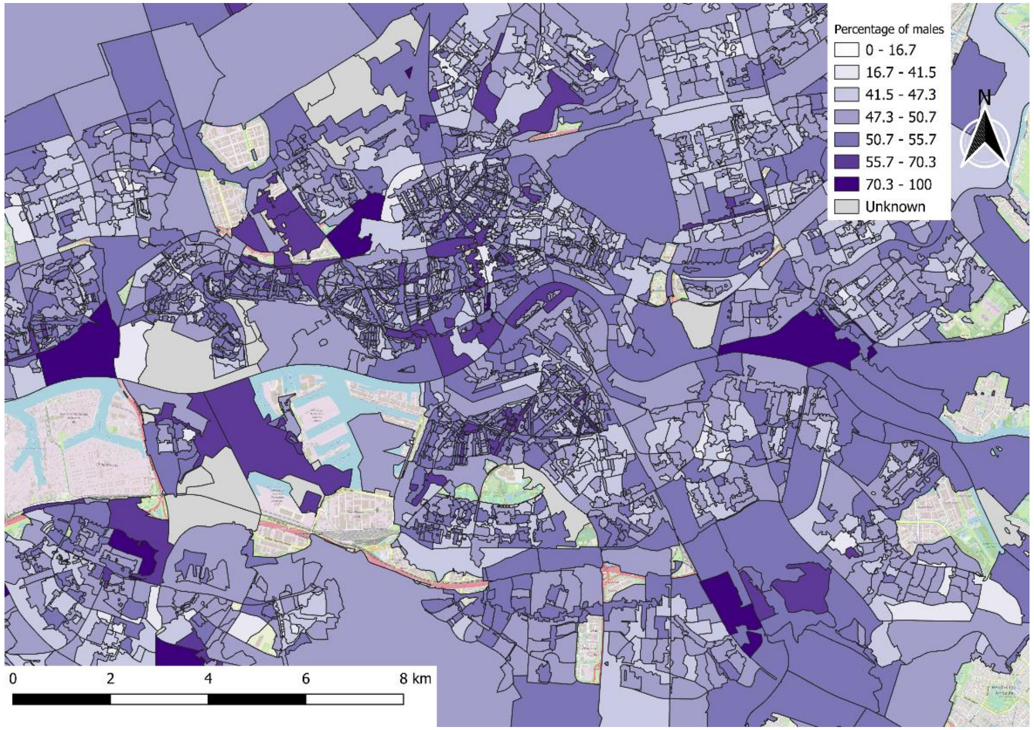

Figure 107 - Percentage of males per PC5 area in Rotterdam

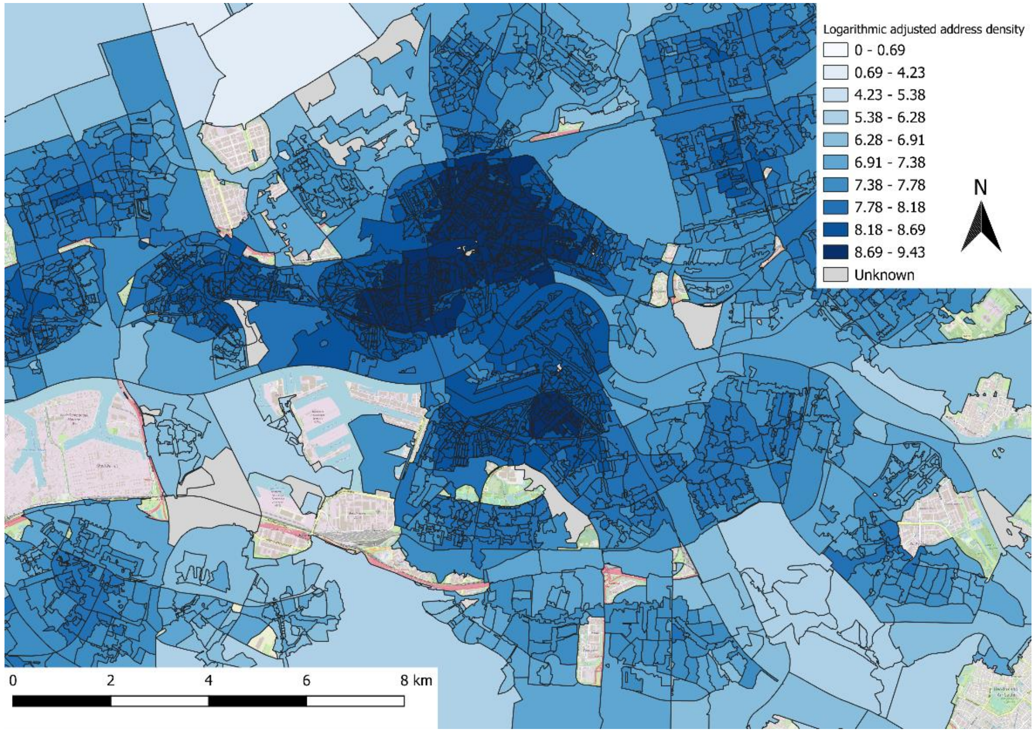

Figure 108 – Logarithmic adjusted address