URBAN BICYCLE SHARING SYSTEMS AND THEIR ROLE AS EGRESS MODE ON COMMUTERS' MODE CHOICE

Master Thesis

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PREFACE

This Master thesis concludes my study Construction Management and Engineering at the Eindhoven University of Technology. Sustainable mobility has always been one of my interests and for my graduation I sought the challenge to bring two different topics together: Bicycle sharing systems and Multimodal train transportation. I travelled around in world cities such as Berlin, New York, and São Paulo, and first became acquainted with bicycle sharing, and the experience was really good. During my student life I was often confronted with the situation of arriving at a train station and do not know how to reach the final destination. Many people experience this problem with me. I believe that the present study contributes to a new phenomenon, that is, bicycle sharing and train integration. This study describes the design of urban bicycle sharing systems and the attributes that influence the transportation mode choice of individuals for commuting trips in the Netherlands.

I would like to take this opportunity to thank all those who contributed to my graduation. Without the help of others, I would not been able to complete my graduation. First, I would like to thank my supervisor Dr. Peter van der Waerden for all the guidance and expertise offered over the entire process. I would also thank Dr. Dujuan Yang for her support and comments. Their feedback has been very valuable for the study.

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Finally, I would like to thank my family and friends who have supported me all times.

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SUMMARY

Bicycle sharing is one of the fastest growing transportation modes of the past decade and has been implemented in many cities around the world. The implementation of bicycle sharing systems has proven to contribute to various environmental and social problems. Recently, there has been increasing awareness regarding the integration of bicycle sharing and train in order to achieve more complete door-to-door journeys by train. This integration is assumed to have the potential to cause a modal shift from the private car. Encouraging a modal shift towards more sustainable transportation alternatives is necessary. The ever-increasing private car use has negatively influenced the quality of life in cities, limiting further economic and social development. One of the main policy goals of the Dutch government is therefore to cause a modal shift from the private car to the train. The train service in the Netherlands, however, is not still organized to be able to attract the current private car users.

The principle of bicycle sharing systems is clear, that is providing bicycles to users over a variety of unattended stations throughout a defined urban area on an “as-needed basis”. This function of bicycle sharing systems fulfills the weakness of the egress trip of train journeys. In order to make train journeys more attractive, the train service must be approached as chain mobility. Bicycle sharing systems offer the potential to minimize negative influences in the egress trip as experienced by travelers. In the Netherlands, with the exception of the OV-fiets (single nationwide public transportation-related bicycle sharing system), only a few small-scale initiatives are operating currently. However, the OV-fiets offers limited flexibility and is considered expensive for frequent use by travelers. The question arises what the effect would be of demand-specific urban bicycle sharing systems in the Netherlands and what attributes the system should have.

Traffic congestion in the morning and evening peak can mainly be attributed to commuter traffic. Realizing a modal shift with this travel motive would contribute to the negative environmental and societal problems urban areas are facing, mainly caused by private car use. It is assumed that the implementation of urban bicycle sharing systems can improve the train service, and therefore increase the attractiveness of commuting trips by train. The aim of this study is to provide insight into the preference of individuals with respect to the design of urban bicycle sharing systems, and the influence of urban bicycle sharing systems in the egress trip of train journeys on individuals’ transportation mode choice regarding commuting trips. This research aim, corresponds with the following research questions:

How should urban bicycle sharing systems be designed in order to maximize the preference of individuals?

What is the influence of urban bicycle sharing systems in the egress trip of multimodal train journeys on individuals’ transportation mode choice relating commuting trips?

In order to investigate both research questions, a stated preference experiment is conducted. Because there is no large-scale urban bicycle sharing system currently operating at the Dutch market intended for commuting, this relates to a hypothetical situation. The bicycle sharing system attributes of the stated preference experiment are explored in the literature review. The stated preference data is collected through an online questionnaire where respondents are recruited by Panel Inzicht, which is an online fieldwork organization in the Netherlands. Two questions are formulated for the selection of respondents. Only the respondents who commute more than once a week by private car or train were guided further by the questionnaire. In total, 385 respondents completed the questionnaire completely, of which 260 private car commuters and 125 train commuters. Four discrete choice analysis are performed: the attributes that influence the preference of (1) private car commuters and (2) train commuters for urban bicycle sharing systems; the (3) attributes that influence the willingness of private car users to shift to the train for commuting trips; and the (4) attributes that influence the willingness of train commuters to use urban bicycle sharing systems as egress mode instead of the current transportation mode. The preference of individuals for urban bicycle sharing systems is analyzed by Multinomial Logit models, and Binary Logit models are estimated for the analysis of transportation mode choice.

Regarding the analysis of urban bicycle sharing system model preference of private car commuters, two attributes are found most influential, the rental fare costs and reliability at starting point. To a lesser extent, the access time, egress time, and reliability at endpoint are also found to influence the preference of individuals. Less decisive, however still significant, is the influence of bicycle type.

Almost identical results are obtained with regard to the attributes that influence the preference of train commuters for urban bicycle sharing systems. The reliability at endpoint has a lower influence compared to the access and egress time. Furthermore, the results show that bicycle type does not influence the preference of train commuters. Based on the alternative specific constant of both models, it can be stated that urban bicycle sharing systems are preferred by private car and train commuters in relation to the OV-fiets.

The willingness to shift from the car to the train by the private car commuters is influenced mainly by the egress time to the urban bicycle sharing system, followed by access time, rental fare, and finally bicycle type. As expected, the alternative specific constant shows that the private car is preferred as commuting mode for this group of respondents.

The willingness to shift from the current egress mode to urban bicycle sharing systems by the train commuters is only found to be influenced by egress time from the bicycle sharing system station to the final destination. The alternative specific constant indicates that the current mode is preferred as egress mode regarding commuting train journeys.

In short, it can be concluded that urban bicycle sharing systems in the egress trip of train journeys can influence the transportation mode choice of both private car and train commuters in the Netherlands. The most important attribute to realize this is egress time to the final destination.

SAMENVATTING

De deelfiets behoort tot een van de snelst groeiende vervoersmiddelen van het afgelopen decennium, en inmiddels over de hele wereld toegepast. De toepassing van deelfietssystemen heeft bewezen bij te dragen aan verschillende milieu- en sociale problemen. Onlangs, is er een toenemend bewustzijn ontstaan voor de integratie van de deelfiets en trein om een completere deur-tot-deur verplaatsing met de trein mogelijk te maken. Deze integratie wordt als potentieel beschouwd om een modale verschuiving van de privéauto naar de trein mogelijk te maken. Het aanmoedigen van een modale verschuiving naar duurzame vervoerswijzen is noodzakelijk. De steeds verder toenemende autogebruik heeft de kwaliteit van het leven in steden door de jaren heen negatief beïnvloed, waardoor een verdere economische en sociale ontwikkeling wordt beperkt. Een van de belangrijkste beleidsdoelen van de Nederlandse overheid is het veroorzaken van een modale verschuiving van de privéauto naar de trein. Echter, de huidige treinservice in Nederland is nog steeds niet voldoende georganiseerd om de huidige autogebruikers te kunnen verleiden.

Het principe van deelfietsen is eenduidig, dat is het aanbieden van fietsen aan gebruikers over een verscheidenheid van onbeheerde stations in een afgebakend stedelijk gebied op basis van een “as-needed-basis” concept. Deze functie van deelfietssystemen komt de zwakte van het natransport in treinverplaatsingen tegemoet. Om treinverplaatsingen aantrekkelijker te maken, dient the trein service als ketenmobiliteit te worden benaderd. Deelfietssystemen zijn potentieel in staat om de ervaren ongemakken tijdens het natransport te minimaliseren. In Nederland, met uitzondering van de OV-fiets, zijn er momenteel slechts enkele kleinschalige initiatieven actief. De OV-fiets biedt echter beperkte flexibiliteit en wordt als duur beschouwd bij frequent gebruik door reizigers. Het is de vraag wat het effect van een vraagspecifiek stedelijk deelfietssysteem in Nederland kan zijn, en welke eigenschappen dit systeem zou moeten bevatten.

De verkeersdrukte in de ochtend- en avondspits kan voornamelijk aan het woon-werkverkeer worden toegeschreven. Het realiseren van een modale verschuiving met dit reismotief kan bijdragen aan de negatieve milieu- en maatschappelijke problemen waar stedelijke gebieden momenteel mee worden geconfronteerd, voornamelijk veroorzaakt door privé-autogebruik. Aangenomen wordt dat de toepassing van stedelijke deelfietssystemen de treinservice kan verbeteren en daardoor de aantrekkelijkheid van woon-werkverplaatsingen met de trein kan bevorderen. Het doel van deze studie is om inzicht te verschaffen in de voorkeur van individuen met betrekking tot het ontwerp van stedelijke deelfietssystemen, en hun invloed te bepalen in het natransport van treinverplaatsingen bij woon-werkverplaatsingen. Dit onderzoeksdoel komt overeen met de volgende onderzoeksvragen:

Hoe moeten stedelijke deelfietssystemen worden ontworpen om de voorkeur van individuen te maximaliseren?

Wat is de invloed van deelfietssystemen in het natransport van multimodale treinverplaatsingen op de vervoerswijzekeuze van individuen met betrekking tot woon-werkverplaatsingen?

Om beide onderzoeksvragen te onderzoeken, wordt een 'stated preference' experiment uitgevoerd. De attributen in het experiment worden onderzocht in de literatuur. De data wordt verzameld via een online vragenlijst waarbij respondenten worden geworven door Panel Inzicht, een online veldwerkorganisatie in Nederland. Twee vragen zijn geformuleerd voor de selectie van respondenten. Alleen de respondenten die meer dan één keer per week pendelen per privéauto of trein werden verder geleid door de vragenlijst. In totaal vulden 385 respondenten de vragenlijst volledig in, waarvan 260 privé-forenzen en 125 treinforenzen. Er worden vier discrete keuze-analyses uitgevoerd: de attributen die van invloed zijn op de voorkeur van (1) privéauto-forenzen en (2) treinforenzen voor stedelijke deelfietssystemen; de (3) attributen die van invloed zijn op de bereidheid van privéauto-forenzen om over te stappen naar de trein bij woon-werkverplaatsingen; en de (4) attributen die de bereidheid beïnvloeden om stedelijke deelfietssystemen te gebruiken als natransportmiddel in plaats van het huidige natransportmiddel door de treinforenzen. De voorkeur van individuen voor stedelijke deelfietssystemen wordt geanalyseerd door Multinomiaal Logit-modellen, en Binaire Logit-modellen worden geschat voor de analyse van de vervoerswijzekeuze.

Met betrekking tot de analyse van de voorkeur van de privéauto-forenzen voor stedelijke deelfietssystemen, zijn twee kenmerken het meest invloedrijk, de ritprijs en de betrouwbaarheid bij het beginpunt. In mindere mate blijken de toegangstijd, uitgangstijd en de betrouwbaarheid bij het eindpunt ook van invloed te zijn op de voorkeur. Minder doorslaggevend is de invloed van het fietstype.

Bijna identieke resultaten worden verkregen met betrekking tot de attributen die de voorkeur van treinforenzen voor stedelijke deelfietssystemen beïnvloeden. De betrouwbaarheid bij het eindpunt heeft een lagere invloed in vergelijking met de toegangs- en uitgangstijd. Bovendien laten de resultaten zien dat het type fiets geen invloed heeft. Op basis van de alternatieve specifieke constante van beide modellen kan gesteld worden dat stedelijke deelfietssystemen de voorkeur genieten met betrekking tot de OV-fiets.

De bereidheid om van de auto naar de trein over te stappen door de privéauto-forenzen, wordt voornamelijk beïnvloed door de uitgangstijd vanaf het stedelijk deelfietssysteem, gevolgd door toegangstijd naar het systeem, ritprijs en ten slotte het fietstype. Zoals verwacht, laat de alternatieve specifieke constante zien dat de privéauto de voorkeur heeft als vervoersmiddel. De bereidheid om over te stappen van het huidige natransportmiddel naar stedelijke deelfietssystemen wordt door de treinforenzen alleen beïnvloed door de uitgangstijd vanaf het deelfietssysteemstation naar de eindbestemming. De alternatieve specifieke constante geeft aan dat de huidige natransportmiddel de voorkeur heeft.

Samenvattend kan worden geconcludeerd dat stedelijke deelfietssystemen de vervoerswijzekeuze van zowel privéautogebruikers and treingebruikers in Nederland kunnen beïnvloeden. Het belangrijkste kenmerk om dit te realiseren is toegangstijd naar de eindbestemming.

ABSTRACT

Bicycle sharing is one of the fastest growing transportation modes of the past decade. The implementation of urban bicycle sharing systems (BSS) has proven to contribute to various environmental and social problems. Recently, there has been increasing awareness regarding the integration of bicycle sharing and train. This integration is assumed to have the potential to cause a modal shift from the private car. The ever-increasing private car use, especially due to commuter traffic, has negatively influenced the quality of life in cities, limiting further economic and social development. Encouraging a modal shift towards more sustainable transportation alternatives is therefore necessary. It is however unknown how urban BSS must be designed in the Dutch context, and their influence in the egress trip of train journeys regarding the transportation mode choice of commuters. A stated preference experiment is applied where data of 385 respondents is collected in the Netherlands. The estimated discrete choice models show that both private car and train commuters add most value to the rental fare and reliability at starting point regarding the preference for urban BSSs. In addition also significant are the attributes access time, egress time, and reliability at endpoint. For the train commuters also the bicycle type is found to be significant. The attributes that increases the utility of private car commuters to shift to the train are bicycle type, rental costs, access time, and egress time, while only egress time increases the utility of train commuters for urban BSSs instead of their current mode. Furthermore, also the socioeconomic characteristics, commuting trip characteristics, and transportation mode-related and BSS-related attitudinal factors are found to influence the preference for urban BSSs and the transportation mode choice of commuters. In general, it can be concluded that the integration of bicycle sharing and train has potential to cause a modal shift in the Netherlands.

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1 INTRODUCTION

1.1 Problem Definition

Our society is becoming more and more motorized and that is not surprising. Mobility fulfills a significant function in people's life and contributes to the quality of life (Steg & Kalfs, 2000). Over the years, people are not making more trips or being longer on travel, but the large amount of private car traffic, mainly due to commuter travel, can be attributed primarily to population growth and increase in the share of private car use (Steg & Kalfs, 2000). Apart from the fact that cars need space that leads to the deterioration of nature, private car use is the main cause of congestion, noise, and air pollution in urban environments (Liddle & Lung, 2010; and Redman et al., 2013). Encouraging a modal shift towards more sustainable transportation alternatives is therefore necessary. The ever-increasing private car use has affected the quality of life in cities, limiting further economic and social development (Krygsman, 2004). In the Netherlands, traffic and transportation account for 21 percent of the total CO_2 emissions, and 53 percent of this is caused by passenger transportation (CBS, 2016). Especially congestion is a major societal problem which involves both personal and social costs. Only in the Netherlands, the costs associated with delays and traffic jams were estimated at 2.3 to 3.0 billion of euros per year (Ministry of Infrastructure and Environment, 2016). Recently, the European commission announced the target to reduce the transport-related CO_2 emissions with 60 percent by 2050, compared to 2000 levels (European Commissions, 2011). This forces governments to consider sustainable alternatives instead of the private car.

In order to mitigate the negative impacts of private car use, policy makers are constantly looking for solutions to increase the use of sustainable transportation alternatives, such as walking, cycling, and public transportation (i.e. train, bus, metro, and tram). A policy goal of the Dutch government is to realize a modal shift from the private car to the train (Ministry of Infrastructure and Environment, 2015). The service quality is essential to increase the attractiveness of the train (Beirão & Cabral, 2007). However, the train service in the Netherlands is not being capable to compete with the private car yet (Steg, 2003). Travelers experience the service as unreliable (Hensher et al., 2003) and inconvenient (Krygsman et al., 2004). The main reason for this, is that the train service is not organized in such a way to achieve complete door-to-door journeys (Harms et al., 2007). To this end, the train service must be approached as chain mobility; including the access (i.e. the trip from residence to home-end train station) and egress trip (i.e. the trip from activity-end train station to final destination) (Givoni & Rietveld, 2007; and Krygsman et al., 2004). A lot of disutility is involved with the access and egress trip, making private car travel more attractive (Krygsman et al., 2004). Integrated transportation is therefore regarded as the key to success to cause a modal shift from the private car to the train (Brons et al., 2009). Especially the physical distances involved in the egress trip have a significant effect on the decision to make use of the train service by travelers (Tilahun et al., 2016). In order to increase the attractiveness of the train service the influence of both access and egress trip must be minimized (Krygsman et al., 2004).

The bicycle is increasingly being promoted to mitigate the traffic-related problems in many cities around the world (Jäppinen et al., 2013; Pucher et al., 2010; and Zhao & Li, 2017). Cycling is regarded as an environmental friendly, fast, flexible, healthy, and low-cost transportation mode (Akar & Clifton, 2009; Jäppinen et al., 2013; Moudon et al., 2005; and Zhao & Li, 2017). The integration of bicycle and train is assumed to contribute to the attractiveness of the train service, and thereby increase the share of sustainable transportation (Martens, 2007; Ministry of Infrastructure and Environment, 2014; and Rietveld & Daniel, 2004). Because the Dutch population can be characterized by a high bicycle ownership, this integration is particularly interesting in the egress phase of train journeys (Jäppinen et al., 2013). In recent years, much attention has been paid to bicycle sharing programs, and initiatives have designated in policy plans worldwide (Bechand-Marleau et al., 2012; DeMaio, 2009; and Zhao & Li, 2017). In order to achieve more complete door-to-door journeys, bicycle sharing systems are considered as potential to improve the overall efficiency of the train service (Shaheen et al., 2010; Fishman et al, 2013).

The principle of bicycle sharing is clear, that is providing bicycles to users over a variety of unattended stations throughout a defined urban area on an "as-needed basis" (DeMaio, 2009; Shaheen & Martin, 2014; and Parkes et al., 2013). The strong emergence of bicycle sharing systems worldwide is due to the public and governmental awareness regarding the negative impacts of private car use and the technological advancements (Fishman et al., 2015). In addition, bicycle sharing systems can help to increase the cycling population, improve the accessibility of urban regions, reduce emissions, and improve public health (Bechand-Marleau et al., 2012; DeMaio, 2009). In 2018, bicycle sharing systems have been implemented in more than 1,600 cities around the world (Meddin & DeMaio, 2012). However, in the Netherlands, with the exception of the OV-fiets, only a few small-scale initiatives, such as the Nextbike and Urbee, are operating currently. The OV-fiets is a single nationwide bicycle sharing system that requires a membership subscription for use (Wang & Zhou, 2017). This public transportation-related system has been introduced as a supplement to the train service and especially intended for the egress trip (NS, 2015). However, the OV-fiets offers limited flexibility and is considered expensive for frequent use by travelers. The question arises what the effect would be of demand-specific urban bicycle sharing systems in the Netherlands and what attributes the system should have.

Traffic congestion in the morning peak can mainly be attributed to commuter traffic. In the Netherlands, commuter traffic accounts for 28 percent of the total kilometers traveled, of which 77 and 10 percent by car and train respectively (CBS, 2016). Realizing a modal shift with this travel motive would therefore contribute to the negative environmental and societal problems. In order to achieve this, sustainable transportation alternatives must be made more competitive in relation to the car. It is assumed that the implementation of urban bicycle sharing systems can improve the train service, and therefore increase the attractiveness of commuting trips by train. However, the design of this system must be coherent with the preferences of potential users.

Many studies examined how the transit service quality can be improved (e.g. dell'Olio et al., 2011; Hensher et al., 2003; and Litman, 2008). A study from Belgium revealed that even free access to public transportation does not lead to an increase in use (De Witte et al., 2005). More effort is needed to achieve a modal shift from the car to more sustainable alternatives. Several studies (e.g. Boarnet et al., 2017; Brons et al., 2009; Givoni & Rietveld, 2007; Krygsman et al., 2004; and La Paix & Geurs, 2015) have emphasized the importance of the access and egress trip on the attractiveness of the train service and potential increase of train use. There is increasing awareness of the potential of bicycle and train integration (De Souza et al., 2017; Jäppinen et al., 2013; and Wang & Liu, 2013), and a considerable amount of studies focused on the Dutch context (e.g. Hendriksen et al., 2010; Martens, 2007; Rietveld & Daniel, 2004; and Van Boggelen & Tijssen, 2007). The integration of bicycle and train has the potential to achieve more complete door-to-door journeys (Chakrabarti, 2017), making the train more competitive with respect to the private car (Givoni & Rietveld, 2007). With the emergence of urban bicycle sharing systems, this offers possibilities for improving chain mobility by train. Most studies in the field of bicycle sharing systems focused on the environmental benefits (e.g. DeMaio, 2009; and Shaheen et al., 2010), demand (e.g. Frade & Ribeiro, 2014), and factors that influence performance (e.g. Karki & Tao, 2016; Liu et al., 2012; and Médard De Chardon et al., 2017). Those studies provide insight into the most important attributes and the potential of an urban bicycle sharing system' design. Only a few studies (e.g. Tilahun et al., 2017) examined the influence of urban bicycle sharing systems regarding commute travel. However, no studies have been found that explores the integration with the train. Although the integration of bicycle sharing system and train is widely promoted (e.g. DeMaio, 2009), there is a scarce in the existing literature (Fuller et al., 2012; and Tilahun et al., 2017). In addition, since no large-scale urban bicycle sharing systems are operating in the Netherlands, there is a lack of studies in the Dutch context. This study aims to contribute and provide insight into the preferences of commuters regarding the design of urban bicycle sharing systems, and the influence of the integration between bicycle sharing and train on the transportation mode choice of commuters.

1.2 Research Objectives and Questions

The aim of this study is to provide insight into the preferences of commuters regarding the design of urban bicycle sharing systems, and the influence of urban bicycle sharing systems in the egress trip of multimodal train journeys on individuals' transportation mode choice regarding commuting trips in the Netherlands. Several authors (e.g. Hoogendoorn-Lanser, 2005; and Krygsman et al., 2004) have emphasized the high disutility associated with the egress trip. For this reason, in order to improve the train service improvements to the egress trip are needed. In the present study, it is hypothesized that the introduction of urban bicycle sharing systems in combination with the current train service in the Netherlands has the potential to improve the attractiveness and reliability of multimodal train journeys, and thereby cause a model shift. The introduction of urban bicycle sharing systems is therefore considered an additional service to achieve more complete door-to-door journeys by train. The other trips parts (i.e. access and train trip) of multimodal train journeys fall outside the scope of the study. Since commuter traffic is problematic and even increasingly in the Netherlands, a modal shift from the private car to the train must be encouraged. This is in line with the policy plans of the Dutch government (Ministry of Infrastructure and Environment, 2015). In order to reduce the complexity of the study and generate more in-depth insights two types of commuters are distinguished, i.e. the (i) *private car commuter* and the (ii) *train commuter*. By doing this, insight can be provided into the behaviors separately. In addition, both types of commuters have a different choice situation. The private car commuters (i.e. the individuals who generally travel by private car to work) are asked if they are willing to shift to the train if an urban bicycle sharing system is available in the egress trip, while the train commuters are asked whether they would use an urban bicycle sharing system instead of their current egress mode. Based on the research objectives the following research questions is formulated:

How should urban bicycle sharing systems be designed in accordance with the preferences of individuals in the Netherlands?

What is the influence of urban bicycle sharing systems in the egress trip of multimodal train journeys on individuals' transportation mode choice relating commuting trips?

In order to answer the main research question, the following sub-questions are formulated:

1. *What is multimodal (train) transportation?*
2. *What are the most relevant attributes of existing (urban) bicycle sharing systems?*
3. *What attributes influence the transportation mode choice of commuter travelers?*
4. *What attributes influence the preference for urban bicycle sharing systems?*
5. *How should urban bicycle sharing systems be designed in the egress trip of train journeys in order to attract the current private car commuters for commuting by train?*
6. *How should urban bicycle sharing systems be designed in the egress trip of train journeys in order to attract the current train commuters to make use of shared bicycles?*

1.3 Research Design

In the previous section the research objectives and questions have been formulated. This section discusses the research design that is developed to achieve the research objectives and provide a substantiated answer to the research questions. The research design of the study is shown in Figure 1 and is discussed below.

Introduction of research

The first step is to identify a problem that is less understood or examined by existing literature. A problem has been identified for this study in the field of public transportation and bicycle sharing systems research. It is important to clearly define the research problem because it leads to the research objectives and questions. Understanding the influence of urban bicycle sharing systems and the sensibility of attributes on the transportation mode choice of individuals regarding commuting trips in the Netherlands is central to this study.

Literature review

Based on the research objectives, three topics are distinguished and elaborately discussed in the literature review, i.e. (i) *multimodal train transportation*, (ii) *bicycle sharing systems*, and

(iii) *transportation mode behavior* of individuals. The literature regarding multimodal train transportation explains the need of chain mobility and the potential of the integration of bicycle and train. In this study, the literature regarding (urban) bicycle sharing systems is most important, where the systems' attributes and user-related preferences are explored. The last part, transportation mode choice, relevant literature is discussed that helps to explain the behavior of individuals and to interpret the research results. The literature review serves as background information, and provides an answer to research sub-questions 1 to 3.