density per PC5 area in Rotterdam

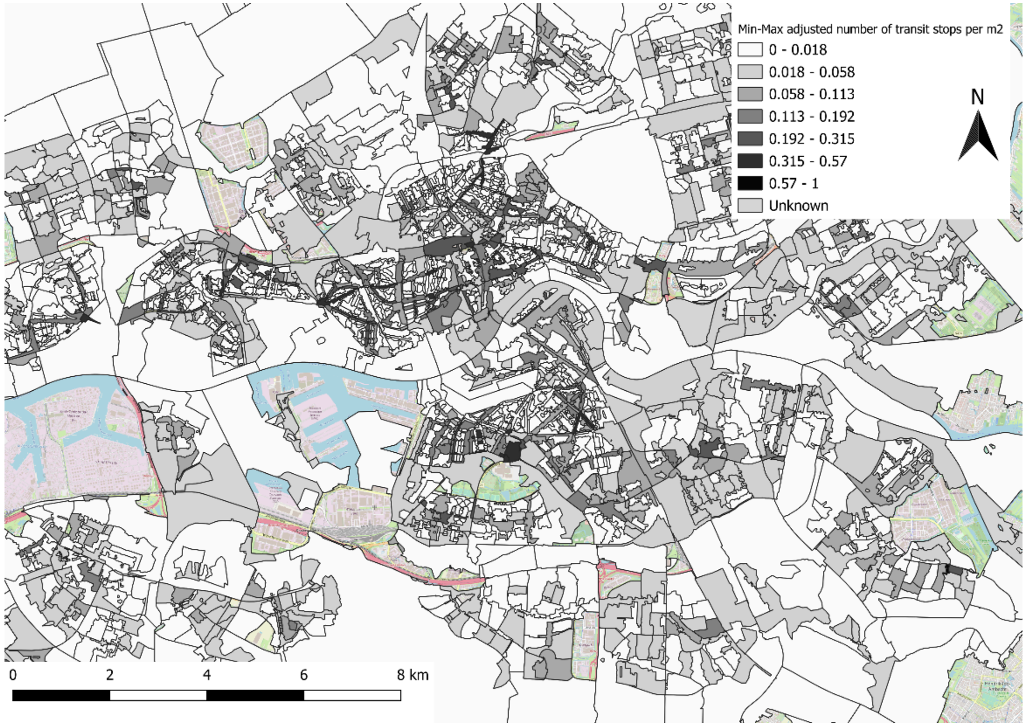

Figure 109 – Min-Max adjusted number of transit stops per PC5 area in Rotterdam

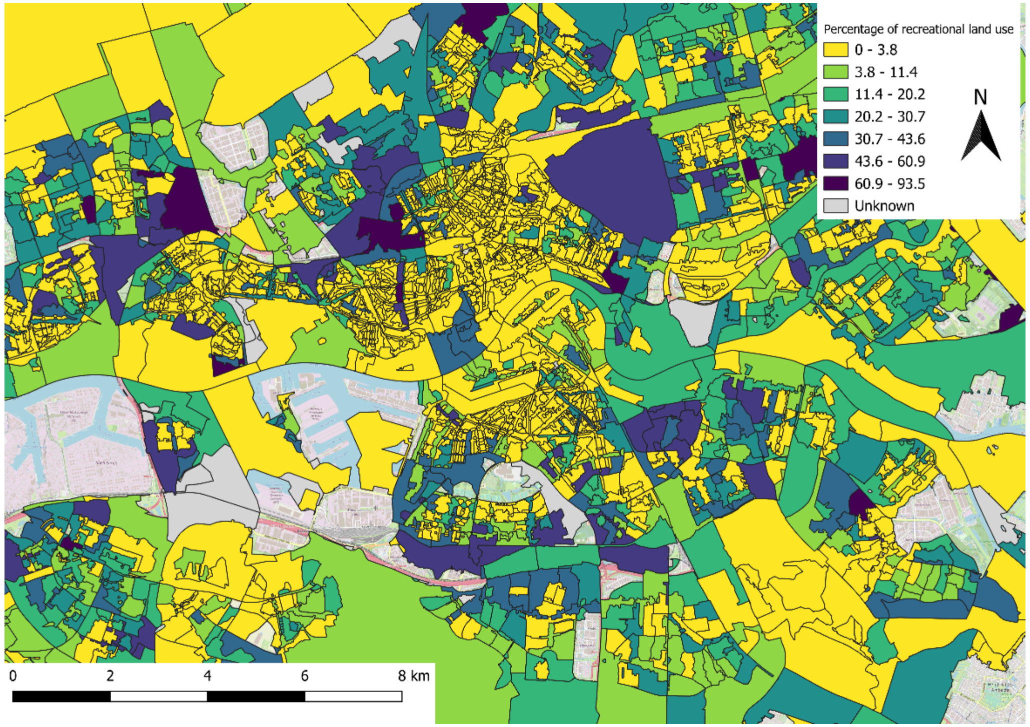

Figure 110 – Percentage of recreational land use per PC5 area in Rotterdam

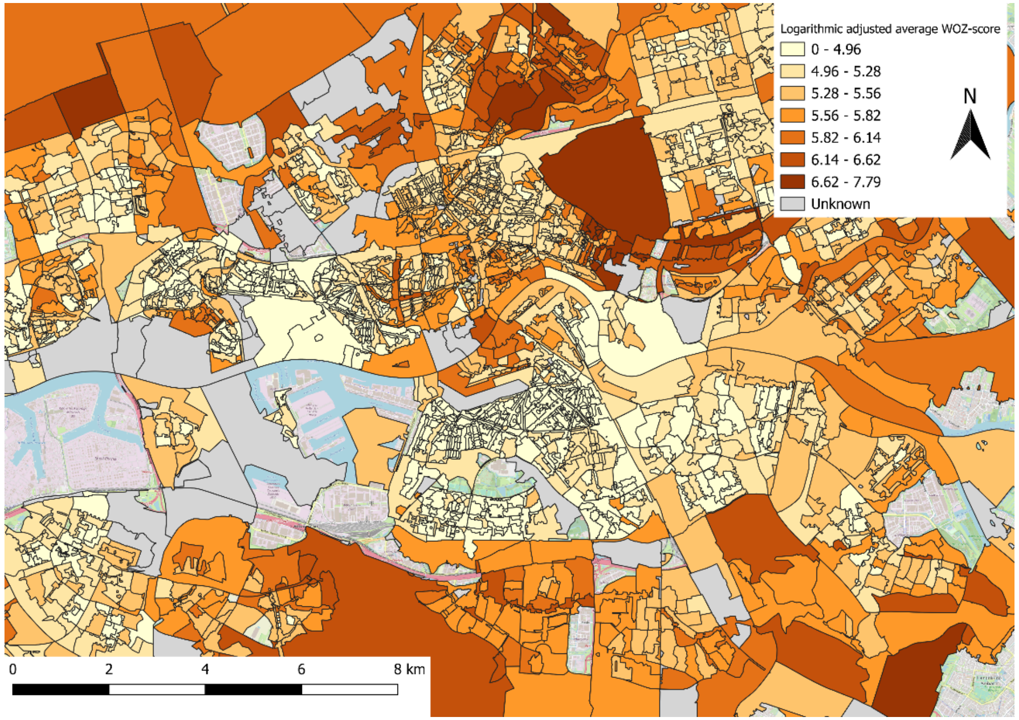

Figure 111 – Logarithmic adjusted average WOZ-score per PC5 area in Rotterdam