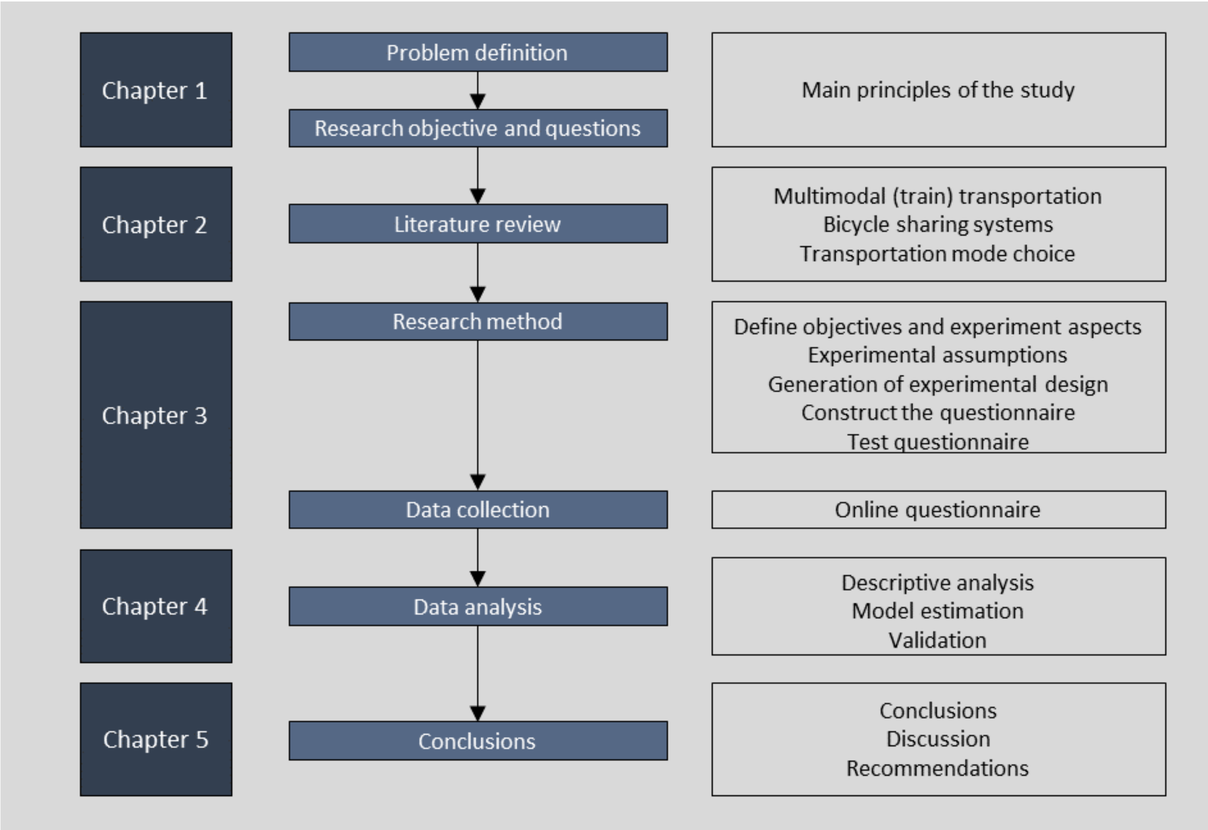


Figure 1. Research design

Research method

The literature review forms the basis for the research method of the study. A widely applied research method in the analysis of transportation demand and mode choice behavior is discrete choice analysis (Ben-Akiva & Lerman, 1985). In principle, discrete choice models aim to analyze and predict the behavior of a decision maker for choosing one alternative from a finite set of mutually exclusive and collectively exhaustive alternatives (Koppelman & Bhat, 2006). Rather than concentrating on one individual, the focus of discrete choice models is on predicting the behavior of a large amount of individuals by determining the influence of attributes of alternatives in their decision making (Ben-Akiva & Lerman, 1985; and Koppelman & Bhat, 2006). Discrete choice models facilitate the estimation of parameters that can be used to predict the behavior of an individual in specific situations. The theory of utility maximization applies, which postulates that an individual chooses the alternative that provides the highest utility (Hensher et al., 2005). In this study, it is assumed that the (urban) bicycle sharing system with the highest utility or attraction is preferred by an individual.

The research model development is dependent on data collection (Ortúzar & Willumsen, 2011). This is because the research model influences the type of data that should be collected. Discrete choice models rely on two types of choice data, i.e. (i) *revealed preference* (RP) and (ii) *stated preference* (SP) *data*. The first type, RP data, refers to the actual or observed choices made by individuals in real-market conditions. With this type of data discrete choice models can be estimated that explain how individuals act in existing environments. However, there are some limitations associated with RP data. Because choices are based on existing situations, models may not be suitable for forecasting behaviors (by combinations of attribute levels), detect the influence of secondary attributes (e.g. service quality-related), and forecast new situations for policy (Ortúzar & Willumsen, 2011). These limitations could be avoided by applying controlled real-life experiments, but in practice this type of experiment is still rare. The second type, SP data, offers a solution when there is no access to real-market data, and refer to the choice of individuals in a hypothetical situation. With SP data the researcher is enabled to investigate the influence of attributes and levels for non-existing alternatives, and how likely that alternative will be chosen by an individual. This makes SP data suitable for forecasting behaviors and policy making intended for the future. Also SP data is characterized by some limitations. For instance, it can be wondered to what extent the choices of an individual would be similar to those in real-life situations. In addition, it is possible that attributes become more or less important in the course of time, which can affect the reliability of the model. In general, however, SP data has major benefits for future implications compared to RP data.

Because there is no large-scale urban bicycle sharing system currently operating in the Dutch market intended for commuting trips, this relates to a hypothetical situation, and therefore SP data is needed for model estimation. The SP data is collected through an online questionnaire. For this, a SP experiment is designed (see Chapter 3) where hypothetical urban bicycle sharing systems are presented to respondents. While the SP experiment the respondents are required to make trade-offs among alternatives that differ in attributes and levels. Based on the SP data insight into the attributes and levels can be provided that influence the preference for an urban bicycle sharing system, specifically aimed at the Dutch market. Besides, the influence of an urban bicycle sharing system in the egress trip of multimodal train journeys on the transportation mode choice of individuals regarding commuting is examined.

The design of SP experiments is complex and requires a lot of time and effort. In this study, the experimental design process is followed as extensively discussed in previous work by Hensher et al. (2005). In total, eight stages are distinguished that should be correctly executed (see Section 3.2.1). For the sake of convenience, the stages are briefly discussed. Firstly, the research objectives of the study are clearly defined, and the relevant aspects such as alternatives, attributes and levels are identified. Next, the experimental assumptions are defined that will be considered during the experimental design generation. Depending on the assumptions made, the design of the experiment is generated and the questionnaire instrument is constructed. Finally, the questionnaire is tested for mistakes in the design before proceeding to field distribution.

Data collection

As discussed above, the SP data relating the urban bicycle sharing system preferences and transportation mode choices of individuals is collected through the SP experiment in the questionnaire. Besides, for analysis, also data about the respondents are collected such as the characteristics of their commuting trip and socioeconomic characteristics. The questionnaire is made available online and respondents were gathered through a Dutch online panel. In addition also individuals from the social network were invited to participate to the questionnaire.

Data analysis

The data that is collected with the questionnaire is extensively analyzed. Firstly, a descriptive analysis is provided of the sample. Results give insight into the characteristics of the group of individuals who have participated to the questionnaire. Furthermore, the descriptive analysis of the sample provides insight whether the sample is representative for in the Dutch context or not. Following, the data is used for model estimation. In relation with the research objectives, two types of logit models are estimated, i.e. (i) *Multinomial Logit model* (MNL) and (ii) *Binary Logit model* (BLM). The estimated models are intended to answer research sub-question 4 to 6.

Conclusions of the research

The last step is drawing the conclusions of the study. The main findings of the study are discussed and an answer is provided to the formulated main research question. Finally, based on the results and conclusions of the study, recommendations are made for further research.

1.5 Thesis Contents

The remainder of the thesis is organized as follows (see Figure 1). Chapter 2 provides an overview of the most relevant existing insights from the literature regarding multimodal train transportation, bicycle sharing systems, and transportation mode choice. Chapter 3 discusses the adopted methodology. The fundamentals of the applied logits models are presented and the stated preference experiment design process is elaborately discussed. Chapter 4 discusses the data that is collected with the questionnaire and the results of the estimated logit models. The thesis ends with the conclusions and discussion of the results, and recommendations in Chapter 5.

2 LITERATURE REVIEW

2.1 INTRODUCTION

Chapter 1 addressed the need to improve the egress trip of multimodal train journeys in order to achieve more complete door-to-door journeys by train. By doing this, it is assumed that the competitiveness between the train versus the private car can be increased. The integration of urban bicycle sharing systems and train is considered to have potential to cause a modal shift from the private car regarding commuting trips in the Netherlands.

This chapter discusses the existing literature that serves as background information in the study. Since this study aims to examine the potential of the integration of bicycle sharing and train in relation to private car use for commuting trips, only the private car and train are considered as transportation modes to realize commuting trips. In Section 2.2 the journey structure of both transportation modes is discussed. Section 2.3 discusses the development of bicycle sharing systems and presents systems in practice. Lastly, the factors that influence the transportation mode choice of individuals, and especially commuters is discussed in Section 2.4.

2.2 UNIMODAL AND MULTIMODAL TRANSPORTATION

This study discuses two types of modalities: the (i) private car and (ii) train. In the literature, the private car is characterized as *unimodal*, while the train is characterized by *multimodal* transportation (Van Nes, 2002). In advance to describe how an unimodal private car journey is structured (see Section 2.2.1) and from which parts a multimodal (train) journey consists of (see Section 2.2.2), the definition of both terms is provided below.

> *"An unimodal journey can be characterized as a journey in which only one modality is used and no transfers are need by the traveler to travel from origin to final destination."*
>
> (Ministry of Infrastructure and Environment, 2014).

In the literature, different definitions exist for multimodal transportation. Most authors (e.g. Ministry of Infrastructure and Environment, 2014; Van Nes, 2002), refer multimodality to the use of two or more different transportation modes in order to complete a single journey from origin to destination, in which at least one transfer is required between transportation modes.

From another perspective, Krygsman (2004) assumes that public transportation (referring to train, bus, tram and metro) journeys are always being multimodal. Individuals are required to *access* the public transportation system and *egress* to their final destination. This implies that public transportation journeys include several *journey parts*, and therefore consist of a *chain of trips* (Givoni & Rietveld, 2007). Given this study focuses on the egress phase of multimodal train journeys, the latter approach is most adequate and followed.

> *"A multimodal journey involves the use of two or more different transportation modes from origin to destination, and includes access to, and egress from the main service, in which transportation mode transfers are required."*
>
> (Givoni & Rietveld, 2007; Krygsman, 2004)

Multimodal transportation involves three main aspects: the (i) *transfers,* (ii) *transportation modes* used*,* and (iii) *trip parts* (Van Nes, 2002). These aspects are discussed below:

- *Transfers* is an important aspect of multimodal transportation. Generally, a distinction can be made between *intermodal* and *intramodal* transfers. Intermodal transfers involve a change of transportation service or modes. This unlike an intramodal transfer, that always occurs within the same transportation service, as for example, a transfer from one train to another.

- *Transportation modes* vary in characteristics, such as speed and comfort. According to Van Nes (2002), a distinction can be made between *private* and *public* transportation modes. The private transportation modes refer to bicycle and private car; while the train, bus, tram and metro belong to public transportation modes. It is assumed that transfers within a multimodal journey involve the integration of private and public transportation modes (Van Nes, 2002).

- *Journey parts* are a function of transfers between transportation services or modes within multimodal transportation. In principle multimodal transportation includes two or more trip parts, or rather *trips*.

Multimodal transportation competes with unimodal transportation. The main advantage of unimodal transportation is that no transfers are involved, and only one transportation mode is used from origin to final destination. For this reason, with unimodal transportation more complete door-to-door journeys can be realized.

2.2.1 Unimodal Car Journey

A car journey is considered a *unimodal journey*. This is because car journeys involve only one transportation mode, which is the car itself. However, referring to Figure 2, a car journey consists of three trip parts. Generally, car journeys begin at home, which is the *origin* (O) of the journey. Before to the car trip, there is always a *walking trip* associated to reach the car. Following, at the moment the traveler gets in the car, the car trip starts. The car trip represents almost the total travel distance and time of the car journey. From the starting point of the car trip the traveler drives to a *parking place* (P) nearby the desired journey *destination* (D). After parking the car, the traveler has to make any effort to reach the final destination. With the aim to minimize effort, travelers choose the closest parking place to the final destination. However, this is not always possible. Mainly in city centers, where there is a lack of space. Evidently, when a too high effort with parking is encountered by travelers, transportation mode alternatives are considered in order to realize the journey. In addition, cost-related factors (e.g. parking fee, taxes) and security also have an influence on the transportation mode choice of car users.

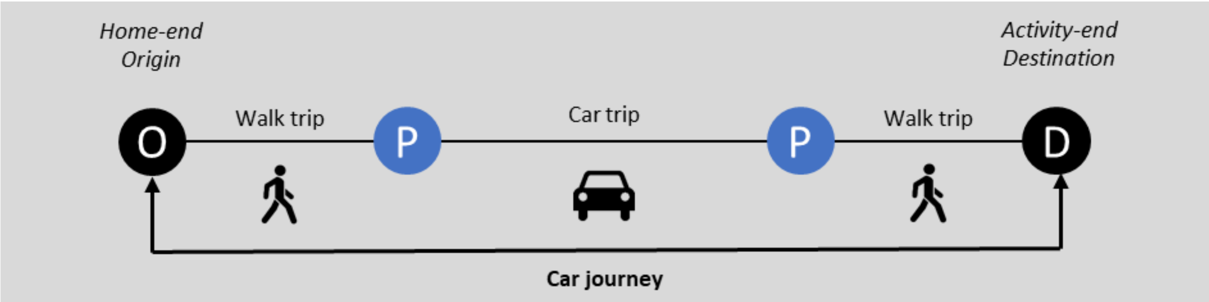


Figure 2. Unimodal private car journey: Overview of trips; based on work by Givoni and Rietveld (2007).

2.2.2 Multimodal Train Journey

Figure 3 presents the structure of multimodal train journeys from origin to final destination, and visualizes the *transfer stations*, types of *transportation modes*, and the *trip parts.*

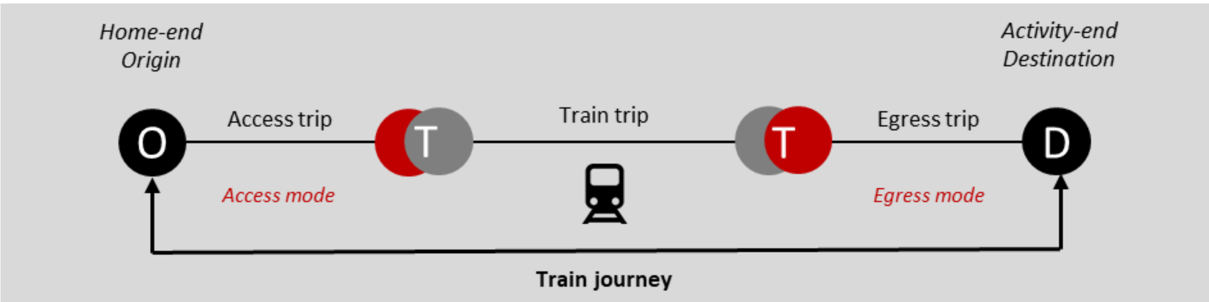


Figure 3. Multimodal Train journey: Overview of trips; based on work from Givoni and Rietveld (2007).

Transfers

The starting point of a travel is determined as the *home-end origin* (O), and demand location as the *activity-end destination* (D). Within train journeys, transfers are involved at specific *transfer stations* (T). A distinction is made between those, that are separated by the main transportation service:

- *Home-end transfer station* (the transfer station, after access trip from origin).
- *Activity-end transfer station* (the transfer station, before egress trip to destination).

Trip parts

As illustrated above, a multimodal train journey consists of a chain of trips. Several works (e.g. Givoni & Banister, 2010; Givoni & Rietveld, 2007), emphasized the importance of trip integration for systems consisting of different parts. By achieving this, more continuous door-to-door journeys can be achieved to travelers (Givoni & Rietveld, 2007).The following three trips can be defined:

- *Access trip* (the trip at the home-end side of the journey).
- *Main (train) trip* (the trip from home-end to activity-end transfer station).
- *Egress trip* (the trip at the activity-end side of the journey).

The *access trip* can be described as the trip at the *home-end side*. In other words, it represents the trip from the origin of individuals (e.g. residence) to the home-end transfer station. The access trip ensures access to the train service.

The *main trip* is the second trip part of train journeys. It involves the travel between at least two transfer stations; one transfer station at the home-end side and one at the activity-end side. As mentioned previously, transferring only between transportation services and modes is considered as an intermodal transfer. This simplifies the stated choice experiment as transfers within a transportation service network can be left out of consideration.

The *egress trip* is the last trip part of the chain. Transfer stations are rarely the final destination of individuals. For this reason, effort in terms of movement by individuals is required. The egress trip represents the travel at the activity-end side, and includes the trip from the activity-end transfer station to the final destination (e.g. work place).

Transportation modes

A multimodal train journey involves the use of two or more different transportation modes. This postulation is in accordance with the definition provided in Section 2.2. Transportation modes used in the access trip are referred to *access modes*, and those used in the egress trip are referred to *egress modes*. According to Krygsman (2004), the main trip is always realized by public transportation modes (i.e. train, bus, metro, or metro). However, this study only the train is considered as *main mode*.

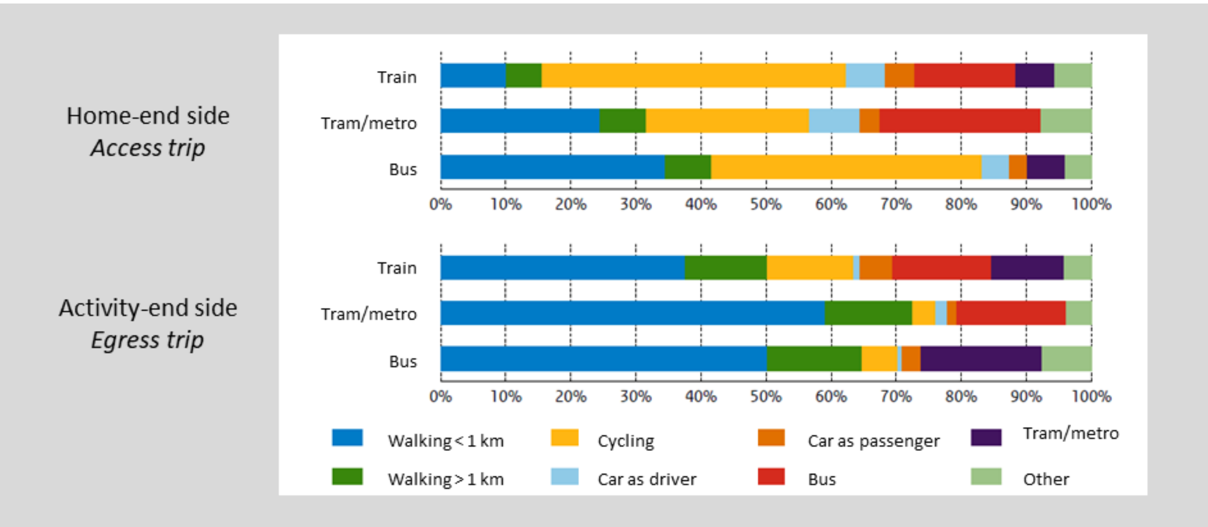


Figure 4. Share of access and egress modes in the Netherlands; from Ministry of Infrastructure and Environment (2014).

In Figure 4 the share of various access and egress modes in the Netherlands is shown per main mode. As presented, access to the home-end transfer station involves mainly a *cycling* trip, representing 47 percent of all access trips. The share of walking is considerably lower (15 percent), whereby most of those (approximately 70 percent) is shorter than 1 kilometer. The high share of cycling is not accidently. The bicycle is a popular transportation mode in the Netherlands, and fully integrated in the Dutch culture. Having a bicycle is therefore not something special, which at the same time offers individuals an additional transportation mode alternative.

Given the share of the egress modes, there are some differences in relation to the access modes. Not cycling is the most popular egress mode, but walking from the activity-end transfer station to destination is most common (i.e. 50 percent). This indicates that half of all destinations are within walking distance from the activity-end transfer station. Planning policies have contributed to this by retaining urban sprawl and encourage mixed land-use (Givoni & Rietveld, 2009). However, some individuals are forced to walk to their destination, for example, when there is no other transportation option they can choose from. This can be a reason for individuals not to opt for the train service. The role of cycling is considered to be modest in the egress phase, and only has a share of 13 percent. Apparently, not having a bicycle at the activity-end side forces individuals to walk or use public transportation (i.e. bus, tram, or metro). Few train travelers have a bicycle available for the egress trip. Having a second bicycle may not affordable to them, or costs related to parking and risk of theft are impediments. In addition, renting a bicycle is not always considered an option to individuals, as the costs involved are perceived too high (Van Boggelen & Tijssen, 2007). It is widely recognized that providing bicycles in the egress trip may increase the share of cycling as egress mode (Martens, 2007; and Rietveld & Daniel, 2004), and may attract individuals to make use of the train service (Jäppinen et al., 2013).

2.2.3 Comparison between journeys

Having discussed the structure of both private car journeys and train journeys, the modalities are compared in terms of time per costs over a displacement. This measure is adopted by Van Nes (2002) to indicate the disutility of the access and egress trip perceived by the traveler.

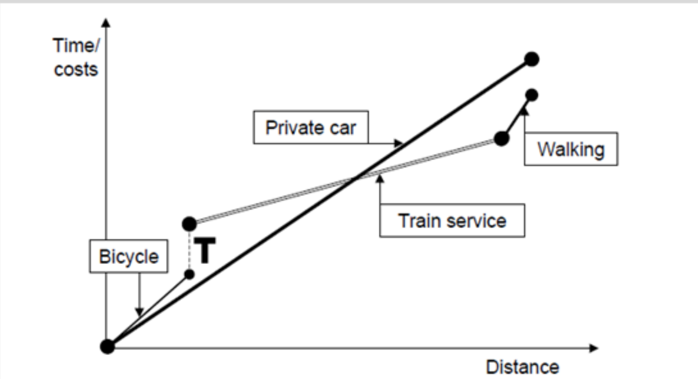


Figure 5. Private car journey versus train journey over travel time and costs; From Van Nes (2002, p. 12)

Figure 5 shows the impact of the access trip, egress trip, and transfers on the attractiveness of train journeys in relation to private car journeys. It should be noted that the private car journey as illustrated does not include the walking trips, which can affect the utility of the journey. The transfer, indicated by “T” in the figure, has a large impact on the attractiveness of the train service, because it is always associated with extra travel time while no distance is covered. This also applies for the access and egress trip, indicating the disutility experienced by travelers in both phases. The train service (i.e. main trip) must compensate the lost utility (i.e. delay and inconvenience) in order to keep the service attractive by users (Van Nes, 2002).

2.2.4 Access and egress travel distance and time

The quality of train journeys is not only determined by the main (train) trip, but it depends also on how individuals’ *access* and *egress* the train service. Both trips contribute to the total travel disutility, and are assumed as the weakest parts of multimodal train journeys (Krygsman et al., 2004). Since most access and egress trips involve a walking or cycling trip, individuals are confronted by physical distances and travel times. These trip characteristics are discusses in this section.

Individuals are only willing to cover a certain amount of distance or time to access train stations and egress to final destinations. Especially walking and cycling have a *travel time threshold* (Krygsman, 2004). If the access or egress trip exceeds an absolute travel time (or distance) threshold, individuals will not make use of the train service and consider other transportation mode alternatives, such as the private car. During the access trip a mean travel distance of 2.3 kilometer is covered, while this is 2.8 kilometer for the egress trip (Krygsman, 2004). This may explains the relative low share of private car use as access and egress mode (see Figure 4). Remarkably, the average travel distance of the egress trip is higher than that of the access trip, while the share of walking trips is considerably higher in the egress phase (i.e. 50 percent) compared to the access phase (i.e. 15 percent). Apparently, longer trips are made by public transportation (i.e. bus, tram, or metro) and bicycle in the egress trip.

Krygsman (2004), investigated the access and egress trip distributions of walking and cycling for commuting-related multimodal train journeys. A part of his work is presented in Figure 6. It is supposed that individuals are willing to walk or cycle 10 minutes to and from the train service (Krygsman, 2004). Assuming that walking and cycling have a mean travel speed of respectively 4 and 12 kilometer per hour, this involves a distance of approximately 700 meter and 2.0 kilometer respectively. Both distances are slightly higher compared to the average distances mentioned earlier.

As illustrated in Figure 6, around 90 percent of the cycling egress trips are longer than 6 minutes (i.e. 1 kilometer), while only 20 percent of those are longer than 16 minutes (3.2 kilometer). It is clear that the physical distances between train station and final destination can have an influence on the transportation mode choice of individuals. On the one hand, a lot of time is lost in the access and egress trip. This is because at a relative short distance, relative long travel times are associated. On the other hand, the train trip has comparable travel times with the private (Bos, 2004; and Post, 2012).

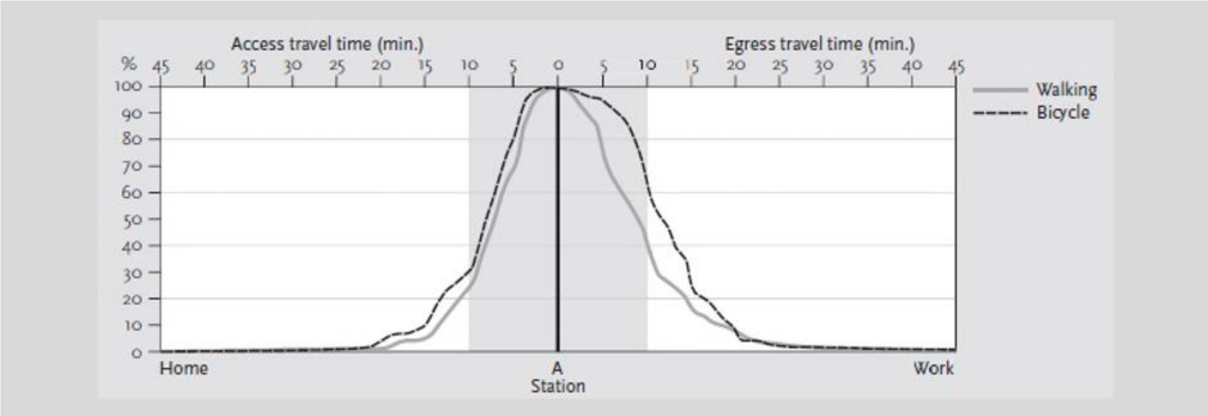


Figure 6. Access and egress travel times for walking and cycling; from Krygsman (2004, p. 126).