Figure 112 – Percentage of people older than 64 years per PC5 area in Utrecht

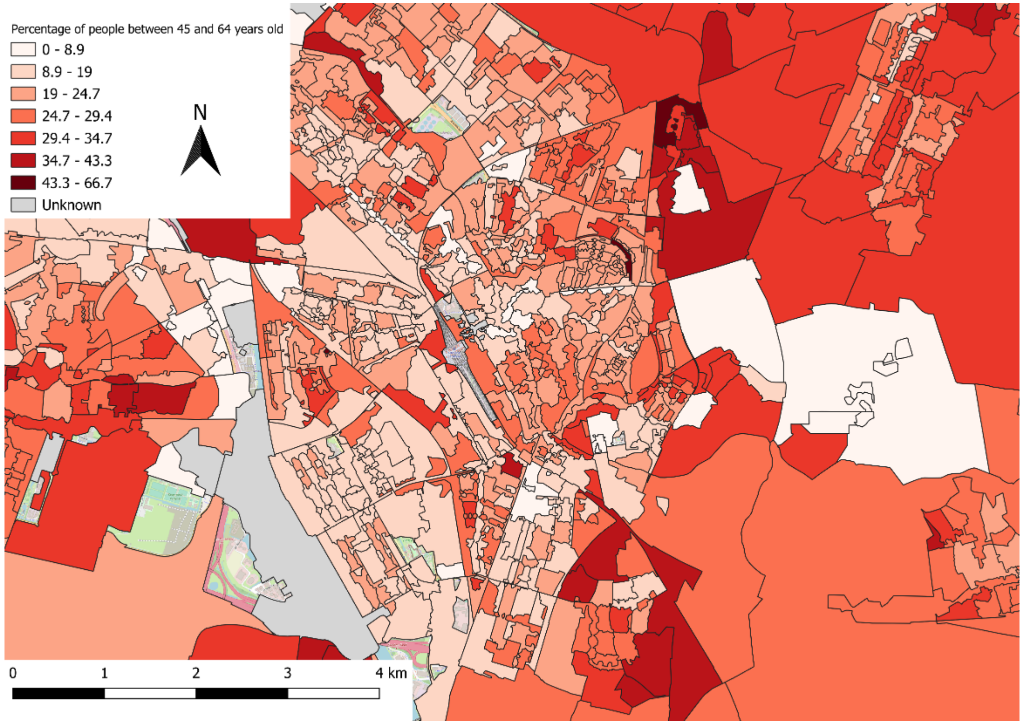

Figure 113 - Percentage of people between 45 and 65 years old per PC5 in Utrecht

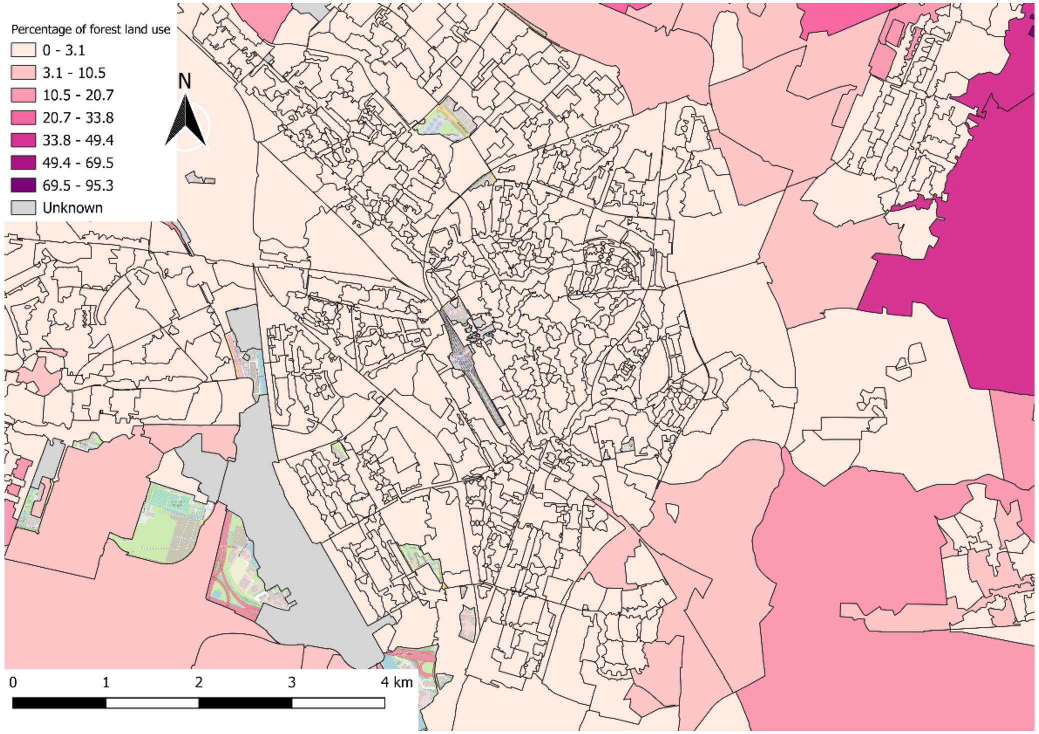

Figure 114 - Percentage of forest land use per PC5 area in Utrecht

Figure 115 - Percentage of households with