In order to achieve more complete door-to-door journeys the egress trip must be better organized and provide travelers an alternative transportation mode, especially for those who cannot make use of the bus service and are forced to walk relatively long distance. Most of the train users do not have a bicycle available in the egress trip, while this could make the train service more attractive for them (Van Boggelen & Tijssen, 2007).

Interconnectivity ratio

The *interconnectivity ratio* reflects the share of access and egress trip time to the total journey travel time (Goel & Tiwari, 2016; Krygsman, 2004). This ratio provides insight into the effort that individuals are willing to make to reach train stations (access trip) and destinations (egress trip). The interconnectivity ratio only reflects the physical occupied time of individuals. *Waiting* and *transfer times* are assumed to be caused by the train service (Krygsman, 2004). The interconnectivity ratio always falls within the range 0 to 1, which ensures comparison between *multimodal chains*. As the ratio value increases, the share of access and egress time takes up to the total journey travel time. Figure 7 shown the interconnectivity ratio of two multimodal chains over increasing journey travel time. Referring to the *bicycle-train-bicycle* chain, all interconnectivity ratio values fall within the range 0.2 to 0.5 (Krygsman, 2004). As illustrated below, at travel times between 40 and 70 minutes the interconnectivity ratio is stable, followed by a gradually decline. In general, access and egress cycling trips together take about 20 to 30 minutes, depending on the total journey time. Providing a seamless integration between the different trip parts is assumed to result in travel time reductions (Givoni & Rietveld, 2007).

Figure 7. Interconnectivity of different multimodal chains; from Krygsman (2004, pg. 126)

2.2.5 Multimodality in the Netherlands

In the Netherlands, multimodal journeys represent a modest role in the mobility, as shown in Figure 8. Although only 3 percent of all journeys are multimodal, they account to a share of 12 percent in the total kilometers traveled (Ministry of Infrastructure and Environment, 2016). The high share of travel kilometers, relative to the low share of number of journeys, reflects a long travel distance per multimodal journey. Considering the share of main transportation modes, the train is used by 61 percent of all multimodal journeys (Ministry of Infrastructure and Environment, 2014). This may explains the relative long travel distance of multimodal journeys, as mentioned before.

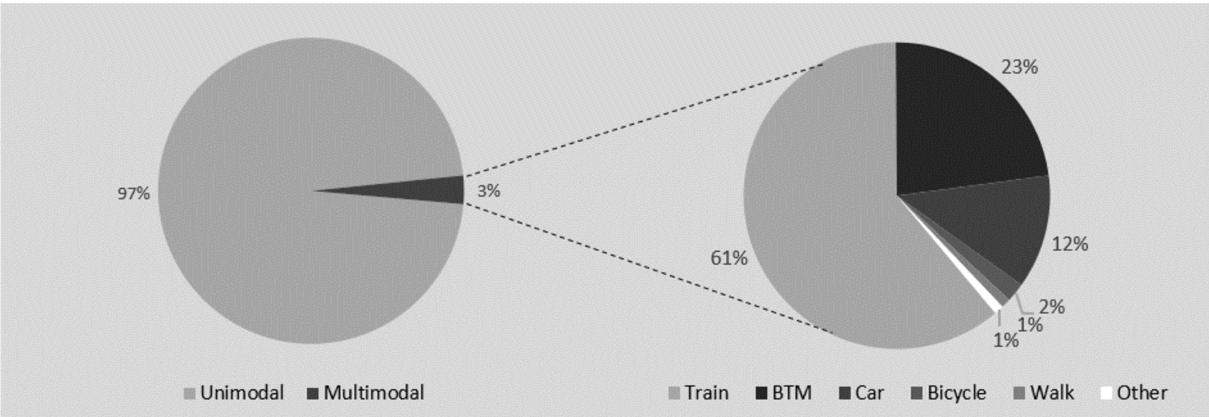


Figure 8. Multimodality and share of transportation modes used, in the Netherlands in 2013; Based on work by Ministry of Infrastructure and Environment (2014, pg. 21).

It is evident that differences apply between urban and rural areas in the share of multimodal journeys. In rural areas access to public transportation service is often limited, while (densely populated) urban areas are provided with an extensive public transportation network. The share of multimodal journeys is highest in the four largest cities (i.e. Amsterdam, The Hague, Rotterdam, and Utrecht), involving shares falling in the range of 7 to 10 percent (Ministry of Infrastructure and Environment, 2014). This is considerably higher than the national average (i.e. 3 percent).

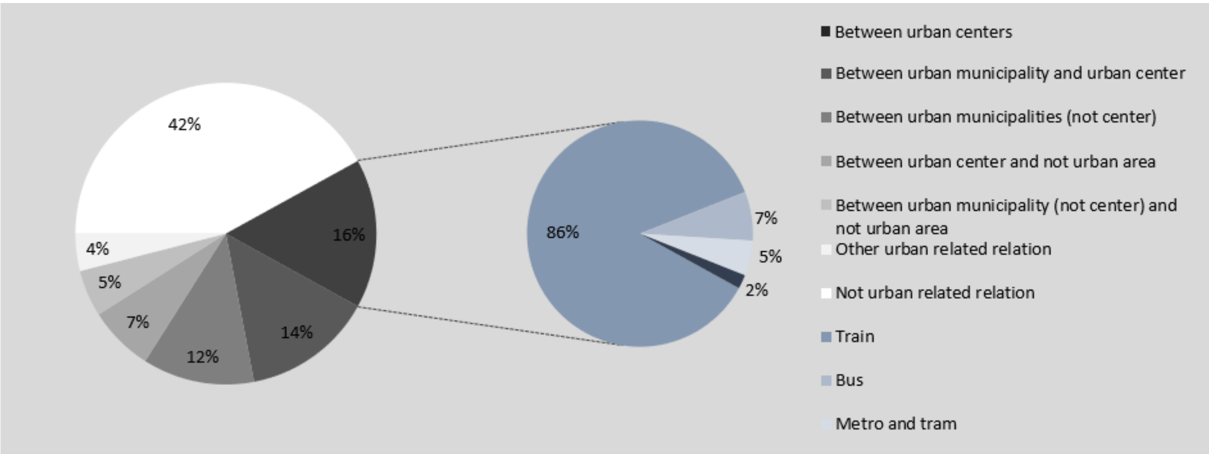


Figure 9. Multimodal journey relation types (left), and multimodality between urban centers (right); based on work by Ministry of Infrastructure and Environment (2014, pg. 103).

So far, insight into the representation of multimodal journeys in the mobility has been provided, and how this relates in different regions. Next, attention is paid to the direction of multimodal journeys, and the mobility (by different transportation modes) *to*, *from*, and *between* urban areas. It is not surprisingly that most multimodal journeys are related to urban areas (i.e. 58 percent); mainly having an origin and destination located in urban centers (i.e. 16 percent). To realize these journeys, the train is by far the most used transportation mode, as shown in Figure 9. Again, indicating that the train is mainly used to travel over longer distances (*intercity travel*). When also considering unimodal journeys *to*, *from* and *between* urban areas, the influence of the train is less significant, however varying from one city to another. The share of public transportation (especially the train) range between 17 to 28 percent in the four largest cities, while this is around 15 percent in other (smaller) cities (Ministry of Infrastructure and Environment, 2014, p. 115).

2.2.6 Integration of transportation systems

As stated by Givoni and Banister (2010), "*integration is probably still one of the most important means to advance sustainable transport and sustainability"* (Givoni & Banister, 2010, p. 1). In particular, integration is important when systems consist of multiple parts and the individual parts have to complement each other to operate together more efficiently. Multimodal (train) transportation consists of several parts (i.e. access, main, egress), and requires therefore integration between the individual parts in order to reduce the societal costs to the minimum. Integration is therefore an important concept to make multimodal transportation more attractive and encourage transportation mode choice towards more sustainable alternatives, such as the train (Givoni & Banister, 2010).

The decision of individuals for choosing a travel option depends on the characteristics of the entire chain of trips of that option. The private car is regarded as more attractive than the train, and other public transportation modes in general. This is because individuals always seek to minimize their costs of travel (i.e. travel time, travel costs, effort, and reliability). The fact that the private car is more attractive, is because it involves the use of only one network, which provides the traveler complete door-to-door transportation (Givoni & Banister, 2010). However, this does not apply for train transportation yet. Although train stations can be easily reached by private transportation modes (e.g. walking, bicycle, and car), the egress trip is considered a barrier to overcome in achieving integration of train transportation.

Ibrahim (2003) distinguishes in total four types of transport integration, i.e. (i) *fare integration,* (ii) *information integration,* (iii) *physical integration*, (iv) *network integration* (Ibrahim, 2003). Fare integration refers to the integration of the ticketing system, which ensures travelers to pay by using a single system, such as a public transportation card. Information integration refers to a system where information of different services (i.e. modalities) is provided. Physical integration relates to ensuring "*seamless*" transportation, where the focus is mainly on the transfer between modalities. Lastly, network integration refers to the incorporation of different services that satisfy a certain performance level, where the total service is improved.

The integration of multiple transportation networks to create an integrated transportation system is not easy to get realized. This implies that different challenges must be overcome. Givoni and Banister (2010), appoints three challenges of transportation network integration:

- The supply of transportation must be integrated in order to provide the traveler the desired transportation from origin to destination (e.g. from residence to workplace);
- The transportation consideration and decision-making should be incorporated by identifying the locations that generate demand; and
- The integration and collaboration between the institutions that are responsible for the transportation network.

In short, the transportation system must not only be organized in order to provide service from station to station, but must consider the entire journey of travelers. For this, determining the demand locations is a key aspect and the system must be able reach these locations. When both conditions are met, collaboration between the responsible institutions must be pursued to ensure alignment of services and quality.

2.3 Bicycle Sharing Systems

Bicycle sharing systems, or rather *bicycle sharing*, have received a lot of attention in recent years. Various bicycle sharing initiatives were introduced around the world, most of which focused on promoting cycling, providing complementary reach of transit modes, and reducing environmental impacts associated with private car use (DeMaio, 2009).

Before discussing how bicycle sharing systems have evolved over time (see Section 2.3.1), presenting some systems in practice (see Section 2.3.2), discussing the potential of bicycle sharing systems (see Section 2.3.3), and the characteristics of systems consists of (see Section 2.3.4), a clear definition of bicycle sharing is provided.

> *"A bicycle provided for short-term (time) use at low-cost (payment), within a network of publicly accessible distribution points. The bicycle sharing system is accessible, easily for use, and contribute to the daily mobility supply, besides other transportation mode alternatives (e.g. train, bus, tram, metro, car, and own bicycle)."*
>
> (Huysmans & Van Iperen, 2017)

Bicycle sharing systems have been introduced in many mobility plans, and however currently (i.e. June 2018) operating in more than 1600 cities around the world (Meddin & DeMaio, 2018). Additionally, it is considered the fastest growing transportation mode, with an average grow of 37 percent annually since 2009 (Meddin, 2015). The development of bicycle sharing systems per continent is presented in Figure 10. The number of bicycle sharing systems is increasing rapidly, mainly in Europe.

Figure 10. Development of bicycle sharing programs around the world (Midgley, 2013)

2.3.1 Bicycle sharing through the years

Although bicycle sharing emerged the last decade principally, the first generation of bicycle sharing systems evolved in the '60s. Since then, many technological advancements have taken place, that gave rise to the rapid expansion worldwide. Based on the developments in the field of bicycle sharing, there have been five generations of systems, as presented in Figure 11.

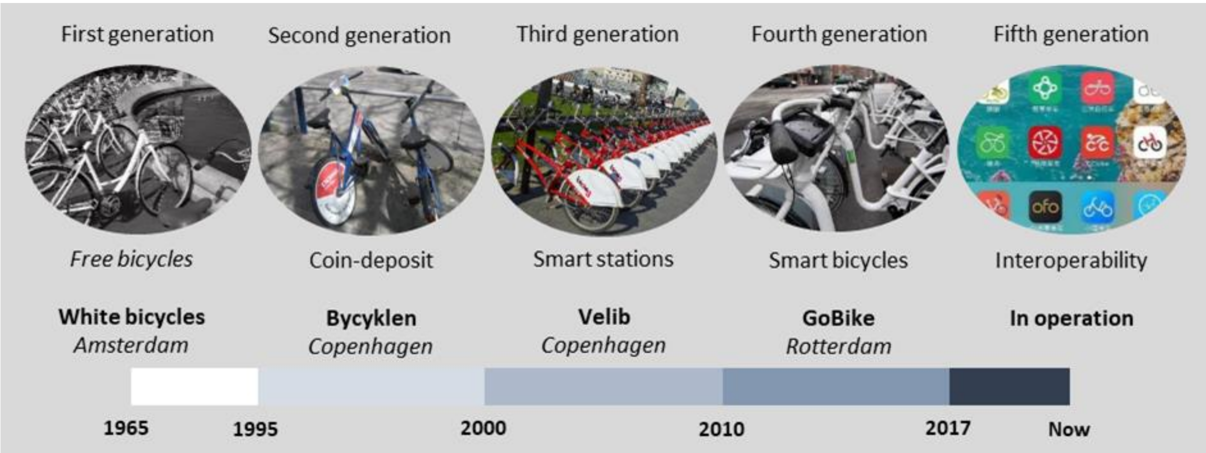


Figure 11. Bicycle sharing system generation: From free bicycles to integrated systems. Based on work by (Huysmans & Van Iperen, 2017).

First generation: Free systems

The first generation of bicycle sharing systems dates from the year of 1965, and originated in Amsterdam, the Netherlands (Shaheen et al., 2010). White painted bicycles, hence also named *White Bikes*, were spread throughout the city for public use (DeMaio, 2009). One could pick up a bicycle, make the ride, and drop it anywhere (no stations) in the city for the next user. The main of goal of the *free bicycles* was to reduce traffic related problems (i.e. congestion, air and noise pollution). However, in short time many bicycles disappeared and this initiative came to an end.

Second generation: Coin-based systems

It took until 1995 before the second generation bicycle sharing systems came into being. In Copenhagen, Denmark, the *Coin-deposit system* was launched (DeMaio, 2009). Such systems were designed with docking stations, spread throughout the city. The use of bicycles, also referred to *Bycyklen's*, was free of charge, however a deposit of 20 Danish Krone was required (Shaheen et al., 2010). Concerns about the system were related to realizing operation efficiency and as there was no limit to the use of the bicycles. As a result, bicycles were occupied over long time or even never been returned (Shaheen et al., 2010).

Third generation: ICT based systems

The problems of vandalism, failure of return, and theft were main reasons for the emergence of third generation bicycle sharing systems, *smart stations.* Due to technological advances improved user identification became possible, but also bicycle reservation, pick up, return, and information tracking was ensured (DeMaio, 2009; Shaheen et al., 2013). To rent a bicycle users are required to provide personal information (e.g. ID details, credit card). In this way, it has been made easier to track users by operators in case of problems, and to charge the costs incurred (Gauthier et al., 2013). Third generation systems are considered as the basis of the rise of bicycle sharing worldwide. In Rennes, France, the first bicycle sharing system operating with smart-card technology was introduced. Later, more robust systems followed, with *Vélo'v* from Lyon in 2005 and the Parisian *Vélib'* in 2007 (DeMaio, 2009). Both, are considered the prototypes of third generation bicycle sharing systems (Gauthier et al., 2013).

Fourth generation: Integration systems

After the third generation bicycle sharing systems, in which implementation of technology has been very important, it was unclear what the contributions of fourth generation bicycle sharing systems would be. According to DeMaio (2009), these contributions were related to increasing the efficiency, sustainability, and the usability of systems. Shaheen et al. (2010) identified fourth generation bicycle sharing systems as multimodal systems, or rather *demand-responsive*. This means an user-centered approach, which includes technological improvements on stations and bicycles to facilitate the use and share, the introduction of electric bicycles, and integration with other (public) transportation services (DeMaio, 2009; Shaheen et al., 2010). In addition, the bicycles are no longer dependent on docking stations, as the technology required for this was integrated into the bicycles, referring to *smart bicycles.*

Fifth generation: Interoperability

Increasing use of smartphones has facilitated user registration, reservation of bicycles, and payment by applications. However, the high number of operators existing in cities (especially in China) has complicated the ease of use of users. Addressing this issue has been resulted in the fifth bicycle sharing system' generation, *interoperability* (Huysmans & Van Iperen., 2017). The main goal is to ensure that users can make use of different bicycle sharing systems operating in the same city or area, with only one registration (Huysmans & Van Iperen, 2017). In the Netherlands, the *Tour de Force* came into action as initiative to address this.

Various bicycle sharing systems are currently operating worldwide, of which most of them are from the third, and increasingly of the fourth generation. In contract to third generation systems, the fourth generation bicycle sharing systems offer great potential in terms of integration with urban and transportation systems (e.g. tariff system, user card), modularity of system (e.g. repositioning of docking stations), demand-responsive approach (e.g. redistribution), and development of environmental friendly technologies (e.g. solar panels, electric bicycles) (Mátrai & Tóth, 2016). This makes fourth generation systems very attractive for implementation. In this study, both third and fourth generation bicycle sharing systems are further analyzed.

2.3.2 Bicycle sharing systems in practice

Before bicycle sharing system implementation, market research is required on the potential effects (Campbell *et al*., 2016). Successfulness or failure depend on the main objectives as defined previously to the project (Médard De Chardon et al., 2016, Ricci, 2015). Objectives related to bicycle sharing systems differ from one system to another, and systems' success in one city does not necessary to be achieved in the other city. This makes generalization of bicycle sharing systems complex. The culture, habits, and infrastructure in countries is found to play a great role in the operation of systems (Campbell et al., 2016). For this reason, systems operating in Europe are easier to generalize to the Dutch situation. However, since cycling is part of the Dutch culture, and the Netherlands is characterized by high quality infrastructure, foreign practices can be misleading in the Dutch context. In order to get a clear understanding of bicycle sharing systems in practice, four systems are highlighted in this section:

i. Vélib' *operating in Paris, France;*
ii. Bycyklen *operating in Copenhagen, Denmark;*
iii. Call-a-Bike *national system, operating in Germany;* and
iv. OV-fiets *national system, operating in the Netherlands.*

The systems mentioned above are considered to be representative, because they use different bicycle types, return forms, and rental pricing systems. Vélib' is the most successful bicycle sharing system in Europe, mainly because of its high densely network. The Bycyklen is a high-tech bicycle sharing system operating with electric bicycles. Although Copenhagen is considered to be one of the best cycling cities in the world, this system has not been successful yet. The last two systems considered are combined with public transportation accessibility. Call-a-Bike is a flexible system that provides bicycle return at other locations than as picked up. The OV-fiets in the only large bicycle sharing system operating in the Netherlands. Although this system has been very successful, it has a number of limitations. Those limitations will be discussed later on this section. This OV-fiets is used as referential bicycle sharing system in this study.

Vélib' in Paris, France

Established in 2007, Vélib' represents the largest bicycle sharing system of Europe. Operating in Paris, France, this system includes over 23,600 bicycles within a network of 1,800 docking stations (Vélib', 2017). Vélib' is a robust bicycle sharing system in which docking station are spread throughout the city and located 300 to 400 meter of each other, facilitating access to its users. The shared bicycles are available to everyone, and for all users the first 30 minutes is free of charge. However, a distinction is made between short-term and long-term subscribers. Short-term subscribers can rent a shared bicycle only at terminals by buying a ticket for a period of one day or a week, costs are 1.50 and 8.00 Euro respectively (Vélib', 2017). By using their subscriber card, long-term subscribers have easily access to a bicycle at any docking station in the city. Subscription is for a period of a year and costs are 29 Euro. Then, the Vélib' shared bicycles can be used any time and day of the year with a maximum rental time duration of 30 minutes. After the first 30 minutes, long-term subscribers have to pay an increasing rental free by each additional half hour.

The large number of docking stations ensure a back-to-many system, and therefore, users do not need to return their bicycle to the pick-up location (i.e. back-to-one). Vélib' is considered a successful bicycle sharing system and recognized all over the world. This is based on its accessibility, flexibility and low fare fee. However, there are also downsides concerning the system, as for instance the need for redistribution of bicycles. The shared bicycle fleet (flow of bicycles) is different for each station, and being never equal between stations. Every day again bicycles have to be redistributed over the docking stations – to provide enough supply at stations and free places for return – resulting in high operation costs. Based on historical data the supply is regulated. However, optimal distribution is hard to achieve. In order to stimulate this users can get 15 minutes extra for free at the next ride, when returning the bicycle at the so called *'V+' (V-Plus)* stations (Vélib', 2017).

Bycyklen in Copenhagen, Denmark

Bycyklen is a fourth generation bicycle sharing system operating in the city of Copenhagen, Denmark. This system followed up the Copenhagen City Bike system, which represents the first system of the second generation (see Section 2.3.1). Upgrading the Copenhagen City Bike system was found to be costly, and the bicycles disappeared from the city after expiration of the contract in 2012 (CPH Post, 2012). As successor the Bycyklen was introduced by GoBike and the government in 2014. Modern and innovative electric bicycles were designed, in which integration with the public transportation network is provided. Users can rent a shared bicycle with the *'Rejsekort'*, i.e. the Danish public transportation card. The bicycles are equipped with a tablet on the steer, ensuring control of the entire renting process (e.g. pick up, return, payment), GPS navigation, and get public transportation information about connections and stations (Bycyklen, 2017).

Registration is required for using a Bycyklen. Although there is no application available, individuals can register themselves on a smartphone or even on the tablet of the bicycle. Users pay a hourly fare fee of approximately 4 Euro (i.e. 30 Danish Crows), but also a deposit by credit card is needed (Bycyklen, 2017). Subscription is possible on monthly basis. The rental fee is generally higher than bicycle sharing systems operating in other European cities. Main reason for this, is that the Bycyklen operates with electric bicycles which have higher usage costs. However, with the Bycyklen a travel speed of 24 kilometer per hour can be achieved. Depending on the riding style of users assistance over a travel distance of 25 kilometers can be provided with a full battery (Bycyklen, 2017). Picking up an electric shared bicycle is possible at all docking stations spread throughout the city. But also *drop zones* are added to the network of stations. This increases the flexibility of the system, however more control and distribution activities (e.g. move bicycles with empty battery) may be required. Users do not needed to return their bicycle to the pickup location. They can return their bicycle at any other docking station or dropping zone in the city, and those locations can be viewed on the tablet.

Initially the objective of the Bycyklen was to provide an alternative mode for commuters. By using the Bycyklen commuters could travel directly to their work, or use it as access or egress mode to public transportation. However, in first instance the bicycles were mainly used by tourists. This was because residents presumed that the Bycyklen' initiative was more suitable for tourists, and therefore they did not use the bicycles (Copenhagenize, 2015). However, after a moderate introduction the use of the Bycyklen bicycles has been increasing.

Call-a-Bike, Germany

Call-a-Bike is a bicycle sharing system that combines public transportation accessibility (Call-a-Bike, 2017). This system is operated by the Deutsche Bahn (i.e. German national railway company), and includes 13,000 bicycles spread over 50 cities in Germany. The so-called *CallBikes* are mainly available at docking stations located at train stations, city squares, and intersections. Important to note is that the system differs from one city to another, in terms of return form or rental fees. The number of registered users have been increasing over the years, and reached 860,000 by 2016 (Call-a-Bike, 2017).

To use a CallBike individuals have to register. This can be done through the Call-a-Bike application, on internet, or at terminals. After registration users have the possibility to rent a CallBike by a phone call or application. Registration is accompanied with an annual membership, and costs 3 euro per year. The rental fee differ by city and can be based on a fix rate per minute or half hour (Gauthier, 2013). In most cities users have to pay for each 30 minutes 1 euro. However, in Hamburg, Stuttgart and Lüneburg the first 30 minutes of use is free of charge (Call-a-bike, 2017). In order to lock a CallBike users have to call the telephone number given on the bicycle which includes the CallBike-ID. Subsequently, by voice a 4-digit opening code is provided that can be entered on the touchscreen lock. The same method applies for returning the bicycle, with the addition of the street name where the bicycle is locked at. However, users can also obtain the 4-digit opening code by using the application. In some cities (e.g. Munich, Frankfurt am Main) bicycles are equipped with GPS in which return can be satisfied by pressing a button. Generally, CallBikes can be picked up at docking stations. However, the return form differs from back-to-many (docking stations) to free Floating (drop zone) by city. For instance, CallBikes can be dropped at many street corners in Munich (Call-a-Bike, 2017).

The Call-a-Bike bicycle sharing system is found to be an addition to the current public transportation system. Travelers can use a CallBike for their access and egress trip. The availability of CallBikes provides them an alternative mode to travel short distances after public transportation use. In addition, the built-in lock ensures that breaks can be made during the ride. Although almost all CallBikes are traditional bicycles, pedelecs are introduced in some cities (i.e. Stuttgart) to travel faster between locations.