children per PC5 area in Utrecht

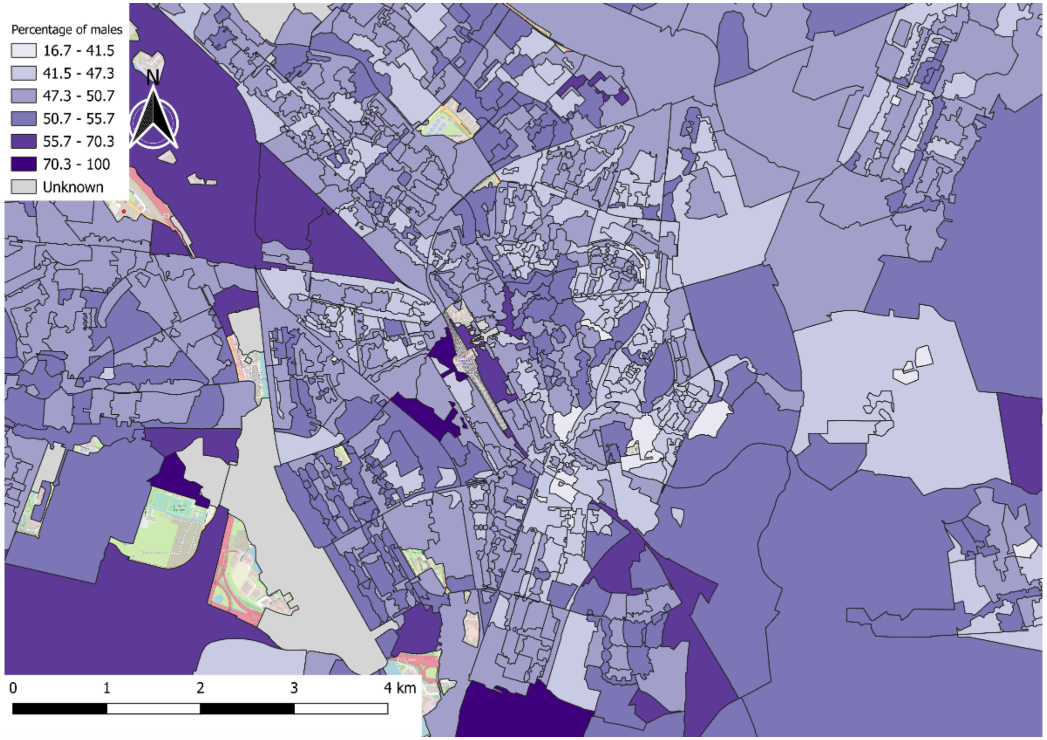

Figure 116 – Percentage of males per PC5 area in Utrecht

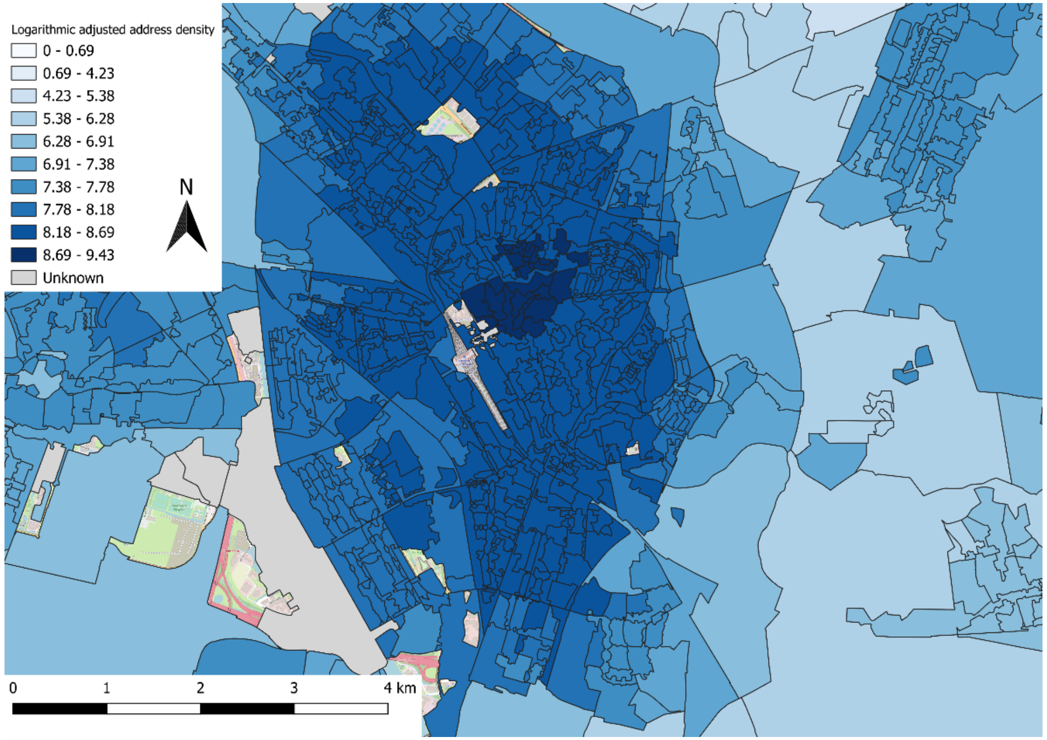

Figure 117 – Logarithmic adjusted address density per PC5 area in Utrecht

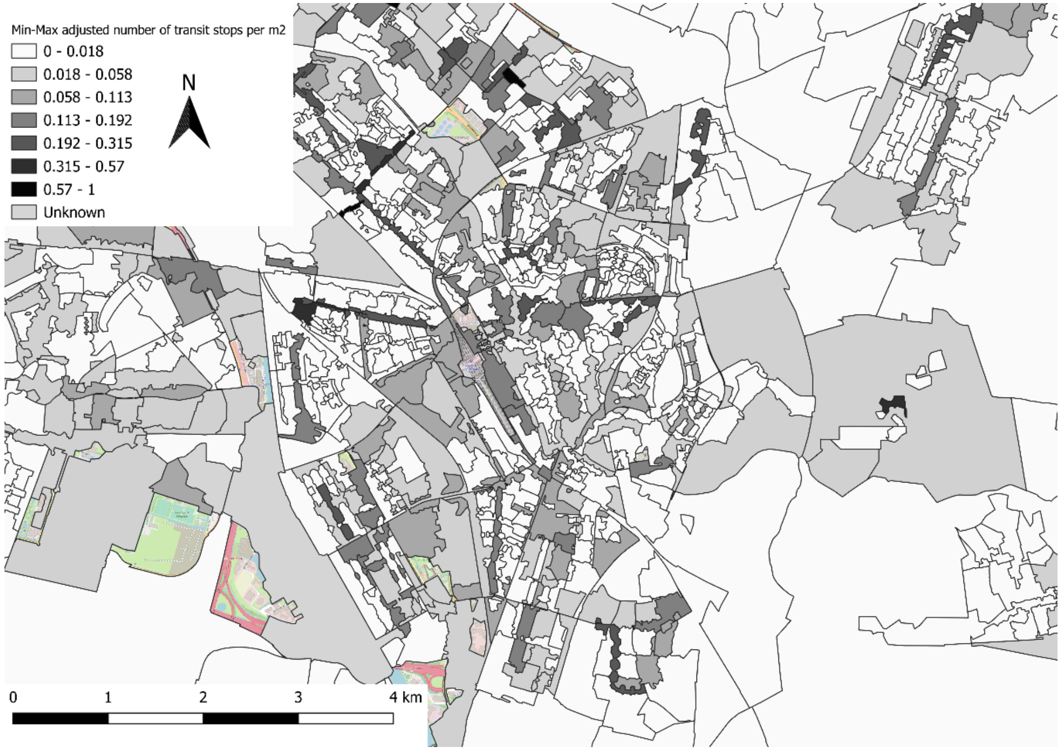

Figure 118 – Min-Max adjusted number of transit stops per m²per PC5 area in Utrecht