OV-fiets, the Netherlands

The *OV-fiets*, is a Dutch nationwide bicycle sharing system which originated in 2003. This system has experienced a strong growth in recent years, and is still growing fast. In 2016, 2.4 million trips were realized by users, and this is 26 percent more compared to the year 2015 (Verkeersnet, 2017). The current OV-fiets network provides bicycles at almost 300 locations. Bicycles are mainly available at stations, bus and metro stops, city centers, and park-and-ride facilities (NS, 2018). This is because, the OV-fiets system serves as an extension of the public transportation network, and involves mainly egress trips. Although the demand of bicycles has exceeded supply, expanding the OV-fiets network is still not the case. The focus of NS (i.e. Nationale Spoorwegen; the Dutch national railway company) is rather increasing the supply at the main train stations, i.e. Amsterdam, The Hague, and Utrecht Central (NS, 2016).

Given the high bicycle ownership in the Netherlands, bicycle sharing systems are less attractive in first instance. However, because most of the travelers only own a bicycle in the access phase of multimodal (train) transportation journeys, there is a need for a fast, reliable, and flexible transportation mode in the egress phase. The OV-fiets provides this alternative to users. However, the system can be characterized by some limitations. In order to rent an OV-fiets users are required to own a public transportation card (i.e. OV-chipcard). Membership is required, however it is free of charge. Subscribers can rent a bicycle for 3.85 euro per trip per day, with a maximum of 3 days consecutively (NS, 2018). The rental fare of the OV-fiets is high compared to other bicycle sharing systems that are currently operating in Europe. For this reason, the system is usually used on an incidental basis. There are three ways to rent an OV-fiets: at a guarded bicycle parking, self-service bicycle parking, and bicycle carousel. In principle by scanning the OV-chipcard of the user an OV-fiets is allocated. During the rental period, users can make unlimited use of the bicycle, in which they can lock and park the bicycle anywhere they want for their travel. In general, the OV-fiets satisfies users in convenience, speed, freedom, and costs (Fietsersbond, 2011; Ministry of Transport and Water Management, 2009). Using the OV-fiets enable travelers to move fast from one place to another, without having to search for a docking station during their trip, at relative low costs. Unlike other bicycle sharing systems, users are always required to return the bicycle to the same location as they picked up. If users deviate from this, extra service costs are charged.

In the past, alternatives were presented for the OV-fiets, such as electric bicycles (e-bicycle) and scooters (Maartens, 2015). Between 2011 and 2014, at a limited number of stations, travelers could rent an e-bicycle. The aim of this initiative was to increase the travel range of travelers. However, objectives have failed and this initiative was stopped at the beginning of 2015 (Maartens, 2015). At that time, e-bicycles were not profitable enough because of the low number of users and high operational costs. Additionally, more parking space was required for e-bicycles, compared to traditional bicycles. The initiative of scooters failed for the same reasons.

The OV-fiets is mainly used for visiting friends or family members (i.e. 42 percent), and is less common for business related trips (i.e. 18 percent) and social recreation (i.e. 13 percent) (Fietsersbond, 2011). This may explains the fact that most of the users (i.e. 56 percent) make use the OV-fiets less than once a month. In general, the OV-fiets users are content with the service provided and indicated convenience (i.e. 79 percent), freedom (i.e. 68 percent), and speed (i.e. 44 percent) as the most important factors for use. On the other hand, a large share of the users (i.e. 41 percent) indicated that they would like to be able to deliver the bicycle at other locations at no or lower costs (Fietsersbond, 2011).

2.3.3 The potential of Bicycle sharing systems

It is widely assumed that bicycle sharing has a positive contribution to social, economic, and environmental aspects (DeMaio, 2009; Handy et al., 2014). This reflects the growing interest in bicycle sharing systems implementation worldwide, in which goals are related to increase the cycling population, reduce congestion, enhance air quality, and improve public health (DeMaio, 2009; Gauthier et al., 2013; Mátrai & Tóth, 2016; and Shaheen et al., 2010). The benefits of bicycle sharing to our society and the potential towards more sustainable transportation in cities are described below.

Contribution to urban quality

Bicycle sharing contributes to the urban quality of life in different ways. It provides individuals a transportation mode alternative to travel over short distances that are beyond their reach on foot, and otherwise have been made by car (Gauthier *et al*., 2013). For instance, a study by Caulfield et al. (2017), revealed that more than 70 percent of the trips take less than 9 minutes. A decline of private car use or increase of public transportation use through bicycle sharing introduction has been the goal of several cities (e.g. Washington, D.C. and London), aiming to reduce congestion and improve the air quality (Midgley, 2011). Wang and Zhou (2017) found that with bicycle sharing introduction, if one percent of the current private car commuters shift to other transportation mode, this will result in a 0.3 percent reduction in congestion levels. The availability of shared bicycles has also an effect on the cycling population. Next to existing cyclists, bicycle sharing programs are able to attract new users, thus increasing the cycling population. In cities such as Barcelona and Paris this relationship has been proven (DeMaio, 2009). More people cycling, contributes to a healthier population, because cycling is an active transportation mode (Gauthier et al., 2013). Although bicycle sharing mainly concerns environmental issues, it can improve the image of cities and possibly create a cycling culture over time (Gauthier et al., 2013).

Integration of transit and bicycle sharing systems

Public transportation and cycling are often promoted to mitigate the negative impacts of private car use. Previous research (e.g. Martens, 2004; Pucher *et al*., 2010; and Rietveld & Daniel, 2004) noted that efficient integration of cycling and public transportation has the potential to increase the share of transit use. However, this integration is seldom seamless, as it does in the Netherlands. Despite cycling is typically Dutch and transfer stations are mainly reached by bicycle, the share of cycling is relatively low in the egress phase (as discussed in 2.2.2). Bicycle sharing has the potential to overcome shortcomings related to bicycle and public transportation integration (Jäppinen *et al*., 2013). The integration between bicycle sharing systems and public transportation aims to encourage travelers to use the bicycle as transfer transportation mode to and from transit stations. However, considering the Dutch situation, where most a large proportion of the population owns a bicycle in the access phase, a bicycle sharing system would contribute to the public transportation service by facilitating transportation in the egress phase. Several authors (e.g. Mátrai & Tóth, 2016) have documented the potential of bicycle sharing systems, and especially in the egress phase. One reason is that cycling has a higher speed compared to walking which could encourage travelers who generally walk to their final destination to use shared bicycles instead, and bicycle sharing systems provide a more flexible service compared to public transportation, such as the bus (Keijer & Rietveld, 2000). Several authors (e.g. Jäppinen et al., 2013; Nadal, 2008; Shaheen et al., 2010) reported that improving the accessibility to and from transfer stations is one of the main goals of bicycle sharing systems. For public transportation, integration with bicycle sharing systems is of value, as it increases its competitiveness in relation to the private car. For instance, Jäppinen et al. (2013) found that the launch of a bicycle sharing system could decrease travel times with public transportation by 10 percent, as a result of reductions in access and egress times. The integration of bicycle sharing systems with the public transportation service have a larger chance to succeed in especially in larger cities. This is because population density is found one of the most important factors of bicycle sharing system performance (Gauthier et al., 2013; Médard de Chardon et al., 2017; and Zhao et al., 2014). In general, larger cities are characterized by more robust public transportation systems, compared to smaller cities (Wang & Zhao, 2017). The allocation of bicycle sharing systems nearby public transportation stops or stations would therefore encourage multimodal transportation by providing more seamless connections. In addition, the system can increase the accessibility to suburbs or work locations (e.g. industrial areas) (Zhao & Li, 2017). In smaller cities, the implementation of bicycle sharing systems can contribute by serving as a complement to the existing public transportation system (Wang & Zhao, 2017). This study considers the integration of bicycle sharing system and train. It does this by providing a bicycle sharing system in the egress phase of multimodal train journeys regarding commuting trips.

2.3.4 Characteristics of bicycle sharing systems

Bicycle sharing systems consist of different characteristics that influence their attractiveness and feasibility from the perspective of the user. Huysmans and Van Iperen (2017) distinguished in total five characteristics that determine the design of bicycle sharing systems. This section briefly discusses these characteristics and defines the bicycle sharing system characteristics that are further considered in the study.

Access to bicycle sharing system

The access to bicycle sharing systems refer to the possibility of individuals to make use of the service provided, the bicycles. In general, bicycle sharing systems can be distinguished by two types of systems' access, i.e. (i) *open systems* and (ii) *closed systems*. Open systems are available to all individuals (the public) for use, while closed systems refer to systems that are only available for a restricted group of individuals, such as employees of a company or tourists.

User registration

Regardless of whether the system is open or closed, user registration is necessary for the use of a bicycle from the system. By user registration, the identity of the user is provided to the operator of the bicycle sharing system. One the one hand, users can register per ride. This means that users must provide personal information at each rental session. On the other hand, one-time registration is more convenient and time efficient for users at regular use. Users have access to the bicycle sharing system for a certain period of time (i.e. for a week, month or year) by using a (public transportation) card or smartphone application. One-time registration is usually applied in modern bicycle sharing systems.

Return structure

The return structure of bicycle sharing systems is more complex, and therefore an important design element. Basically, there are three return structures, as presented in Figure 12. The first return structure is *back-to-one*. Bicycle sharing systems with this return structure, ensures pick up and return of bicycles at the same location, the docking station. A more flexible system can be provided by the *back-to-many* structure. Users do not need to return their bicycle to the same location as picked up, but they are able to return at other locations as the system provide to them. The last return structure defined is *free floating*, and this is the most flexible one. There are no docking stations available, but however a geographic area is defined. Within this area the bicycle can be returned and made available for use to others. Bicycles operating with a free floating return structure are equipped with an intelligent lock. This lock type prevents lockage of the bicycle outside the determined geographical area. Consequently as the bicycle cannot be locked, payment cannot be completed. As a result, costs keeps increasing for the user until the bicycle is moved into the geographical area.

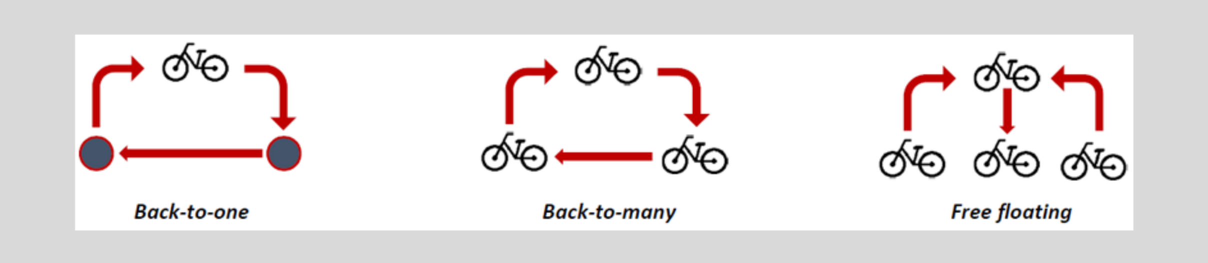


Figure 12. Return forms of bicycle sharing systems; based on work by Huysmans & Van Iperen (2017)

For the sake of simplicity, bicycle sharing systems can be divided into *fixed* and *flexible* systems (DeMaio, 2009). Many bicycle sharing systems are operating according the flexible return structure, such as Vélib' and Call-a-bike (see Section 2.3.3). The OV-fiets uses a fixed return structure, which means that users are required to return the bicycle at the same location as it was picked up.

Number of locations

The number of locations or the network of bicycle sharing systems is an important characteristic of the design. In principle three types of networks can be distinguished, i.e. (i) *single location networks*, (ii) *restricted networks*, and (iii) *high density networks* (Huysmans & Van Iperen, 2017). Traditional bicycle sharing systems that require both pick-up and return of the bicycle at the same location can be characterized by a single location network. Such systems often require registration per use. Bicycle sharing systems that have a limited number of locations spread over a city or spread over a large region can be characterized by a restricted network. High density network bicycle sharing systems are often operating in urban areas and characterized by many stations within an specific area.

The accessibility of bicycle sharing systems depends on the number of distribution points or rather docking stations in an area (Gauthier et al., 2013). Increasing the number of docking stations, i.e. the density of the network, within a certain area ensures that individuals have to cover shorter distances to access the system. The general guideline for the distance between docking stations is 300 meter, which is equivalent to 4 minutes walking (Gauthier et al., 2013; Shaheen et al., 2010). The preferred maximum distance from the public transportation service to the bicycle sharing system is 400 meters (Shaheen et al., 2010).

Type of locations

The network of bicycle sharing systems also depends on the type of locations where the bicycles can be picked-up and returned. In general, five types of locations can be distinguished:

i. Residence locations;
ii. Work locations;
iii. Tourist or recreational attractions;
iv. Public transportation stops or main stations; and
v. Park & Bike locations.

The network of bicycle sharing systems can have different types of locations. However, it should be noted that the type of location is dependent on the potential users (i.e. the individuals the system aims to reach) of the system (Municipality of Amsterdam, 2017).

Based on the five design characteristics discussed in this section, in total five types of bicycle sharing systems can be distinguished as shown in Figure 13. The current OV-fiets system belongs to a *public transportation* bicycle sharing system. This system is characterized by a large scale network with docking stations spread throughout the Netherlands. Most of the pick-up locations are located nearby public transportation stops and stations. However, in relation to urban bicycle sharing systems, the OV-fiets system offers less flexibility. Urban bicycle sharing systems are characterized by a high density network of locations within a specific defined area. This increases the flexibility of users to realize trips. Having many bicycle sharing stations implies that users need to walk less to reach a station (access), and walk less after bicycle return (egress). In this study, it is assumed that urban bicycle sharing systems can contribute to the integration with public transportation, and especially the train. Urban bicycle sharing systems should serve as egress mode from the train station at the activity-end side to the final destination (i.e. work location).

	Corporate	Park & Bike	Traditional	Public transportation	Urban
System access	Closed	Closed	Open	Open	Open
Registration	One-time	One-time	Per use	One-time	One-time
Return	Back-to-one (Fixed)	Back-to-one (Fixed)	Back-to-one (Fixed)	Back-to-one (Fixed)	Back-to-many (Flexible)
Network	Small scale Restricted	Small scale Restricted	Single location	Large scale restricted	High density
Locations	Company PT stops and stations	Transferia	Urban	PT stops and stations	Urban

Figure 13. Types of bicycle sharing systems; based on work by (Huysmans et al., 2016; and Municipality of Amsterdam, 2017)

Next to the five above described bicycle sharing systems characteristics, there are other system characteristics explored in the literature that have an effect on the attractiveness of the system. These characteristics are:

i. Bicycle type
ii. Rental fare

Type of shared bicycle

Assuming that individuals have their own preferences, this make it difficult to provide a shared bicycle that satisfy the preferences of all (potential) users. Many factors have to be considered when designing a shared bicycle for public use. Basic design aspects relate to (physical) size of individuals (i.e. weight, length). Shared bicycles should be appropriate for all individuals for travel, and therefore be easily adjustable to different sizes. In addition, it is also important how shared bicycles look like. Generally, shared bicycles have a distinctive appearance, referring to their operator. Since individuals add value to their appearance while in public, the design of bicycles may attract or even discourage individuals to use bicycles of operators or shared bicycles at all. Especially shared bicycle use by business individuals is found to be influenced negatively (Heijningen, 2016). Considering practical factors, the bicycle has to be robust, requiring low maintenance, and secure in use. Additionally, aspects related to theft or vandalism have to be taken into account. The bicycle have to be designed in a such way preventing or limiting the chance of theft and vandalism. For this reason, shared bicycles have to be equipped with a tracking mechanism which ensures the possibility of the bicycle to be tracked by the sharing operator when required to do so. Shared electric bicycles differ in some aspects from the traditional (non-electric) shared bicycles. Evidently, electric bicycles are equipped with battery and require charging facilities. The battery provides assistance and ensures individuals to move faster and with less effort. Additionally, some shared electric bicycles are equipped with modern gadgets to make the ride attractive and convenient. One example is the GoBike, which is originally a Danish system. This bicycle type has a tablet with built-in GPS, luggage rack on front, LED lights, and puncture free tires (Bycyklen, 2014). With the tablet, the shared bicycle can be unlocked and locked, and payment be done. In addition, providing information regarding the availability of bicycles, public transportation connections, and location of docking stations is possible to users. Such bicycles are commonly referred to Smart Bicycles. The introduction of shared electric bicycles in systems is intended to decrease the impact of areas, making the use of bicycle sharing systems more attractive (Mátrai & Tóth, 2016).

Pricing

There are several cost structures for bicycle sharing systems. A common cost structure used for urban bicycle sharing systems (i.e. high density network) is free 30-minutes use (Gauthier et al., 2013). After this period of time the user is charged by every additional 30 minutes. The focus of such bicycle sharing systems is rather on increase the cycling population, than generating high revenues. Bicycle sharing systems with a free 30-minutes cost structure are operating in for example Lyon (Vélo'v'), Paris (Vélib'), Montreal (Bixi), and Madrid (BiciMAD) (Mátrai & Tóth, 2016). The rental fare after the expiry of the free 30-minutes use differ by system, and varies from 0.60 euro (BiciMAD) to 1.45 euro (Bixi) (Mátrai & Tóth, 2016). The German nationwide bicycle sharing system (Call-a-Bike) uses for a specific bicycle type (pedelecs) a cost structure where users pay 12 eurocent per minute (Call-a-Bike, 2018). The OV-fiets in the Netherlands operates with a daily cost structure. A main reason for this, is that promoting cycling is not the principle objective of the system, but proving an alternative transportation mode for the egress trip.

2.3.5 Bicycle sharing system mode choice

In the previous sections knowledge has been gained regarding bicycle sharing systems that are operating abroad, the Dutch bicycle sharing system OV-fiets, and the elements of bicycle sharing system design. This section discusses the most relevant insights from the literature that will be used in the SP experiment (Chapter 3). This relates to the attributes that influence the attractiveness of the use of bicycle sharing systems. The bicycle sharing system mode choice is approached from three perspectives:

i. Trip-related characteristics;
ii. Bicycle sharing system-related characteristics; and
iii. User-related characteristics.

Although it is assumed that the cycling culture in the Netherlands can influence the feasibility of bicycle sharing systems in the Dutch cities, the implementation of bicycle sharing systems can offer travelers an additional sustainable transportation alternative (Heijningen, 2016). This is especially the case in the egress trip of train journeys, when travelers do not have the own bicycle at hand and, in particular, are forced to walk or use public transportation to reach the final destination (discussed in Section 2.2.2). Rather than allocating bicycle sharing system station at residential locations (i.e. for the access trip), the stations should be allocated at public transportation stops and stations, work locations, tourist and recreational attractions, and in city centers. A good example in practice is the German Call-a-Bike bicycle sharing system, which offers great flexibility to users at the locations of need.

Trip-related characteristics
The willingness to use the service provided by bicycle sharing systems is influenced by the current travel patterns of individuals. In order to promote the use of bicycle sharing systems, the system must be regarded by individuals as an improvement to the current travel patterns. For example, if the integration between bus and train is seamless, and the bus service is reliable in the egress phase, the chance of failure of bicycle sharing systems is considerable. The same applies when travelers experience a too high effort to use the system. The current trip patterns are therefore important to analyze.

The following trip characteristics will be analyzed:

- Frequency of commuting;
- Current (main) commuting transportation mode;
- Total travel time;
- Egress travel time; and
- Residence and work location.

Bicycle sharing system characteristics
The bicycle sharing system characteristics or attributes are already explained in Section 2.3.4. Incorporating of all attributes in the SP experiment would make the experiment unnecessarily complex for the respondents. For this reason only the most relevant characteristics that are expected to influence the mode choice of individuals will be further considered. The selected

attributes do not only relate to the characteristics of the bicycle sharing system, but also relate to the commuting (egress) trip itself. The following attributes are selected:

- Return option;
- Bicycle type;
- Reservation option;
- Rental fare;
- Density of bicycle sharing system stations (access and egress time);
- Reliability of the system (waiting time).

User characteristics

The socioeconomic characteristics of users are expected to influence the preference for a bicycle sharing system. In addition, past experiences may influence the view of individuals for bicycle sharing system use. For this reason also their experience with the OV-fiets is important. Furthermore, attributes, habits and social norms are found to influence the travel behavior, and therefore the transportation mode choice of individuals (Ajzen, 1991; Aarts, 1996). The following attributes and factors are analyzed:

- Socioeconomic characteristics (gender, age, education level, household type);
- Experience with OV-fiets;
- Attitudinal factors regarding commuting (main) transportation mode; and
- Attitudinal factors regarding bicycle sharing systems.

2.4 Transportation Mode Choice

"*It is widely recognized that attempts to address unsustainable patterns of travel involve a detailed understanding of travel behavior and the reasons for choosing one mode of transport over another"* (Anable, 2005, p. 1). There are various arguments for which individuals decide to use the private car instead of other transportation modes. Travel behavior is traditionally approached from the perspective of time, costs, and socioeconomic factors; based on the *Theory of Maximum Utility* (Schneider, 2013). This theory postulates that each individual seeks to maximize its utility, and chooses the transportation mode with the highest utility (Ortúzar & Willumsen, 2001). However, many studies applied psychological theories to predict transportation mode choice (Anable, 2005). In particular the *Theory of Planned Behavior*, in which several psychological factors are brought together by Ajzen (1991). It is widely recognized that the Theory of Planned Behavior model have a high predictive power (Anable, 2005; Hendriksen *et al*., 2010). This approach assumes that individuals have different *needs* and *preferences*, and therefore consider transportation mode alternatives from their own perspective. Rather than maximum utility, this approach is supposed to provide a more complete understanding to mode choices.

2.4.1 The Theory of Planned Behavior

According to Ajzen (1991, p. 1), "*explaining human behavior in all its complexity is a difficult task"*. This reflects precisely the purpose of The *Theory of Planned Behavior*. In order to predict and explain human behavior, a number of conditions have to be met. First, a particular behavior can only be followed if individuals consider that behavior alternative; and second, interventions should be avoided, since those may affect intentions or perceptions of individuals of being capable to follow a specific behavior. The theory of planned behavior postulates that behavior is a function of *beliefs*: The (i) *behavioral beliefs* refer to the influence of attitudes towards a specific behavior; (ii) *normative beliefs* refer to views and expectations of others; and (iii) *control beliefs* involve perceptions of behavior control (Ajzen, 1991; Anable, 2005). The intention to follow a specific behavior is determined by three independently related determinants: *Attitudes* reflect all important convictions and values of an individual towards the behavior; *social norms* refer to the convictions as expected from the social environment of an individual, and the pressure associated by following or not following the behavior; and *perceived behavioral control* is a function of controlling beliefs in accordance with the perceived ease or difficulty of following the behavior (Ajzen, 1991; Hendriksen *et al*., 2010). In principle, a behavior change can be achieved by changing any of these factors (Hendriksen *et al*., 2010).

Inclusion of habits in Theory of Planned Behavior

Next to attitudes, social norms, and perceived behavioral control, also *habits* influence the decision making process of individuals (Aarts, 1996). Specific decisions often made in the past, or rather recurring patterns, ensure decisions being made less consciously and reasoned (Diana and Mokhtarian, 2009). Individuals with a *weak habit* consider all possible alternatives to them, while a *strong habit* limits the deliberation process; increasing the variability among individuals (Aarts *et al*., 1998). Since travel behavior cannot be fully explained rationally, as however assumed by Ajzen (1991), expanding the model with habit increases the predictability of transportation mode choices (Aarts, 1996; Hendriksen *et al*., 2010).

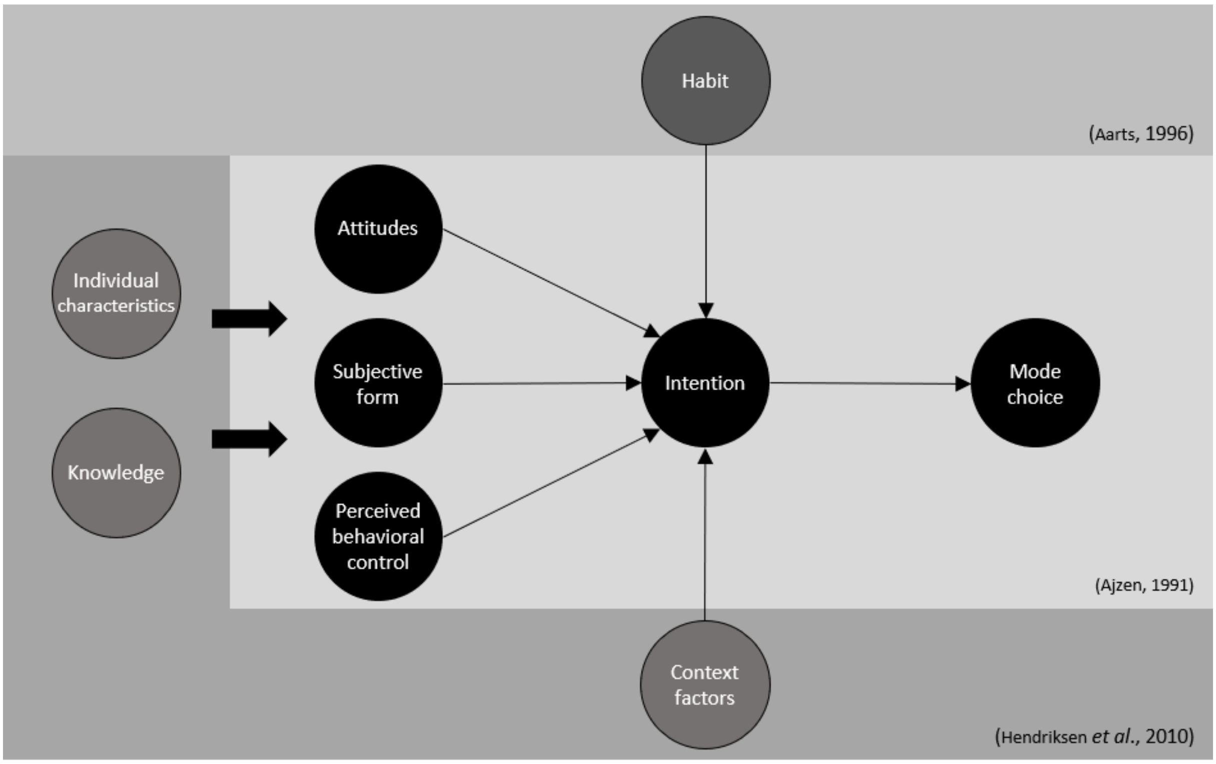


Figure 14. Theory of Planned Behavior from Ajzen (1991); further elaborated by Aarts (1996) and Hendriksen et al. (2010).

Inclusion of context, knowledge, and socioeconomic factors
Besides the intrapersonal determinants as mentioned above, the transportation mode choice of individuals is also influenced by *context factors, socioeconomic factors* and individual's *knowledge* (Hendriksen *et al.*, 2010). The *context factors* refer to the journey or trip characteristics; socioeconomic factors involve the characteristics of individuals; and knowledge refer to the ability of individuals to consider other transportation mode alternatives. Both, socioeconomic factors and knowledge have an indirect influence on the transportation mode choice. In Figure 14 the elaborated Theory of Planned Behavior model is presented.

2.4.2 Personal factors

This section discusses the *personal factors* of the elaborated Theory of Planned Behavior model, as illustrated in previous section. The factors that are discussed relate to an *individual*. However, this does not mean that the *environment* (with respect to relatives, colleagues, etc.) of an individual is left out of consideration. Views of others can well exert an indirect or rather direct influence on the travel behavior of any individual (Hendriksen et al., 2010).

Individual characteristics
Various studies (e.g. Beirão & Cabral, 2007; Cervero & Duncan, 2003; Krygsman, 2004) in the field of travel behavior included *individual characteristics*; referring to demographic and socioeconomic characteristics. It is assumed that individual characteristics do not provide a direct basis for explaining transportation mode choice (Schneider, 2013), but are rather indicative to more complex determinants, such as attitudes and habits (Anable, 2005; Welles, 2003). The most often analyzed individual characteristics were used: *age, gender, education level, household income,* and *car ownership*. Other identified characteristics are *environmental concern, access to household modes* (i.e. bicycle, electric bicycle, and private car) used by Campbell *et al.* (2016); *physical disability, public transportation card ownership,* and *access to lease car* in Yap et al. (2016).

Attitudes
The *attitudes* concerning a transportation mode is found to have an influence on the transportation mode choice of individuals (Harms *et al.,* 2007; Welles, 2003; Şimşekoğlu *et al*., 2015). Attitudes reflect the cognitive evaluation process, that are based on expectancy beliefs and the desirability of consequences of choosing for a specific transportation mode (Steg, 2005). In principle, individuals choose the transportation mode that best meet their level of expectancy. How transportation modes are perceived depend on *instrumental factors* (e.g. speed, convenience, and comfort) (Anable, 2005; Hensher *et al.*, 2003; Langendonck, 2009), but also feelings reflecting *affective* and *symbolic* (*social*) *factors* (e.g. power, freedom, status) as well have a considerable effect (Steg, 2005).

The way individuals perceive a specific transportation mode, is also determined by the extent to which one make use of that transportation mode (Harms et al., 2007). This relationship has been proven in work by Harms et al. (2007), in which the perception of individuals on 13 *quality attributes* were examined to public transportation, car, and bicycle use. Attributes as *comfort*, *convenience*, *relaxion*, *speed*, *pleasure*, *safety*, *independence,* and *flexibility* are referred to the car. Public transportation is poorly assessed by travelers, compared to the car and bicycle. Main reason for this, is that public transportation does not door-to-door journey transportation. Therefore, improving the access and egress trip of public transportation journeys may contribute in getting a more positive view. The car is by nature the most attractive transportation mode (Beirão & Cabral, 2007).

Social norms

The mode choice behavior of people can be influenced by their social environment. Basically three elements of social norms can be distinguished: *subjective norms*, *social pressure*, and *exemplary behavior* (Hendriksen et al., 2010). Together, these elements influence the image people have towards a certain transportation mode. On the one hand, this is partly determined by past experiences, and on the other hand, by external factors. The conception of others may encourage people to stick a certain behavior. For example, if most employees travel to work by public transportation, this can be considered as exemplary behavior. Employees who travel to work by car may perceive a social pressure (e.g. from organization or other employees) due to their deviant behavior. Heinen (2008) found that when people experience social pressure from their colleagues as a result of cycling to work, they tend to cycle more often to work.

Perceived behavioral control

Based on own experiences and those of others, people access whether they are able to follow a certain behavior (Hendriksen et al., 2010). In this way, it may happen that a transportation mode alternative is not considered by people, as this alternative is even faster than the chosen transportation mode. For instance, traveling in urban areas is generally faster by bicycle than by car at short distances. However, car users do not perceive the bicycle as a faster transportation mode at those distances. From their perspective, they expect traveling longer by bicycle to their desired destination. The perceived behavioral control relates to the perception of people regarding the travel speed, time, and distance of transportation modes. Therefore, it plays an important role in the mode choice of people between the train and car.

Habit

Habitual travel behavior refers to actions and choices that are carried out automatically (Ministry of Infrastructure and Environment, 2014). This can lead to a routine process in which people make choices more unconsciously. It is widely assumed that people who use a particular transportation mode regularly, tend to consider it as an alternative in the future (Klöckner & Matthies, 2004; Loukopoulos & Gärling, 2005; Schneider, 2013). Additionally, repeated travel behavior becomes more dominant over time affecting the deliberation of people to choose other transportation modes (Gärling & Axhausen, 2003). For instance, car habit is negatively associated with the intention or actual use of public transportation (Şimşekoğlu, Nordfjærn, & Rundmo, 2015). This indicates that people who mainly use the car, tend to be less willing or even consider to use public transportation (or any other transportation mode). Generally, habits are interrupt in two ways: firstly, in case people experience life changes or events (Bamberg, 2006; Klöckner, 2004); and secondly, when people perceive their travel to be more beneficial with another transportation mode (Schneider, 2013). However, if circumstances are kept unchanged, habits are not influenced.

2.3.3 Situational factors

Traveling involves *costs* which have an influence on the mode choice of people. Although travel cost are often referred to *monetary costs*, it also includes *travel time* and *effort* (Van Hagen, 2011; Schakenbos *et al*., 2016). These three cost elements determine the level of disutility for a specific transportation mode (Schakenbos *et al*., 2016). Since people seek to reduce the total costs to its minimum (i.e. Theory of Maximum Utilitity), the mode that provides them the least travel costs is chosen (Ewing and Cevero, 2010; Schneider, 2013). Besides trip disutility, *availability of public transportation* is also an important determinant (Krygsman, Dijst, and Arentze, 2004).

3 METHODOLOGY

3.1 Introduction

As discussed in Chapter 2, the egress trip is regarded as a weak part in the chain of trips of public transportation. This is especially the case when travelling by train – which is the focus in this study, travelers experience such a high level of unreliability and inconvenience that this can affect their transportation mode choice. The implementation of urban bicycle sharing systems is proposed as a supplement to the train service to achieve more complete door-to-door train journeys. Since the Netherlands is dealing with high congestion levels due to commuter traffic, this travel purpose is employed with a further distinction being made between two types of commuters: the current (i) *private car* and (ii) *train* commuters. This study aims to examine the attributes that influence the preference of individuals for urban bicycle sharing systems, and to investigate the influence of urban bicycle sharing systems in the egress trip of train journeys on the transportation mode choice of individuals for commuting trips. The methodology that will be adopted must be supportive.

This chapter discusses the methodology of the present study and is structured as follows. In the following section the theory of discrete choice models is explained (Section 3.2). This is followed by the elaboration of the experimental design (Section 3.3). Subsequently, the method of data collection is described (Section 3.4). Finally, the conclusions are presented with respect to the research method adopted (Section 3.5).

3.2 Theory of Discrete Choice Modeling

In daily life, everyone is confronted with choice situations including more than one choice, or simply alternatives. Decision-making does not only mean choosing one of the alternatives, but it is rather a complete process. For this, the decision maker (i.e. an individual or group of individuals) is required to consider a set of alternatives constrained by the environment, evaluate each of these, and apply a decision rule after which a choice among the alternatives follows (Ben-Akiva & Lerman, 2005; Koppelman & Bhat, 2006). Although the set of alternatives must be universal, however it may occur that not all alternatives are actually considered by an individual. This subset of alternatives includes only the alternatives that are feasible and observable by the individual. For example, if an individual does not have a bicycle available for use, he or she cannot consider this alternative transportation mode at all to realize trips. A choice stems from the valuation of the characteristics or attributes that reflect alternatives. This allows researchers to investigate whether there are relationships between the attributes of choices made by individuals. The method that has proven its capability to provide insight into the behavior of individuals by modelling their mode choice process, is discrete choice models (Ben-Akiva & Lerman, 1985).

According to Koppelman and Bhat (2006, p. 1), the application of discrete choice models is "*to analyze and predict a decision maker's choice of one alternative from a finite set of mutually exclusive and collectively exhaustive alternatives"*. In other words, the decision maker must be provided with all possible alternatives, be able to choose at least one of these, and the number of alternatives must be finite. Predicting the behavior of one individual is never the goal itself, but it is about the behavior of a group of individuals. In this study, the population is defined by all private car and train commuters in the Netherlands, which make at least one commuting trip per week. For them, it is aimed to provide insight into the attributes that influence their preference for urban bicycle sharing systems, and the influence of urban bicycle sharing systems on their transportation mode choice. Rather than choices, discrete choice models give an indication to the preferences of individuals that can lead to a real-life decision. Assuming that decisions are made rationally, the preference for a specific alternative is defined by the total utility that an alternative obtains from its attributes. This will be further described below.

3.2.1 Choice and Utility Theory

The attractiveness of an alternative is reflected by the utility of that alternative (Hensher et al., 2005). The utility represents a value that is attached to an alternative by individuals. Since individuals always seek to maximize their utility, it can be assumed that the alternative with the highest utility will be selected. This refers to the *Theory of Utility Maximization* which is the commonly applied decision rule in decision making (Koppelman & Bhat, 2006). As noted by Koppelman and Bhat (2006), the utility maximization decision rule is robust and provides a good representation of the choice behavior of individuals. For the application of the utility maximization rule, a function is required that contains the attributes of alternatives and the individuals, and describes the utility of an individual for each of the alternatives. The choice behavior of individuals is influenced by both *observed influences*, *V,* and *unobserved influences*, *ε*. The utility function, *U*, associated with a specific alternative, *i,* chosen by individual, *q*, is expressed in Equation (1).

$$U_{\mathrm{iq}} = V_{\mathrm{iq}} + \varepsilon_{\mathrm{iq}} \tag{1}$$

Where:

U_{iq}, is the utility associated with alternative *i* and individual *q*;
V_{iq}, is the representative component of utility (observed influences); and
$\varepsilon_{\mathrm{iq}}$, is the random or error component of utility (unobserved influences).

The observed proportion of the utility of an alternative is a function of the attributes of the alternative and the individuals' parameters (Koppelman & Bhat, 2006). Although, the unobserved influence is unknown by the researcher – and therefore treated as a random factor – this does not imply that the utility of an alternative is equal to the observed influence. The observed influence or representative component of utility is defined as a linear equation and can be expressed as follows: Equation (2)

$$V_{\mathrm{iq}} = \beta_{0i} + \beta_1 f(X_{1i}) + \beta_2 f(X_{2i}) + \beta_3 f(X_{3i}) + \cdots + \beta_K f(X_{Ki}) \quad (2)$$

Where:

β_{0i}, is the alternative-specific constant;
β_K, is the weight of a parameter of attribute *k*; and
X_{Ki}, is the value of attribute *k* associated with alternative *i*.

Given the theory of utility maximization, the alternative with the highest utility will be selected by the individual. Based on this assumption, the probability of choosing an alternative can be calculated. As denoted in Equation (3), the probability of alternative, *i,* being selected by individual*, q,* is equal to the probability of the utility of alternative, *i*, being greater than or equal to the utility of alternative, *j*.

$$P(i|C_{\mathrm{q}}) = P(U_{i\mathrm{q}} \geq U_{\mathrm{jq}}, \forall j \in C_q) \quad (3)$$

Where:

P_{iq}, is the probability of alternative *i* being selected by individual *q*;
$U_{i\mathrm{q}}$, is the utility associated with alternative *i* for individual *q;* and
$U_{j\mathrm{q}}$, is the utility associated with alternative *j* for individual *q*.

3.2.1 Logit models

After having discussed the main principles of choice modelling, attention will be paid to the logit models that are applied in the present study. It is widely assumed that logit models are capable to model complex transportation mode choice behaviors of any population (i.e. group of individuals (Khan, 2007; Yen & Chen, 2017). The mathematical framework of logit models is based on the theory of utility maximization. This has been elaborately discussed in previous work from Ben-Akiva and Lerman (1985).

Two types of logit models will be discussed in this study:

- Binary Logit model; and
- Multinomial Logit model.

The main difference between these two logit models, lies in the number of alternatives that are included to the model. As the name reveals, *Binary Logit* (BL) models are capable to model only two discrete alternatives, whereas *Multinomial Logit* (MNL) models are suitable to model higher numbers of alternatives (Khan, 2007). Both type of logit models are applied in the present study. This will be further discussed in Section 4.3.

In general, three assumptions applies for logit models regarding the random component of utility (ε_{q}) (Khan, 2007): The random component of utility is,

i. Gumbel distributed;
ii. Independently distributed; and
iii. Identically distributed.

The first assumption indicates that the utilities of an alternative should be assumed as the linear sum of attributes, and have the same scale parameter. Usually, the last two assumptions are combined and referred to *Independence of Irrelevant Alternatives* (IIA), which means that the alternatives used are independent of each other.

As mentioned previously, BL models and MNL models differ from each other by the number of alternatives than can be included to the model. This implies that both models are expressed differently. The probability of an individual choosing alternative, *i,* by individual, *q*, is given in Equation (4) and (5) for BL models and MNL models respectively.

$$P_q(i) = \frac{\exp(V_{\mathrm{iq}})}{\exp(V_{\mathrm{iq}})+\exp(V_{\mathrm{jq}})} \quad \forall i \in C_q \tag{4}$$

$$P_q(i) = \frac{\exp(V_{\mathrm{iq}})}{\sum_{j\in C_q} \exp(V_{jq})} \quad \forall i \in C_q \tag{5}$$

Where:

P_{iq}, is the probability of alternative *i* being selected by individual *q*;

The mathematical technique of *Maximum Likelihood Estimation* (MLE) is one of the most used to estimate the estimators, or parameters of discrete choice models (Hensher et al., 2005). According to Ben-Akiva and Lerman (1985, p. 20), the estimators can be described as *"the value of the parameters for which the observed sample is most likely to have occurred"*. In other words, the MLE is used to estimate the parameters that explain the choice behavior of a population. To calculate the parameters by MLE function, the observations of a (random) sample must be independently related (Wittink, 2011). Accordingly, the likelihood of the whole sample is the product of the likelihoods of the individual observations, as indicated with the symbol, $\prod$, in Equation (6). The MLE function contains an indicator variable, y_{in}, where it is defined by value of 1 if individual, *q*, choose alternative, *i*, or a value equal to 0 if alternative, *j*, is chosen. The MLE function can be expressed as follows:

$$L(\beta) = \prod_{q=1}^{Q} \prod_{\mathrm{i}\in C_{\mathrm{n}}} P_q(i)^{y_{\mathrm{iq}}} \tag{6}$$

Where:

L, is the likelihood of the model assigned to the vector of the alternatives;
P_{iq}, is the probability of alternative *i* being selected by individual q;
y_{in}, is the indicator variable $\begin{cases} 1 \; if \; individual \; q \; choose \; alternative \; i \\ 0 \; is \; individual \; q \; choose \; alternative \; j \end{cases}$

The MLE function presented above can be transformed into the *Log Likelihood* (LL) function, as denoted in Equation (7). Several authors (e.g. Abdel-Aal, 2017; Ben-Akiva & Lerman, 1985; Khan, 2007) have documented this approach as being more convenient for use compared to the MLE function. Since the Log-function is monotonous, the values of the parameters do not change. To calculate the LL function, the natural algorithm, ln, of the probability of alternative, *i*, being selected by individual, *q*, is solved.

$$LL(\beta) = \sum_{\mathrm{n}=1}^{Q} \sum_{\mathrm{i} \in Cq} y_{iq} \times ln(P_{\mathrm{iq}}) \qquad (7)$$

In order to provide insight into the significance of Logit models two descriptive measures, i.e. the (i) *Log Likelihood* (LL) *ratio-test* and the (ii) *Log Likelihood* (LL) *ratio-index*, will be discussed that are used in the present study.

Firstly, LL ratio-test, also referred to –2LL is briefly discussed. For this test, the LL function of the *unrestricted*, LL_U, and *restricted*, LL_R, model is compared with the *Chi-squared statistic,* χ^2, as expressed in Equation (8). Assume *K* for the number of estimated parameters. The value of the chi-square statistic can be determined from the distribution table, depending on the number of degrees of freedom (i.e. $K_U - K_R$) and level of confidence used. If the difference between the unrestricted and restricted model is considerably that exceeds the chi-squared statistic (i.e. $\chi^2 < -2\mathrm{LL}$), the null hypothesis can be rejected, which postulates that the unrestricted model is not better than the restricted model (Koppelman & Bhat, 2006).

$$\textit{Likelihood ratio-test} = \chi^2 = -2(LL_R - LL_U) \qquad (8)$$

Where:

LL_R, is the likelihood of the restricted model; and
LL_U, is the likelihood of the unrestricted model.

It should be noted that in the remainder of this study, the unrestricted model, LL_U, is referred to the *optimal model,* LL_β, and the restricted model, LL_R, is referred to the *null model*, LL_0. This is done to allow a better interpretation of the model results as discussed in Chapter 4.

The second measure of logit models is the LL ratio-index, which is reflected by the rho-squared value (ρ^2). This measure describes the overall goodness of fit between two statistical models, i.e. how well a model performs in relation to a second model (Hensher et al., 2005). Three LL functions of logit models can be distinguished (Koppelman & Bhat, 2006):

i. Null model (LL_0);
ii. Constants-only model (LL_c); and
iii. Optimal model (LL_β).

Considering the LL function of the null model and optimal model, the rho-squared value in fact represents the relationship between these LL functions. How to calculate the rho-squared, is expressed in Equation (9).

$$\rho_0^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{9}$$

Where:

ρ_0^2, is the ratio between the reference model and estimated model;
$LL(\beta)$, is the likelihood of the optimal model (estimated); and
$LL(0)$, is the likelihood of the null model (reference).

By definition, the value obtained from Equation 8 ranges between 0 (no fit) and 1 (perfect fit). Although many authors (e.g., Ben-Akiva & Lerman, 1985; Koppelman & Bhat, 2006), remarked that no guidelines exist for the rho-squared value, more recent studies (e.g., and Khan, 2007; Ortúzar and Willumsen, 2011) assume a value of 0.3 or higher to represent a good model fit, which is equivalent to a R-squared value of 0.6 in linear models (Hensher et al., 2005).

3.3 Design of Stated Preference Experiment

This section discusses the process that is used to generate the experimental design. Experiments have one principal goal, that is, ensuring observation into the effect of the *response variable* by manipulating the levels of one or more other variables (Hensher et al., 2005, p. 100). It should be noted that the terms "variable" and "attribute" are used interchangeably in this chapter.

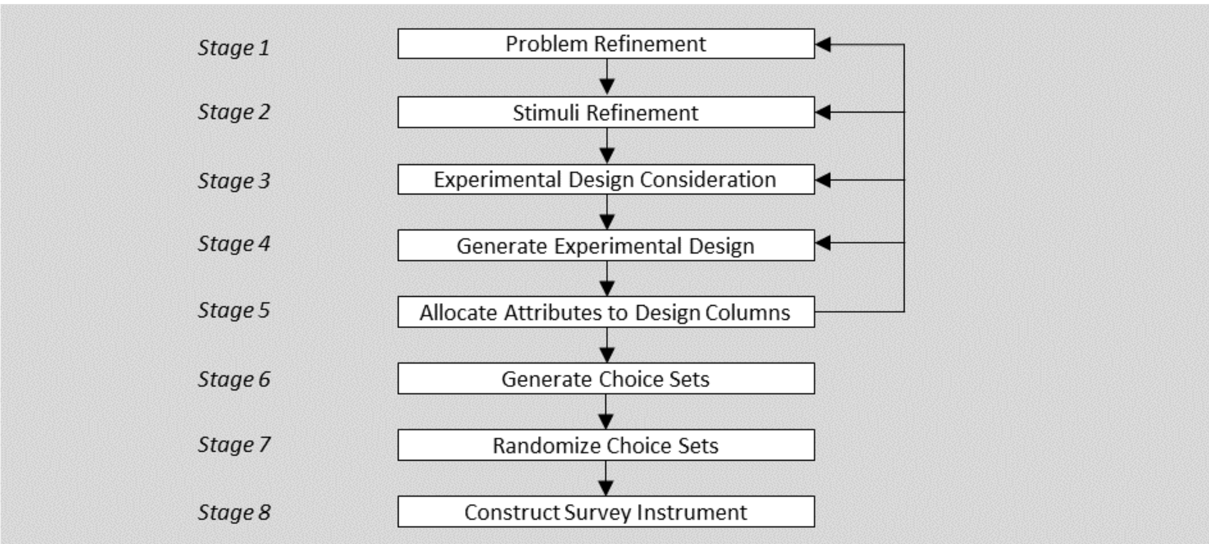


Figure 15. Stated Preference Experiment design processes based on work by Hensher et al. (2005 p. 102).

In the present study, the approach by Hensher et al. (2005) is followed, whereby eight stages are established to design the Stated Preference (SP) experiment. Figure 15 gives an overview of the relevant stages. Step by step, these stages are described in the following sections.

3.3.1 Problem Refinement

A modal shift towards more sustainable transportation alternatives (e.g. bicycle, train) is required to address the problems our society is currently facing; as a result of the ever increasing private car use. Especially commuter traffic deserves attention, which is the focus in this study. A clear definition of the research problem forms the basis to provide insight into what the study aims at the final end (Hensher et al., 2005). Given the research objectives as defined in Section 1.4, the following formulation can be provided:

> *"This study aims to examine the attributes that influence the preference of individuals for urban BSSs, and whether urban BSSs in the egress trip of train journeys influences the transportation mode choice of individuals regarding commuting travel."*

The underlying idea of this formulation is that the implementation of urban BSSs in the egress phase of multimodal train journeys can contribute to more complete door-to-door journeys. Since the egress trip is one of the weakest parts of the chain of trips of multimodal train journeys (see Section 2.2.4), the implementation of urban BSS may enhance the service in this way from the perspective of travelers.

In so far, the theoretical background (Chapter 2) has provided an answer to the research questions relating to multimodal (train) transportation (*research question 1*), bicycle sharing systems (*research question 2*), and the factors that influence the transportation mode choice of commuters (*research question 3*). However, there are still three research questions that need to be answered by means of the experiment.

> Research question 4:
> *What attributes influence the preference for urban bicycle sharing systems?*
>
> Research question 5:
> *How should urban bicycle sharing systems be designed in the egress trip of train journeys in order to attract the <u>current private car commuters</u> for commuting by train?*
>
> Research question 6:
> *How should urban bicycle sharing systems be designed in the egress trip of train journeys in order to attract the <u>current train commuters</u> to make use of shared bicycles?*

Since the integration between urban BSS and train is not natural in the Netherlands, this refers to a hypothetical situation (i.e. a choice situation not existing or fully integrated yet into a population) that will be presented to the respondents. Given this assumption, a SP experiment is a suitable method to provide an answer to the research questions mentioned above.

In order to reduce the complexity of the SP experiment, the research questions are analyzed separately based on the subdivision that is made within the sample. This implies that only the current private car commuters and train commuters will be invited to participate to the SP experiment. Considering the research objectives of the study, the other respondents or type of commuters are not relevant to be analyzed, and will be therefore rejected from the SP experiment. Furthermore, the present study focuses exclusively on multimodal journeys where the train is used as main transportation mode for commuting trips. In this way, insight can be provided into the potential of model shift of the current private car commuters to the train. The urban BSS is presented to respondents as egress mode to travel from the train station to the work location. The first stage of multimodal journeys, the access trip, has been omitted during the SP experiment. This is in line with the scope of the study, which is exploring the influence of urban BSSs in the egress trip on the transportation mode choice of individuals.

The general setup of the SP experiment is shown in Figure 16. Two sub-experiments can be distinguished which both consist of two parts or elements. Research question 4 relates to the *bicycle sharing system* part, in which the attributes regarding the preference for choosing an urban BSS in relation to an OV-fiets are investigated. The second part, *transportation mode choice*, investigates the influence of the attributes on the transportation mode choice of commuters. A subdivision between two types of commuters enables to explore whether differences exist between them in terms of BSS preference. It is hypothesized that private car commuters add more value to waiting times compared to the train commuters, as the latter are used to do this more often.