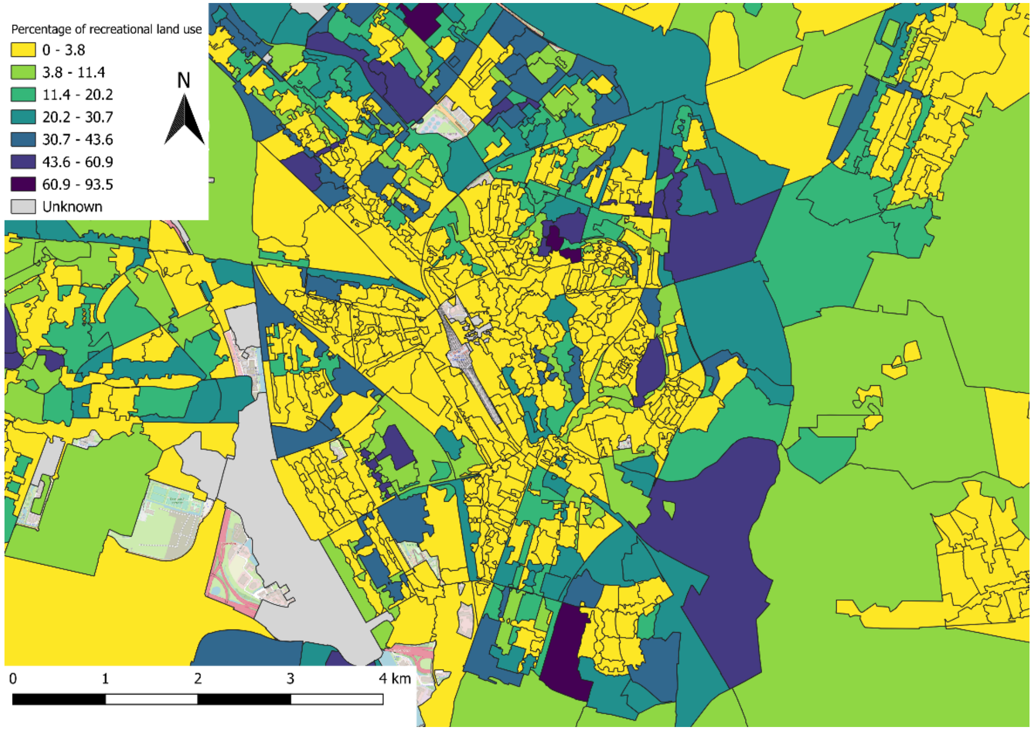

Figure 119 – Percentage of recreational land use per PC5 area in Utrecht

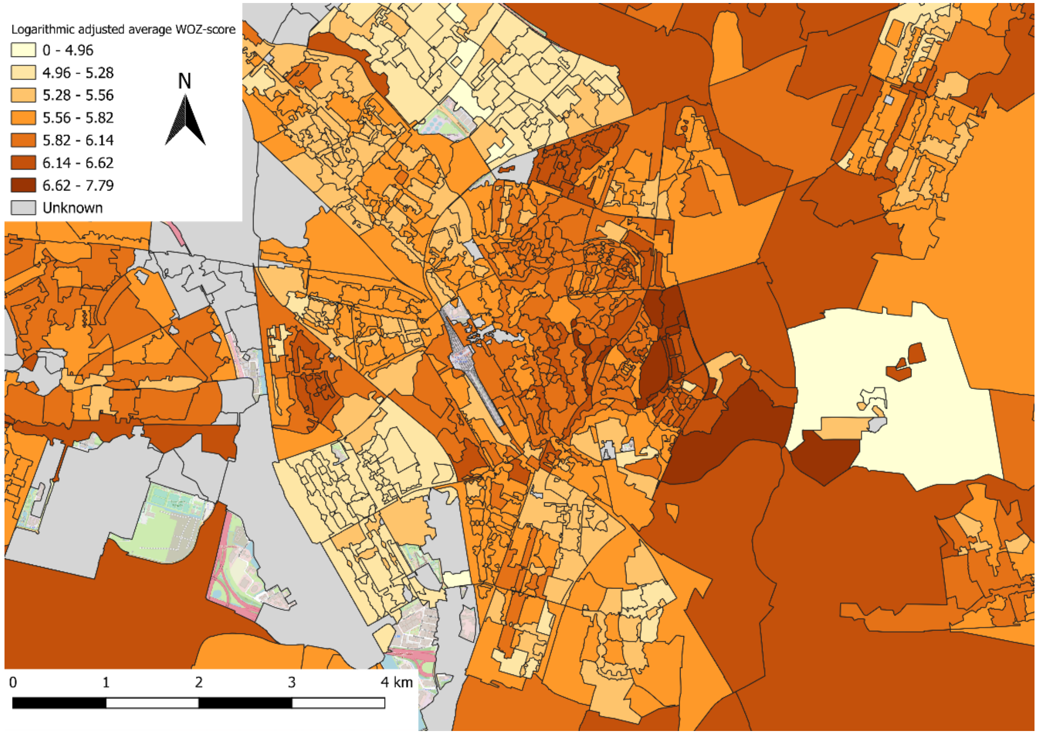

Figure 120 – Logarithmic adjusted average WOZ-score per PC5 area in Utrecht