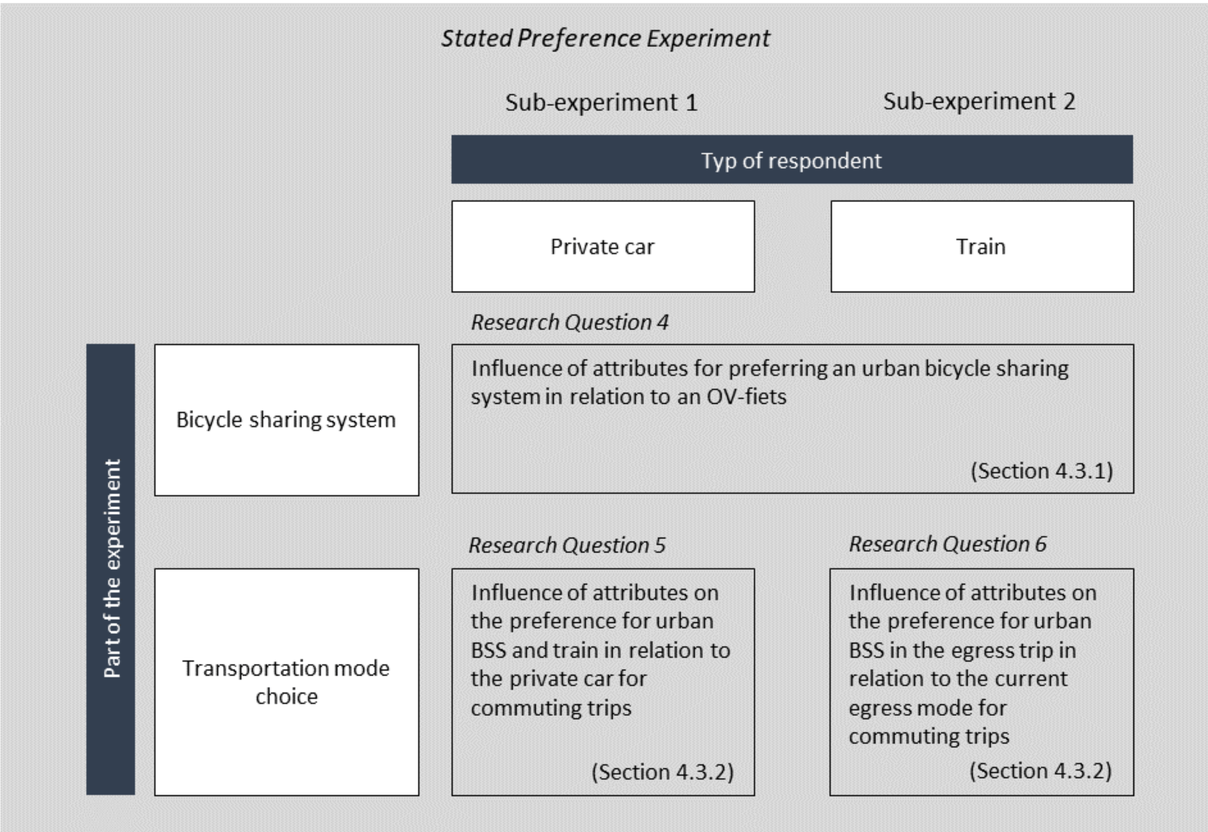


Figure 16. Sub-experiments and elements of the Stated Preference experiment

3.3.2 Stimuli Refinement

In the previous section the research problem has been briefly refined. This section discusses the *stimuli refinement* of the experimental design process. In this stage the various *alternatives*, *attributes*, and *attribute levels* will be identified. According to Hensher et al. (2005, p. 104), the list of alternatives should be *"universal"* but "*finite*", meaning that all alternatives must be presented to the respondents that falls within the context of the study. By fulfilling this condition, the utility maximization rule is not violated. However, in case of too many alternatives, culling some alternatives may be need in order to reduce the complexity. The alternatives that have been defined for both sub-experiments will be discussed below.

The SP experiment of the present study consists of two sub-experiments that can be further subdivided into two parts or tasks (see Figure 16). In the first part of both sub-experiments, the respondents are required to indicate their preference with respect to *three alternatives*, i.e. (i) *urban BSS 1*, (ii) *urban BSS 2*, and (iii) *OV-fiets*. The first two alternatives are *flexible* (i.e. varies in attributes levels), while the third alternative is *fixed* (i.e. constant set of attribute levels) all over the SP experiment. Limiting to three alternatives, ensures to keep the SP experiment understandable for the respondents, and additionally to generate more in-depth insight into the attributes regarding the preference for an urban BSS. The flexible alternatives are *unlabeled*, while the fixed alternative is *labeled* as *'OV-fiets'*. Since the OV-fiets is an existing BSS in the Netherlands, it is supposed that most of the respondents may ever have used or heard about the system. For those, this possibly helps to compare the alternatives.

With respect to the transportation mode choice-part of the sub-experiments, two labeled alternatives are assigned to each. The private car commuters (sub-experiment 1) are asked to make a transportation mode choice regarding to their commuting trips, between the (i) *private car* and the (ii) *train*. By doing so, insight into the influence of each attribute on the transportation mode choice (i.e. the willingness to shift to the train for commuting trips) can be determined. Two other alternatives applies for the train commuters (sub-experiment 2). This is because the train commuters are asked if they would choose a (i) *shared bicycle* as egress mode instead of their (ii) *current egress mode* used. This analysis provides insight whether train commuters are willing to use urban BSSs in the egress trip.

After defining the alternatives of the experiment, the second phase of the stimuli refinement stage follows. In this phase the attributes and related levels of the alternatives are defined. Basically, the attributes represent the characteristics of alternatives that are further specified by values, the levels. Considering sub-experiment 1, the set of attributes is for all alternatives fixed. However, it should be noted that alternative 3, OV-fiets, has a reduced number of attributes. This is because not all attributes can be are relevant or can be assigned to the OV-fiets. The other two alternatives, urban BSS 1 and urban BSS 2, have the same set of attributes and only differ in levels. Defining the attributes is a complex task that requires attention to the concept of *inter-attribute correlation* (Hensher et al., 2005). This can be explained as the cognitive perception of the respondent in which different attributes are linked to each other.

Next to the attributes, also the levels have to be defined. The first concern is regarding how many levels each attribute should contain. Hensher et al. (2005, p. 107) noted that the amount of information assigned to an attribute is relative to the number of levels in the utility space.

From three attribute levels a non-linear relationship can be detected. For this reason, it is attempted to obtain three levels in each attribute.

Referring to Table 1, the attributes and number of related attribute levels that will be used in the SP experiment are listed. Except for the attribute 'bicycle type' (two levels), all the other attributes include three levels. As mentioned above, the OV-fiets alternative have a reduced number of attributes. Since a daily rental fare applies to the OV-fiets, users do not need to return the bicycle to a station that is closest to their work location. For this reason, the attributes 'egress time' (because users can park the bicycle as closest to work location) and 'reliability at endpoint' (because the bicycle is always at disposal of users) are rejected. Besides defining the number of levels also the range of the levels requires attention. This is especially for the attributes including numerical values, such as *time* in '*minutes'* or *costs* in '*amount of euros'*. This will be further discussed in the next section.

3.3.3 Experimental Design Consideration

This stage introduces the design that will be used in the SP experiment. Several experimental designs exist. The *full factorial design* is commonly applied, in which all possible *treatment combinations* are listed (Hensher et al., 2005). A treatment combination can be described as a combination of attributes, in which each has unique levels. Because the experiment includes in total *seven* attributes, of which *six* attributes having three levels and *one* having two levels, when applying a full factorial design, the experiment would consist of 1458 (i.e. 2^1x3^6) treatment combinations. This number of combinations is by far not feasible to examine in this study. Consequently, a *fractional factorial design* is used that will be further described below.

Defining the attributes that influence the preference for choosing an urban BSS, involve an *unlabeled* experiment; in which generic titles are used for the alternatives presented to the respondents. It should be noted that the *labeled* alternative (i.e. OV-fiets) is fixed all over the experiment. The titles used for the alternatives (i.e. urban BSS 1 and 2) do not provide any information about the urban BSSs themselves, but these only ensure that a distinction between the presented alternatives is possible. Hensher et al. (2005, pp. 112-113) highlighted several advantages of unlabeled experiments in relation to labeled experiments, such as no requirement to define all alternatives in the universal set of alternatives; less chance of correlations between alternatives and attributes; and the problem of historical accumulation of utility. Furthermore, for unlabeled experiments applies a reduced number of treatment combinations. As mentioned before, a fractional factorial design will be applied to reduce the number of treatment combinations. In this way, it is hoped to avoid considerable cognitive burden on respondents and decrease the response unreliability. To avoid an inefficient design, as a result of random selection, the number of treatment combinations is reduced by the statistical concept of *orthogonality*. This mathematical technique ensures that the attributes are independently related to each other, thus having zero correlations within the SP experiment (Ortúzar & Willumsen, 2011).

Only the *main effects* are considered in this study. Hensher et al. (2005, p. 116) describe the main effects as the direct independent influence of each attribute on the response variable. Referring to Equation (2), this relates to the effect of each attribute, X_{Ki}, has to the variable

V_{iq}, depending on its associated weight, β_K. In advance to generate the experimental design, it is required to determine the design coding of the SP experiment. In fact, each design code represents one attribute level. In Table 1 is shown which design code is assigned to each attribute level. Given three attribute levels, the coding format used includes the numbers 0, 1, and 2, in which '0' represents the reference level in the experiment. Furthermore, to each design code an attribute-level label is assigned. This will be discussed in Section 3.3.5.

Table 1. Attribute levels and design coding of the bicycle sharing system alternatives

	Attributes (number of levels)	*Alternatives*			
		Urban BSS 1 and 2 (*Flexible*)		OV-fiets (*Fixed*)	
		Design coding / attribute label			
A	Type of bicycle	0	Traditional	-	Traditional
	(2 levels)	1	Electric		
B	Reservation option	0	None	-	OV-chipcard
	(3 levels)	1	OV-chipcard		
		2	Application		
C	Rental fare	0	0.50 euro	-	3.85 euro
	(3 levels)	1	1.00 euro		
		2	1.50 euro		
D	Access time	0	1 minutes	-	1 minutes
	(3 levels)	1	5 minutes		
		2	3 minutes		
E	Egress time	0	5 minutes	-	0 minutes
	(3 levels)	1	3 minutes		
		2	1 minutes		
F	Reliability at starting point	0	5 minutes	-	*None*
	(3 levels)	1	10 minutes		
		2	0 minutes		
G	Reliability at endpoint	0	5 minutes	-	*None*
	(3 levels)	1	0 minutes		
		2	10 minutes		

3.3.4 Generate Experimental Design

Previous section discussed that a fractional design with main effects only will be applied in the experiment. The next stage in the experimental design is the *experimental design generation*. This is conducted by using the software package of SPSS version 23. Having included all (7) BSS attributes, the *Orthogonal Design* can be generated. The output of the orthogonal design is presented in Table 2. As shown, the experimental design consists of in total 32 treatment combinations.

Table 2. Orthogonal fractional design: Fixed bicycle sharing system Alternative

Treatment combination	*Attribute*						
	A	B	C	D	E	F	G
1	0	0	0	0	0	0	0
2	0	0	0	0	0	2	1
3	0	0	0	2	1	1	0
4	0	0	0	2	2	0	2
5	0	0	1	0	2	0	0
6	0	0	1	1	0	0	2
7	0	0	2	0	1	2	1
8	0	0	2	1	0	1	0
9	0	1	1	0	2	1	1
10	0	1	1	2	0	2	0
11	0	1	2	0	1	0	0
12	0	1	2	2	0	0	2
13	0	2	0	0	0	0	0
14	0	2	0	0	0	1	1
15	0	2	0	1	1	0	2
16	0	2	0	1	2	2	0
17	1	0	0	0	1	0	0
18	1	0	0	0	2	2	2
19	1	0	0	2	0	0	1
20	1	0	0	2	0	1	0
21	1	0	1	0	0	0	0
22	1	0	1	1	1	0	1
23	1	0	2	0	0	2	2
24	1	0	2	1	2	1	0
25	1	1	0	0	1	1	2
26	1	1	0	0	2	0	0
27	1	1	0	1	0	0	1
28	1	1	0	1	0	2	0
29	1	2	1	0	0	1	2
30	1	2	1	2	1	2	0
31	1	2	2	0	0	0	0
32	1	2	2	2	2	0	1

In order to prove that orthogonality applies to the experiment, a correlation analysis has been performed. Since there are no correlations between the attributes (i.e. r = 0.000), it can be stated that orthogonality is achieved in this experiment.

3.3.5 Generate Choice Sets

This section discusses what a choice set is, how it is generated, and which choice sets will be used in the SP experiment. Hensher et al. (2005, p. 116) define a choice set as a *mechanism* in which information is presented to respondents concerning the alternatives, attributes, and levels that are defined within the hypothetical context of the study. Basically, the first step towards the generation of choice sets has already been taken in the previous section. The generated treatment combinations, represent the various alternatives of the SP experiment, however expressed in a coding structure (see Table 2). While this design is useful, it is not suitable for field distribution. Below, it is described how the treatment combinations are transformed into workable choice sets.

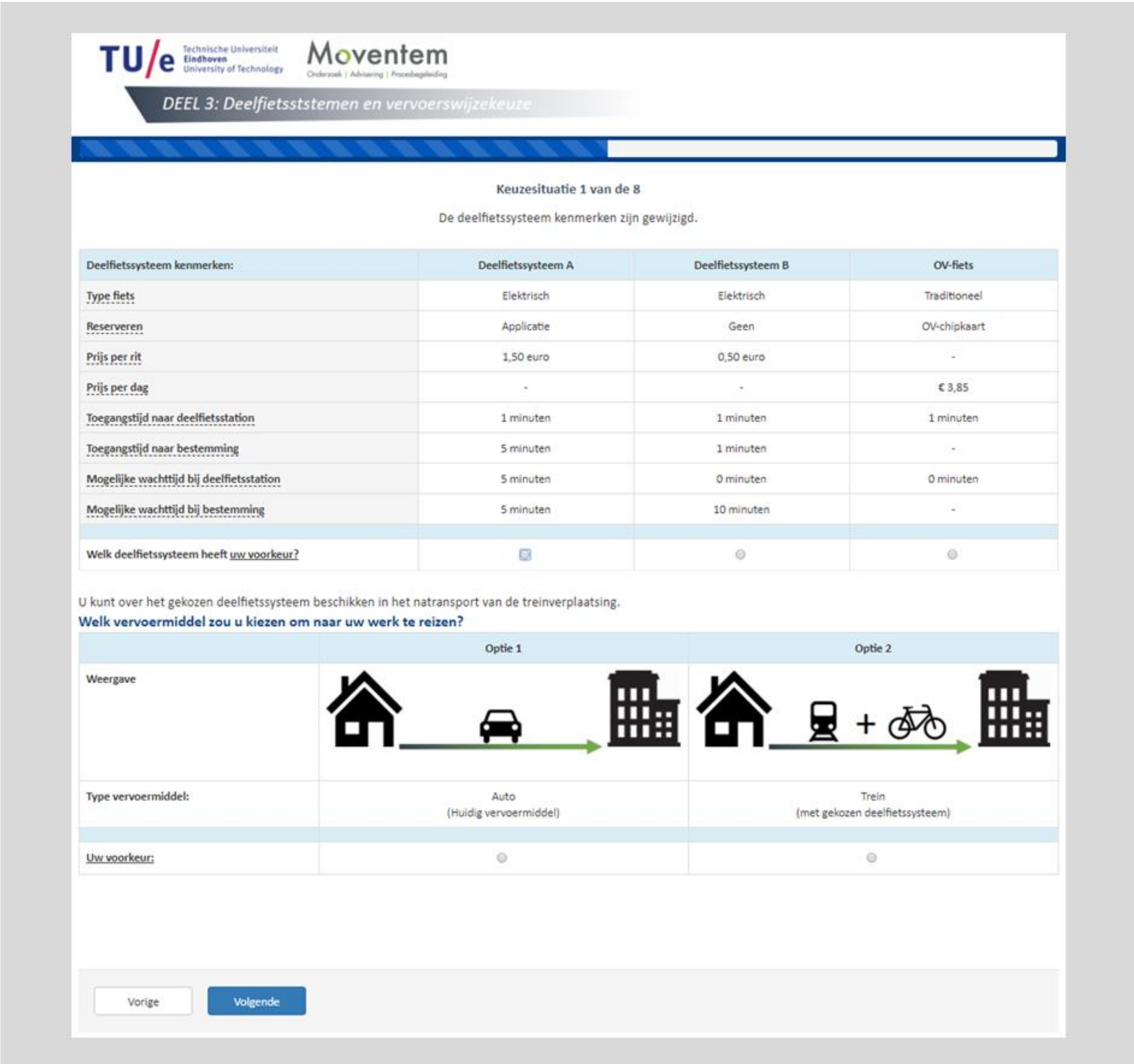
The first step in choice set generation is attaching the attribute-level labels to the design. Given that each attribute level is *unique* within the SP experiment, there is no standard approach for replacing the design codes by the attribute-level labels. It is up to the researcher to decide which label will be allocated to which design code. However, while doing this, the researcher must be aware to the emergence of extremely positive or negative alternatives. To show this, the reader must ignore the design coding as provided in Table 1, since this design is the final one that will be used to generate the choice sets later on.

In order to determine whether *dominant* alternatives (i.e. alternatives that would always or never be chosen by the respondent) are present in the experimental design, the attribute-level labels are allocated in a structured manner. Firstly, the attribute-level labels are allocated in ascending order, based on its numerical value. This applies only for the *time*- and *cost*-related attributes. Secondly, to each attribute level a score is assigned. Assuming that an attribute has three levels, a score of '0' is assigned to the lowest numerical value; '1' to the next value; and '2' to the highest value. Removing alternatives with extreme scores would affect the orthogonality of the design. In seeking to remove the dominant alternatives from the experimental design, the attribute-level labels were recoded again and again. Finally, an experimental design is generated including only one dominant alternative (i.e. treatment combination 8) as shown in Appendix A.

3.3.6 Randomize Choice Sets

Randomizing the choice sets has clearly a purpose, and that is to prevent misleading or inefficient data afterwards. During the SP experiment, the respondents are asked to repeatedly make a choice between three alternatives. If these alternatives are presented in a specific order, this may lead to biased results. Hensher et al. (2005) noted that respondents experience a learning process during experiments, whereby choices made at the beginning may differ in utility or preference from those at the end of the experiment. In order to avoid biased results, two measures have been taken. Firstly, the 'learning' of respondents is facilitated by presenting a 'practice' choice set (i.e. the first) in the beginning of the SP experiment; and secondly, all choice sets are randomized.

Two different ways of choice-set randomization are applied in the experimental design. First, the alternatives are combined differently into choice sets. Second, the order of which the choice-sets are presented to respondents in the SP experiment is also randomized. It should be noted that for the randomization only the flexible alternatives (i.e. urban BSS 1 and 2) are considered. The third alternative, OV-fiets, is included afterwards because the attribute levels of this alternative are fixed. The randomization of alternatives and choice-sets is performed in Excel, by using the function *"=ASELECT()"*. From the 32 alternatives, in total 16 profiles have been generated as shown in Appendix B. Given that each respondent is provided by *eight choice-sets* (with three alternatives) during the SP experiment, two unique choice experiments are created. In order to overcome the chance of biased results, the profiles are randomized three times. This implies that in total 48 different profiles have been generated. In this way, a total of six unique choice experiments including eight choice sets are created. A complete task, including the urban bicycle sharing system and transportation mode choice experiment part, is presented in Figure 17.


TU/e Technische Universiteit Eindhoven University of Technology

Moventem Onderzoek | Advisering | Procesbegeleiding

DEEL 3: Deelfietsststemen en vervoerswijzekeuze

Keuzesituatie 1 van de 8

De deelfietssysteem kenmerken zijn gewijzigd.

Deelfietssysteem kenmerken:	Deelfietssysteem A	Deelfietssysteem B	OV-fiets
Type fiets	Elektrisch	Elektrisch	Traditioneel
Reserveren	Applicatie	Geen	OV-chipkaart
Prijs per rit	1,50 euro	0,50 euro	-
Prijs per dag	-	-	€ 3,85
Toegangstijd naar deelfietsstation	1 minuten	1 minuten	1 minuten
Toegangstijd naar bestemming	5 minuten	1 minuten	-
Mogelijke wachttijd bij deelfietsstation	5 minuten	0 minuten	0 minuten
Mogelijke wachttijd bij bestemming	5 minuten	10 minuten	-
Welk deelfietssysteem heeft uw voorkeur?			

U kunt over het gekozen deelfietssysteem beschikken in het natransport van de treinverplaatsing.

Welk vervoermiddel zou u kiezen om naar uw werk te reizen?

	Optie 1	Optie 2
Weergave		
Type vervoermiddel:	Auto (Huidig vervoermiddel)	Trein (met gekozen deelfietssysteem)
Uw voorkeur:		

Vorige Volgende

Figure 17. Choice set as provided to respondents in the questionnaire

3.3.8 Construct Questionnaire

After having defined the choice sets that will be used in the SP experiment, all that remains is to *construct the questionnaire* itself. This relates to the eighth and also last stage of the experimental design process. Constructing a questionnaire requires effort, as this process should be structured in a such way that the collected data contributes to answer the research questions. Before discussing the different parts of the questionnaire, first the *context* of the experiment is briefly explained.

As stated by Hensher et al. (2005, p. 173), "*Every choice we make as human beings is made within a decision context*". This statement highlights two important aspects that must be considered while designing experiments, that is ‘*human beings’* (the respondents) and *‘decision context’* (the situation within the respondents are placed to make a decision). The group of individuals or target population the SP experiment focuses on can be described as follows:

> *“All commuters of the Netherlands, that are aged 15 years or older who travel at least once a week from their home location to work location, and usually use the private car or the train as transportation mode to realize their commuting trips”.*

This description has been used to select the respondents who belong to the target population of the study. It should be noted that the target population is a part of the total Dutch population of commuters. An indication of the total target population will be provided in Chapter 4. Since only the Dutch commuters as specified in the description falls within the scope of the study, the questionnaire was drawn up in Dutch; assuming that all respondents master the language of instruction. The questionnaire consists of five main parts that can be further subdivided into the following seven sub-parts:

i. Introduction to questionnaire (*part 1*);
ii. Selection of respondents (*part 1*);
iii. Commuting trip characteristics (*part 2*);
iv. Transportation mode-related statements (*part 3*);
v. BSS-related statements (*part 4*);
vi. BSS preference and transportation mode choice (*part 4*);
vii. Socioeconomic factors (*part 5*).

Each part of the questionnaire will be described below. In advance, it is worth to mention that a descriptive story is provided at the beginning of each part of the questionnaire. Accordingly, it is hoped that enough understanding is gained by the respondent to fill the questionnaire further in a knowingly manner.

The *first part* of the questionnaire is the introduction. Here, the respondents are informed about what the research aims to achieve and how the questionnaire is structured. Then, two questions are presented for the selection of respondents. The first question relates to the *frequency of commuting trips.* The respondents who commute ‘*less often than once a week’* or *‘never’*, were rejected from the questionnaire. The second question relates to the *most frequently used transportation mode for commuting trips*. Since the present study focuses only on the commuters that use the private car or train to realize commuting trips, the commuters who travel usually by ‘*other modes’* (e.g. bicycle, bus) to their work place were also rejected from the questionnaire. Based on these two questions, a large proportion of respondents who were not of interest to the study could be screened out of the questionnaire.

In the *second part* of the questionnaire, the respondents are asked about the characteristics of their most realized commuting trip. It should be noted that these questions relate to the most used transportation mode (i.e. the private car or train) to commute. The questions regarding the trip characteristics provide insight into the current travel behavior of the respondents. In addition, this data can be used to support the results of the study.

Having defined the most frequently used transportation mode for commuting and the related trip characteristics, the *third part* of the questionnaire presents in total eight transportation mode-related attitudinal factors to the respondents. The respondents are asked to what extent they agree with each of the attitudinal factors. The aim of this part is to get insight into the influence of the behavioral factors such as attitudes, habits, etc. (see Section 2.4.1), concerning the most used transportation mode. It is supposed, that the willingness of the respondents to shift from the private car to the train diminishes when respondents have a strong private car habit.

The fourth part of the questionnaire is dedicated to the SP experiment. What is meant to be achieved with the SP experiment has already been discussed in Section 3.3.1. Prior to the SP experiment, a total of six BSS-related attitudinal factors are presented to the respondents. This has been done to gain insight into how respondents view BSS. Next, the alternatives and attributes (discussed in Section 3.3.2) of the SP experiment are explained. To make the context of the SP experiment easier to understand, figures were used. Then, an example task (see example in Figure 17) is presented to the respondents. In this way, it is hoped to teach the respondents sufficiently, so that they can perform the SP experiment as consistently as possible. After the example choice set has been completed, eight choice sets will follow.

Eventually, in the fifth and last part of the questionnaire the socioeconomic characteristics of the respondents are asked. The characteristics that will be asked include: '*gender*', '*year of birth*', '*education level*', '*household composition', 'driving license possession', OV-chipcard ownership',* and '*transportation mode availability for commuting*'. According to existing literature, these factors do not contribute to explaining the transportation mode choice of individuals. However, these factors are useful to provide insight into the characteristics of the sample. Having finished this part, the questionnaire ends.

3.4 DATA COLLECTION

The design of the SP experiment and the questionnaire were discussed in the previous sections. Next, the process of data collection will be discussed. This process should not be underestimated, as this may affect the results of the study. Referring to Section 3.3.1, the two types of respondents were distinguished that belong to the target population of the study. Since the context of choice of both types of respondents is different, the questionnaire must be clearly structured to ensure that the right set of questions and choice sets are presented to each type of respondent.

Hensher et al. (2005) emphasize the necessity of testing the questionnaire instrument before field distribution. The questionnaire of the present study has been tested for a period of one week. In total, 12 respondents completed the questionnaire in the test phase and provided feedback for improvements. At the same time, the collected data were analyzed in order to verify whether the output.

The target population is selected based on their frequency of commuting and most frequently used transportation mode to realize these trips. By this selection, it is ensured that only the respondents who have sufficient experience with commuting, and additionally relevant for mode choice in practice can participate to the questionnaire. Figure 18 shows the routing of the questionnaire. Each part of the questionnaire has already been discussed in Section 3.3.8.

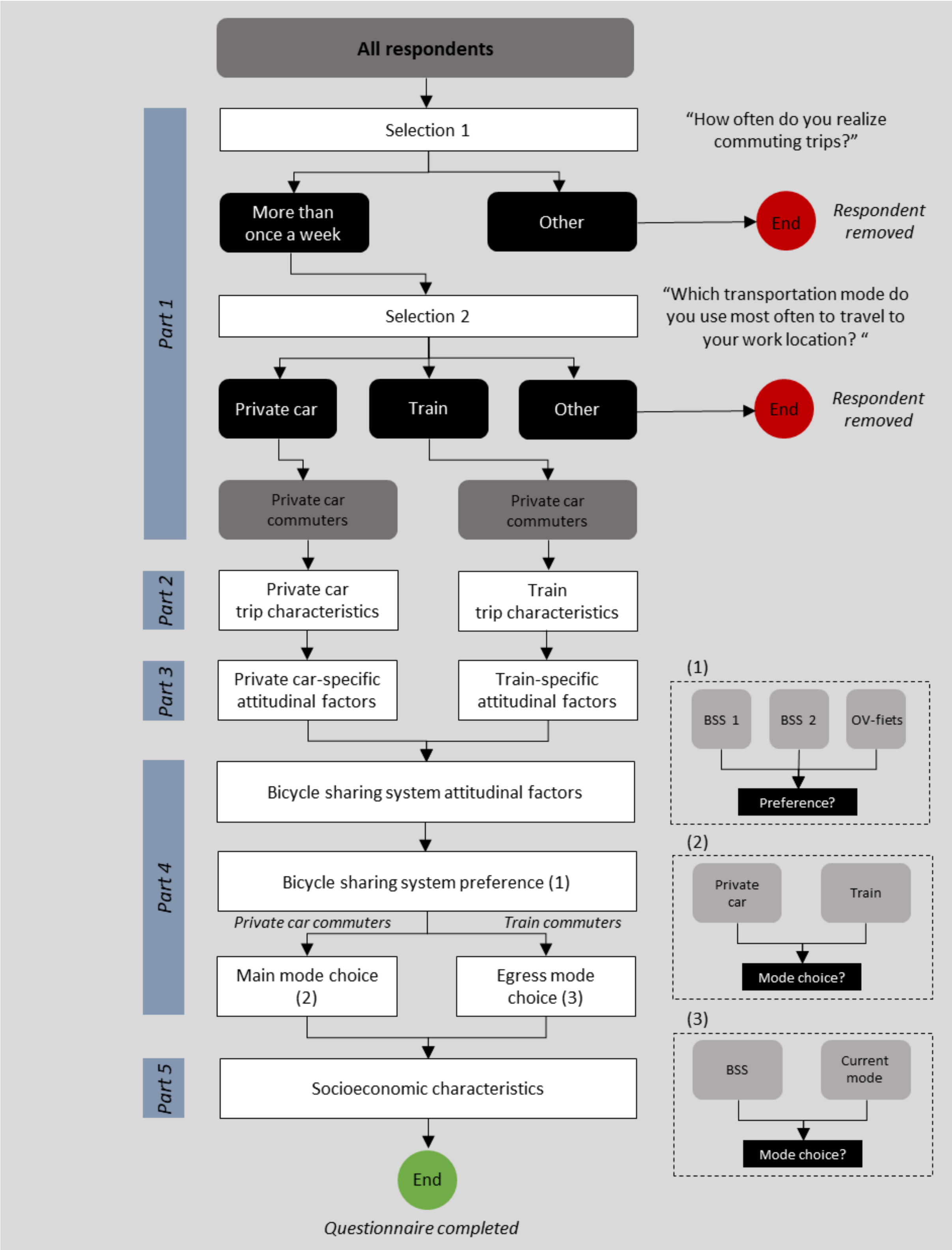


Figure 18. Routing of the questionnaire

The sample is aimed to be representative for the Dutch population of commuters regarding the socioeconomic characteristics. The data is collected through an online questionnaire where respondents are recruited by Panel Inzicht, which is an online fieldwork organization in the Netherlands. This ensures data collection with comparable distributions to the Dutch (target) population. Furthermore, also individuals from the social network are invited to participated to the questionnaire. With the exception that only respondents aged 15 to 67 years are allowed to participate to the questionnaire, no further sampling restrictions have been formulated. Indicating that respondents can be gathered throughout the Netherlands.

4 RESULTS

4.1 Introduction

Chapter 3 discussed the research method and design of the questionnaire. As mentioned, the design determines the quantity and quality of the response and data of the questionnaire. This is especially a challenge in experimental designs, because respondents are required to make decisions between alternatives repeatedly. During the designing of the questionnaire, the focus was on the collection of the most relevant data in order to avoid additional burden to respondents. In principle, the data to be collected should support the research objectives of the study. Consequently, data were collected about the travel behavior of commuters in the Netherlands. Primarily, this data should provide insight into two main subjects, that is, the attributes that influence the preference for choosing urban BSSs and the attributes that influence the transportation mode choice of commuters.

This chapter discusses the data that were collected through the online questionnaire. In the following section the descriptive analysis is presented (Section 4.2). This is followed by the model analysis, which include the estimation of the attribute parameters (Section 4.3). Finally, the main results of the estimated models are discussed (Section 4.4).

4.2 Descriptive Analysis

A total of 910 respondents started the questionnaire, of which 385 (i.e. 42.3 percent) of them completed the questionnaire according to the predefined requirements. The process of data cleaning is shown in Figure 19. In order to select the target population, two questions were asked in the introduction part of the questionnaire. The first question relates to the *frequency of commuting*. The respondents who indicated to travel less frequently than once a week or even never from their residence to a work location were excluded from the questionnaire. The second question relates to the most used transportation mode to realize the commuting trips. In accordance with the research objectives, only the respondents who travel most frequently by (i) *private car* or (ii) *train* are of interest in this study, and therefore further guided by the questionnaire. In order to estimate the models with a dataset that is reliable as possible, the data of the respondents is checked based on the following criteria:

- All questions in the questionnaire must be completed (status: *finished*);
- If the completion time is less than 6 minutes, it is assumed that the respondent did not correctly filled in the questionnaire (estimated completion time: *12 minutes*);

- If the travel time is not feasible between the home and work location, the respondent is excluded by not answering seriously;
- If the exact same answer is given to all (14) attitudinal factors, the respondent is also excluded by inconsistently answering the questionnaire.

The above set of criteria is assumed to provide a good basis for data cleaning, and therefore to explore inaccuracies in the datasets. By this way, data of N = 260 private car and N = 125 train commuters was collected through the online questionnaire.

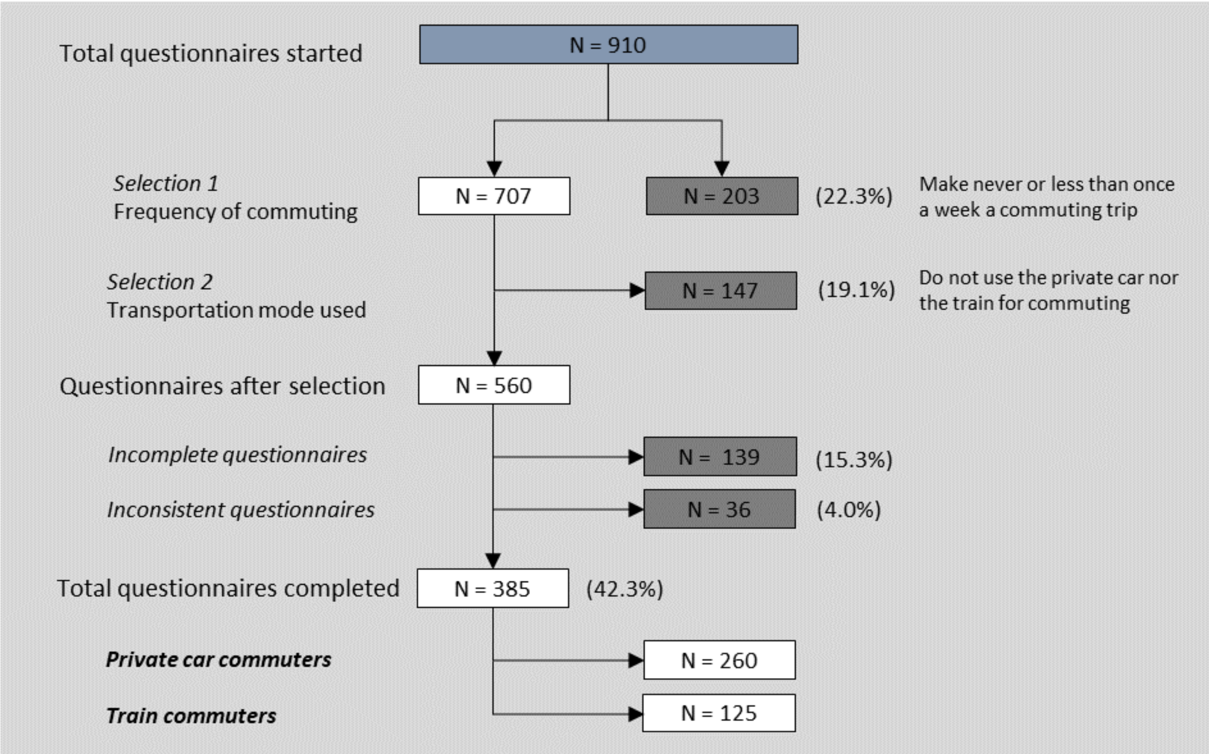


Figure 19. Data cleaning process of the questionnaire

4.2.1 Socioeconomic characteristics

This section discusses the socioeconomic characteristics of the respondents. Two important reasons underlie the decision to collect and analyze this data. Firstly, insight can be provided into the individuals or group of individuals (i.e. sample) who participated to the online questionnaire. Secondly, the composition of the sample can be used to support the research results. In order to determine whether the sample is representative in the Dutch context, the data is compared with the target population. The target population is estimated with the data that is published by the Central Bureau of Statistics (CBS). The descriptive analysis is based on the full dataset (i.e. N = 385).

Gender

The gender is the first socioeconomic characteristic that is discussed. The distribution is shown in Table 3. As can be seen, there is a small majority of men in the sample compared to women. This difference can be explained by the fact that more men are active in the labor force in the

Netherlands (CBS, 2015). Given the distribution of the target population, it can be assumed that the sample is representative regarding gender.

Table 3. Distribution of gender of the sample and target population

Gender	Frequency	Research [%]	Population* [%]	Deviation [%]
Male	209	54.3	52.0	+ 2.3
Female	176	45.7	48.0	- 2.3

* Estimation of the target population (CBS, 2015)

Age

The respondents were asked to indicate their year of birth. With this data the age of the respondents is calculated. In order to check whether the sample is similar to the target population, age groups of ten years are designated (i.e. this approach is also used by CBS). As listed in Table 4, there is an overrepresentation of respondents within the age group of 25 to 34 years. This may be due to the influence of social network. However, this is not considered as such a deviation that will influence the research results. More attention deserves the underrepresentation of respondents aged between 15 and 24 years. A possible explanation lies in the fact that many respondents of this age group (i.e. < 18 years) were excluded from the questionnaire, because of the selection requirements were not met. In general, it can be stated that the sample has a similar distributions compared to the target population of the Netherlands.

Table 4. Distribution of age of the sample and target population

Age group	Frequency	Research [%]	Population* [%]	Deviation [%]
From 15 till 24 years	23	6.0	17.1	- 11.1
From 25 till 34 years	105	27.3	21.8	+ 5.5
From 35 till 44 years	81	21.0	20.2	+ 0.8
From 45 till 54 years	87	22.6	22.9	- 0.3
From 55 till 64 years	77	20.0	16.5	+ 3.5
From 65 and older	12	3.1	1.6	+ 1.5

* Estimation of the target population (CBS, 2015)

Table 5. Distribution of education level of the sample and target population

Education level	Frequency	Research [%]	Population* [%]	Deviation [%]
Secondary vocational education	78	20.3	33.6	- 13.3
Higher professional education	178	46.2	22.0	+ 24.2
University education	110	28.6	12.2	+ 16.4
Other	19	4.9	32.1	- 27.2

* Estimation of the target population (CBS, 2015)

Education level

Referring to Table 5, the dominance of highly educated individuals in the sample is evident. The proportion of respondents with a university or higher professional education accounts for 74.8 percent. Although the distribution of the sample is not equivalent to that of the target population, there are enough respondents present within each education level group. Hence, it is not expected that the skewed distribution will have a strong effect on the study results of the study.

Household composition

The distribution of household types of the sample is shown in Table 6. As can be seen, the distribution of the sample deviates hardly from the target population. For this reason, the target population of the Netherlands is well represented by the sample based on the household composition.

Table 6. Distribution of household composition of the sample and target population

Household composition	Frequency	Research [%]	Population* [%]	Deviation [%]
Single household	73	19.0	15.3	+ 3.7
Single household with children	15	3.9	3.4	+ 0.5
Partnership with children	152	39.5	38.9	- 0.6
Partnership without children	114	29.6	25.1	+ 4.5
Other	31	8.1	17.3	- 9.2

In this section the descriptive analysis of the socioeconomic characteristics of the respondents has been discussed. From the analysis, it can be assumed that the dataset shows great similarities with the Dutch population. However, it should be considered that the target population is only an estimate. Although reliable data from the Central Bureau of Statistics (CBS) have been used, further research should be conducted to determine whether the estimated target population is actually a representation of the Dutch population targeted by this study. The respondents were selected based on their frequency of commuting and most frequently used transportation mode to realize commuting trips. As a result, many individuals with similar characteristics could be present in the sample. Based on the results discussed in this section, however, this is still unproven. Hence, the dataset is assumed to be useful to continue the analysis.

4.2.2 Commuting trip characteristics

In order to provide insight into the current travel behavior of the respondents with respect to their commuting trips, the characteristics of these trips were asked in the second part of the questionnaire. This section discusses the trip characteristics of the sample in more detail. By doing so, the sample will be subdivided into two types of commuters:

i. The private car commuters (N = 260); and
ii. The train commuters (N = 125).

This subdivision is in line with the research objectives (see Section 1.2). The *private car commuters* represent the group of respondents who travel generally by private car from their residence to work location; and the *train commuters* represent the group of respondents who do this by train. It is assumed that both types of commuters can differ in decision making and preferences, and therefore analyzing their trip patterns might be useful to serve as an explanation of the models that will be estimated in Section 4.3.

Residence and work location

Figure 20 provides an overview of the residence locations and work locations of the private car commuters over the Netherlands. As shown, the twelve provinces of the Netherlands are represented, however, in total seven provinces have a low response. Most of the private car commuters have their residence in the province of Gelderland and Noord-Brabant. It might be possible that this is influenced by the social network. A similar distribution applies to the work locations. The provinces that are part of the Randstad (i.e. Noord-Holland, Utrecht, and Zuid-Holland) represent 31.5 and 38.5 percent of residence and work locations of the private car commuters respectively.

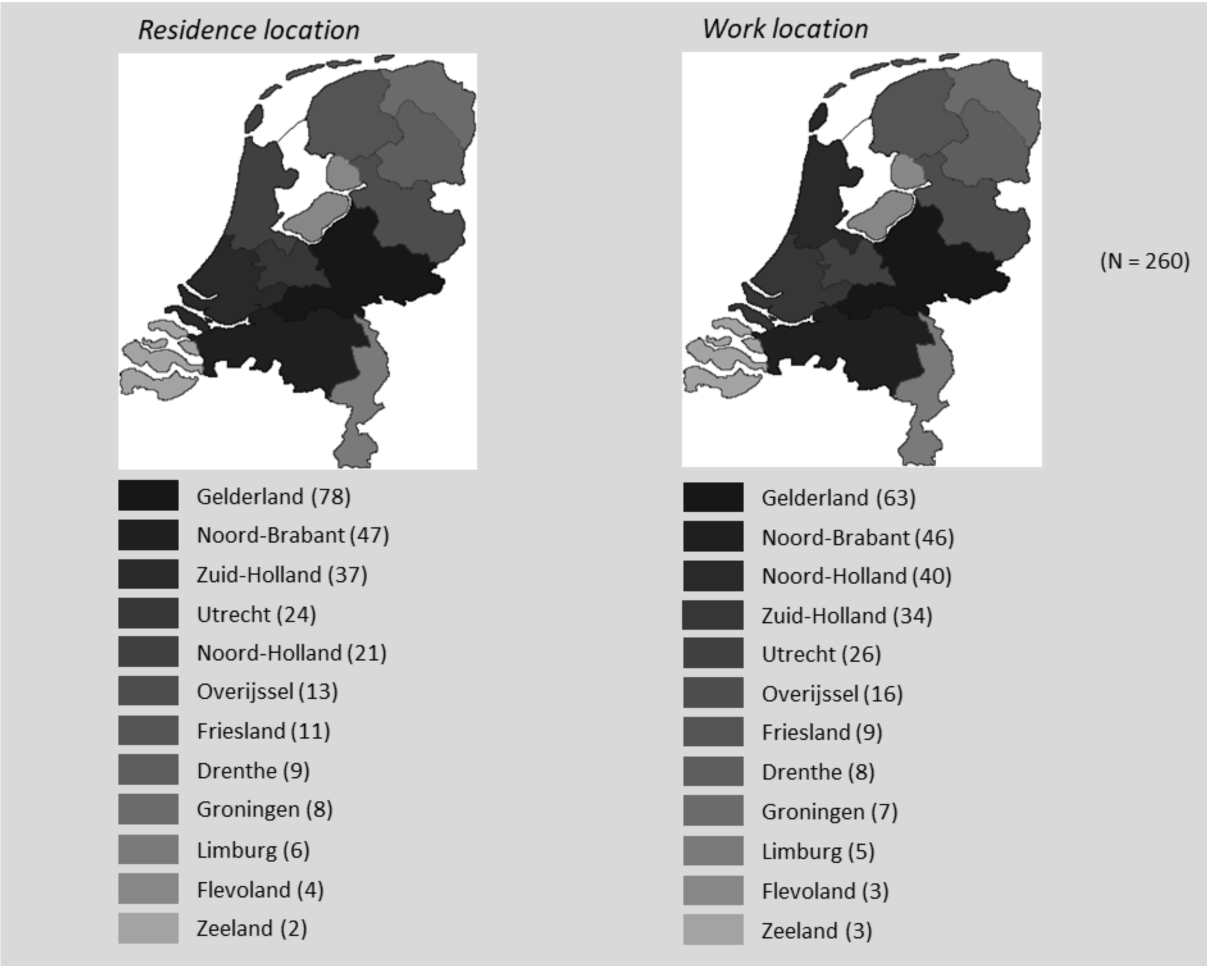


Figure 20. Residence location (left) and work location (right) of the private car commuters over the Netherlands

Considering the residence and work locations of the train commuters, some assumptions can be made. As shown in Figure 21, there are no respondents neither living or working in the province of Zeeland. This can be explained by the fact that the proximity (i.e. the distance in kilometers) to train stations in this province is considerably higher than the national average, which limits the access of individuals to the train service (CBS, 2016). The majority of the residence (i.e. 50.4 percent) and work locations (i.e. 73.6 percent) of the train commuters are located in the provinces that are part of the Randstad. A possible explanation for this can be that the Randstad is characterized by a dense railway network (CBS, 2016), making commuting by train a serious alternative.

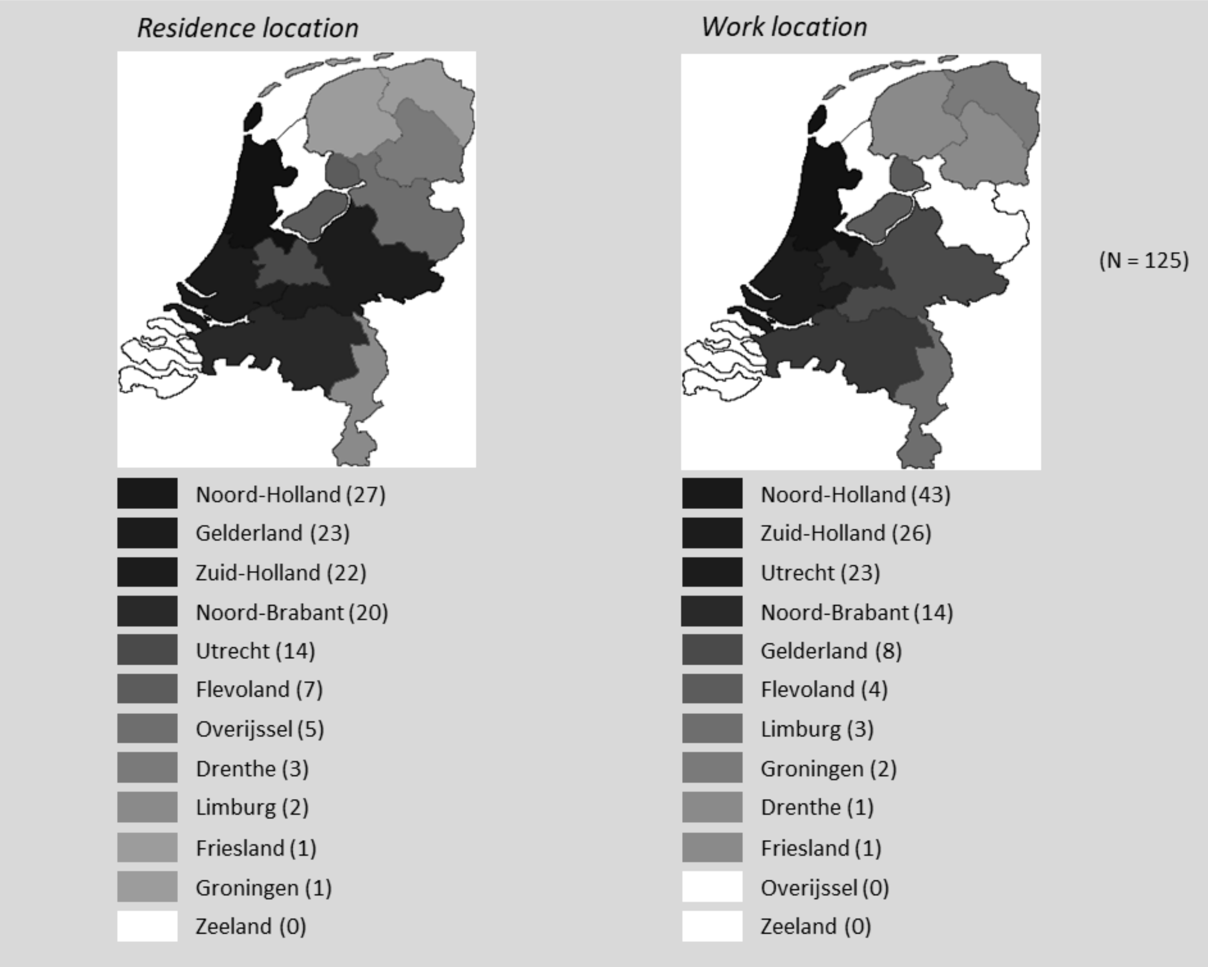


Figure 21. Residence location (left) and work location (right) of the train commuters over the Netherlands

Frequency of commuting trips

The respondents were asked how often they generally make a commuting trip. This was one of the two questions meant for the selection of respondents in the questionnaire. Figure 22 shows the distribution of the frequency of commuting trips of the whole sample, private car commuters, and train commuters. It should be noted that the respondents who travel less than once per week or even never from their residence to a work location were excluded from the questionnaire.

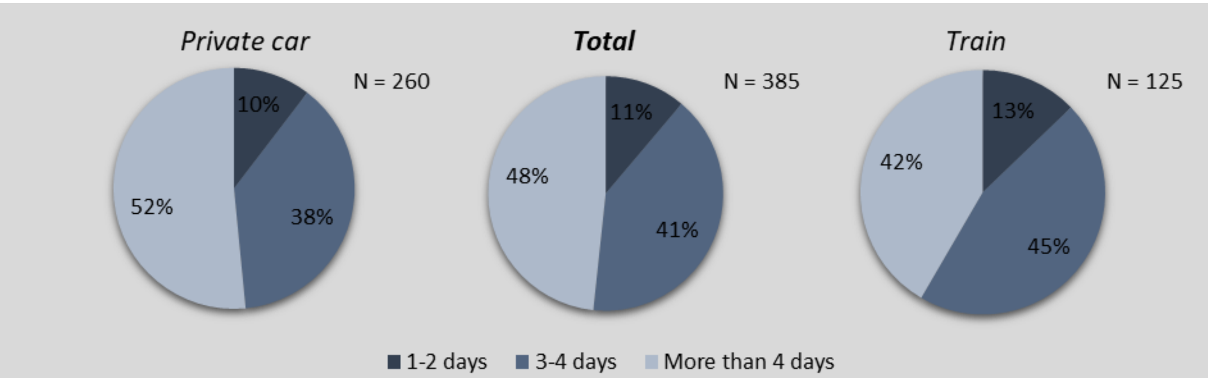


Figure 22. Commuting frequency: An overview of the sample

As shown, the sample is represented by approximately 90 percent of individuals who travel three or more days per week from their residence to their work location. The proportion of private car commuters working more than four days per week is higher than that of the train commuters, respectively 52 and 42 percent. It is plausible that when individuals have to realize a (commuting) trip more frequently, they tend to choose the most favorable transportation mode for them; and insights from the literature suggest that is in most cases the private car is preferred.

Travel time of the commuting trips

As discussed in the literature review, the transportation mode choice of individuals is primarily determined by travel time, and especially for the private car users (see results above). Data is gathered about the duration of the commuting trips of the respondents. The cumulative distribution of commuting trips of the sample over the travel time is shown in Figure 23.

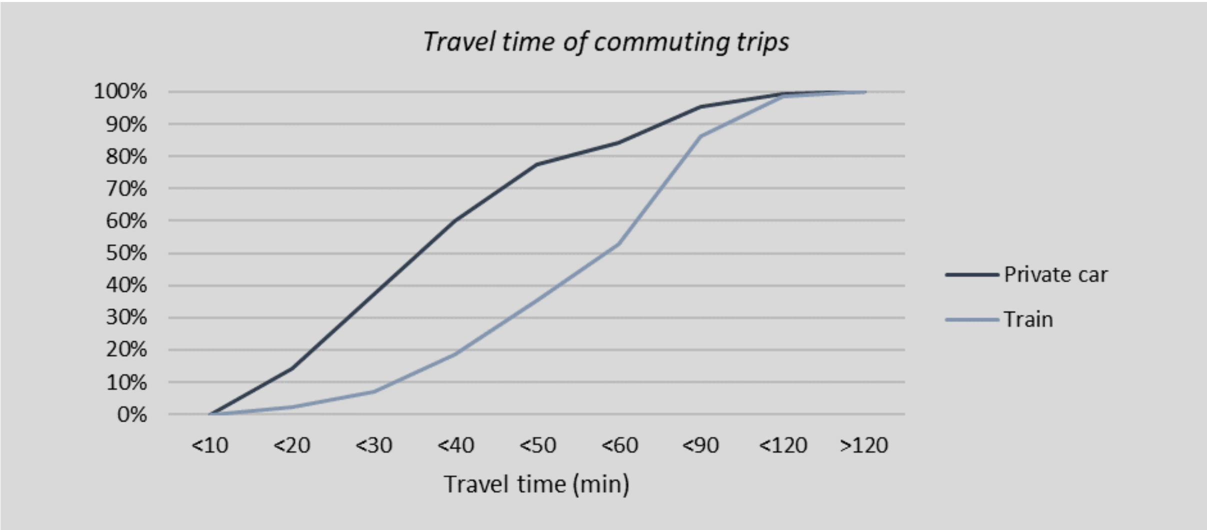


Figure 23. Cumulative distribution of commuting trips over travel time

The commuting trips by private car are relatively shorter compared to those by train. In total, about 60 percent of the commuting trips by private car take less than 40 minutes, whereas this is only about 20 percent of the train journeys. In addition, nearly half of the commuting trips by train (i.e. 47.2 percent) take even more than 60 minutes. Comparable commuting trips by private car are much less evident (i.e. 15.8 percent). The average travel time is 38 and 58 minutes respectively for private car and train commuters. Since both averages are higher than the national average of 34 minutes (CBS, 2017), which also includes shorter commuting trips on foot or by bicycle, this can be a good representation of the target population.

Access and egress transportation

As discussed in Section 2.2.2, a train journey could be split into parts (i.e. the access trip, main trip, and egress trip). From the respondents that generally travel to work by train, data is collected regarding to the characteristics of their access and egress trip. Three interesting features are worth to be discussed. That is, the distribution of access and egress modes used to reach the train station and work location respectively, and the travel time of the egress trip. The access trip time was not asked to the respondents, since it is not relevant for the study. Figure 24 shows the distribution of access modes when traveling to work by train. As can be seen, the bicycle is the most used transportation mode to access the home-end train station, followed by walking and BTM. These results are in line with findings from the literature .

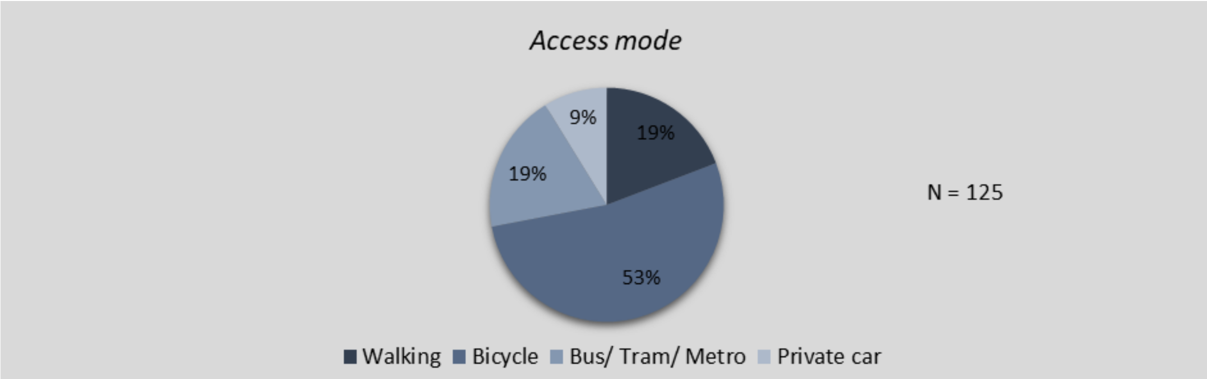


Figure 24. Distribution of the access modes used for commuting trips by train

As illustrated in Figure 25, most of the egress trips are realized on foot and by BTM, this is respectively 52.0 and 32.0 percent. Also these results are comparable to the findings from the literature. However, it should be noted that the target population of the study differs from the general population of the Netherlands as previous literature was based on.

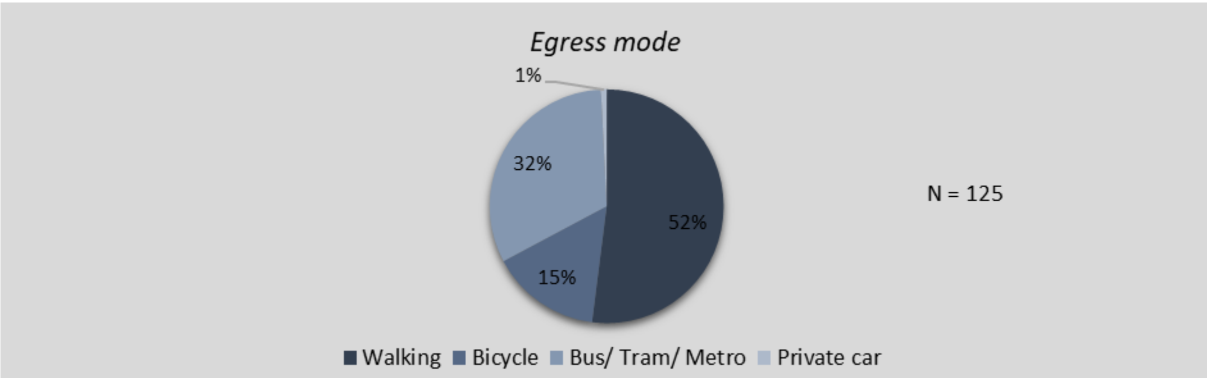


Figure 25. Distribution of the egress modes for commuting trips by train

The cumulative distribution of the egress trip times per egress mode is presented in Figure 26. Due to the dataset includes only one respondent that egresses by car, this data have been left out from this analysis. As shown, slow transportation modes (i.e. walking and cycling) are mainly used for egress trips with a duration of less than 10 minutes. This finding could be supported by the literature (see Section 2.2.4). As mentioned, both walking and cycling have a travel time threshold of 10 minutes. When this threshold is exceeded, individuals will evaluate their current travel behavior and determine whether changes can take place to optimize it. A modal shift to faster (motorized) transportation modes seems to be obvious, such as shifting to the BTM. Considering the egress trip times of the BTM, these are equally distributed over the travel time intervals. Further, the dataset does not include any egress trip that falls within the range of 1 till 5 minutes. This may indicate that individuals prefer walking or cycling at shorter distances in relation to taking the BTM.

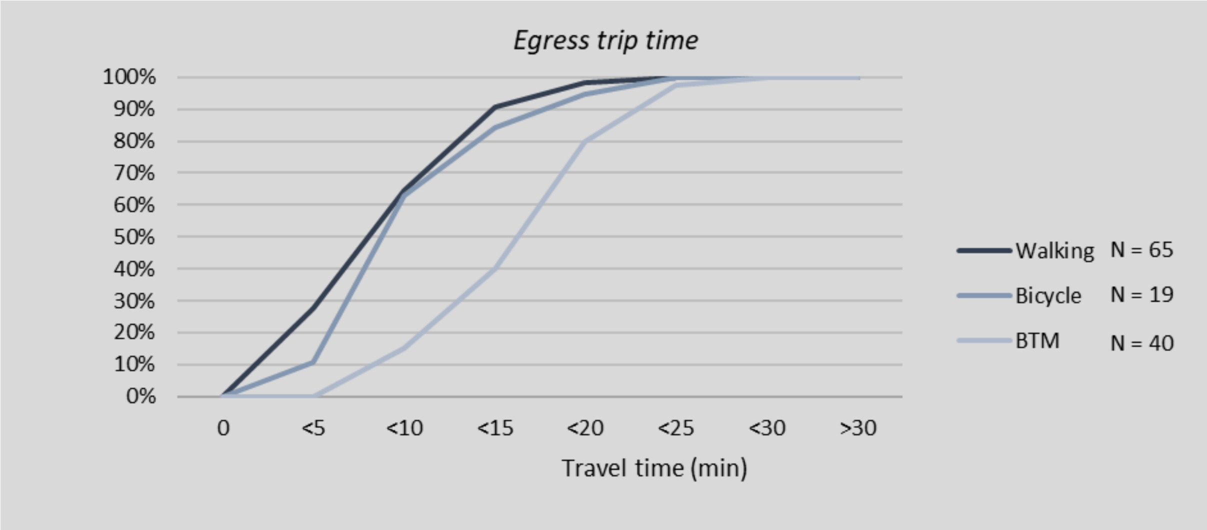


Figure 26. Cumulative distribution of egress modes over trip time

4.2.3 Transportation mode-related factors

Several factors or influences exist on which individuals could relate their transportation mode choice. The most relevant factors of transportation mode choice of individuals have been discussed in Section 2.4. Figure 27 gives an overview of the transportation mode choice factors of the sample. As shown, the respondents who usually travel to their work location by private car indicated that travel time (i.e. 49.6 percent) is the most important factor for choosing the private car over other transportation modes. Only 9.6 percent of the private car commuters indicated the travel costs is the main factor of transportation mode choice.

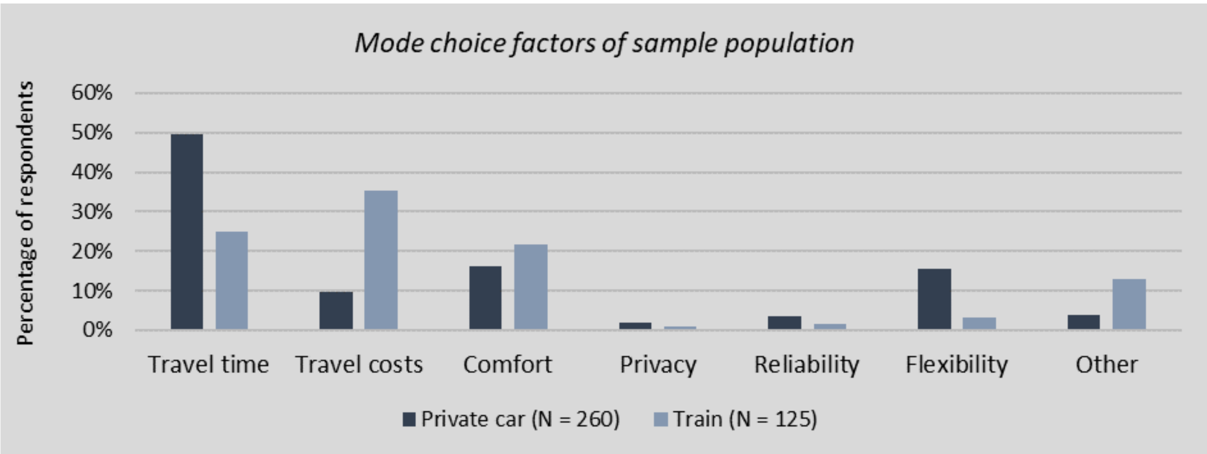


Figure 27. Distribution of mode choice factors of the private car and train commuters

Considering the train commuters, the travel costs are the main reason for deciding to realize commuting trips by train (i.e. 35.2 percent), while travel time (i.e. 24.8 percent) is also an important factor. A possible explanation for this could be that the travel costs (i.e. train ticket) are reimbursed by the employer of the respondents, which encourages them to travel to work by train. Unfortunately, no data were collected to support this assumption. Moreover, less decisive for the transportation mode choice, comfort was indicated as the most important factor by 16.2 and 21.6 percent of the private car and train commuters respectively.

Transportation mode-related factors

The transportation mode choice of individuals can be influenced by personal factors, such as attributes and habits (see Section 2.4.2). In order to analyze whether those factors have an effect on the current travel behavior of the sample, statements were formulated, the *transportation mode-related attitudinal factors*. Depending on the transportation mode used to commute, the corresponding set of attitudinal factors are presented to the respondents. Subsequently, the respondents were asked to which extent they *agree* or *disagree* with the attitudinal factors. The results of the private car commuters are shown in Figure 28, and those of the train commuters in Figure 29. The relevant results will be discussed below.

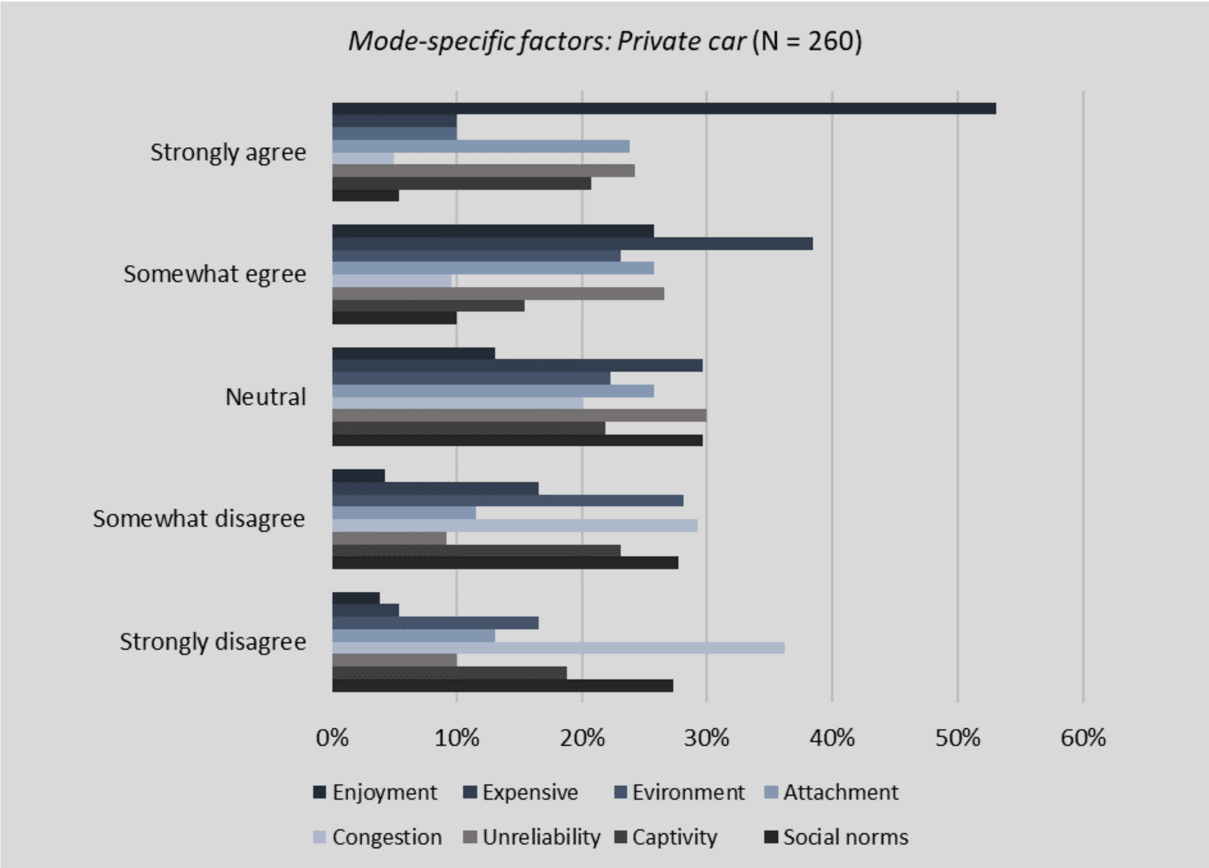


Figure 28. Distribution of mode-related factors related to the private car

Considering the private car commuters, 78.9 percent of them enjoy driving (i.e. strongly agree and somewhat agree), but at least 48.5 percent confirmed driving is expensive. This may indicate that enjoying to drive a car possibly cause the travel costs to be less decisive in the transportation mode choice. Environmental concern with regard to driving less often, only 33.1 percent of the private car commuters would do so. However, 49.6 percent of them indicated that they would travel less often to work by private car if the train would be as fast. This result confirms again the importance of travel time for individuals in their transportation mode choice process. Furthermore, the private car commuters confirmed that they do not travel less often by train because of the reason of the unreliability of connections, such as for the egress trip (i.e. 50.8 percent); they use the car because there is no other possibility for commuting (i.e. 36.2 percent); and social pressure from colleagues would not encourage them to commute by train (i.e. 55.0 percent).

The proportion of train commuters who enjoy traveling to work by train is 62.4 percent. As expected, the enjoyment of the transportation mode used for commuting trips is higher for the private car commuters compared to the train commuters. This has been supported by the literature. Besides, a considerable larger proportion of train commuters (i.e. 68.8 percent) perceive their most frequently used transportation mode for commuting as expensive. This is noteworthy, since travel costs was indicated as the most important mode choice factor by train commuters. The environmental concern is found to be higher for the train commuters, 48.8 percent indicated to travel more often by train due to the environment. The attachment to the train is measured by asking the respondents to what extent they would travel preferably by train when changing to a new job. In total, 56.0 percent agreed with this. In addition, the train commuters were asked whether the egress trip is a limitation to them to travel by train in general, only 11.2 percent confirmed this. This may be due to the fact that individuals have arranged their train journey in such a way that they see no improvement. Moreover, the influence of social norms is not evident to the train commuters, only 10.4 percent would travel more often by train if they were expected to do so.

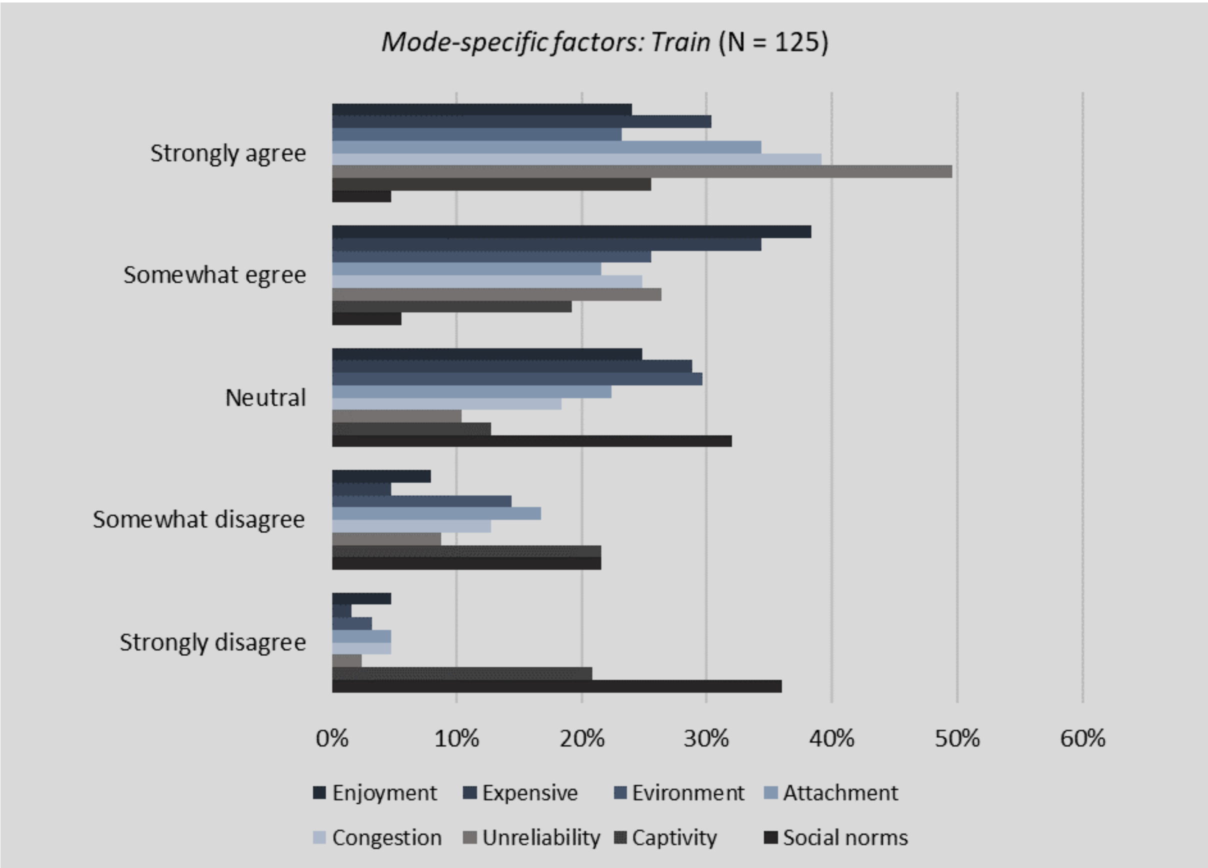


Figure 29. Distribution of mode-related factors related to the train

Further analysis must provide insight into how the private car commuters that are open to shift to the train can be encouraged to do this and how the train commuters could be retained.

4.2.4 BSS-related factors

Lastly, the results of the BSS-related attitudinal factors are presented. The respondents were asked to what extent they agree or disagree with the different BSS-related attitudinal factors. Figure 30 shows the results of the private car commuters, and Figure 31 the results of the train commuters. The most relevant results will be further discussed below.

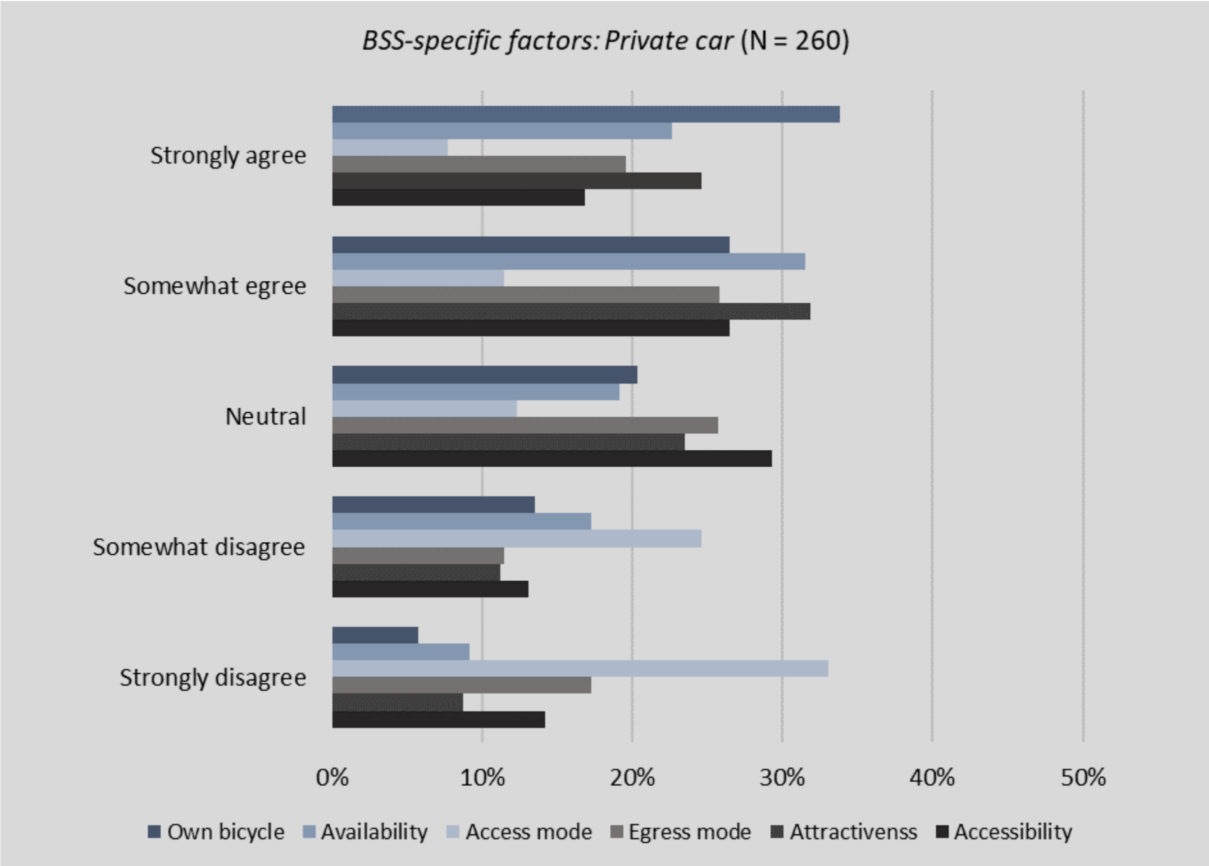


Figure 30. Distribution of BSS-related factors related to the private car commuters

Approximately 60 percent of the respondents indicated that they prefer using their own bicycle instead of a shared bicycle. This is confirmed in the literature, since individuals attach value to property (Harms et al., 2007). Therefore, shared bicycles seem attractive only when the own bicycle is not available for use, respectively 54.2 and 60.0 percent of the private car and train commuters confirmed this. The respondents indicated that a shared bicycle is more attractive in the egress trip compared to the access trip of train journeys. Since bicycle ownership is high in the Netherlands, this finding can be supported. Hereby, the private car commuters are less positive (i.e. 45.4 percent) with respect to a sharing bicycle in the egress trip compared to the train commuters (i.e. 68.0 percent). Moreover, around 60 percent of the respondents indicated that a shared bicycle is more attractive than taking the bus, where 43.4 and 50.4 percent of the private car and train commuters assume that a shared bicycle would increase the accessibility to their work location (from the train station).

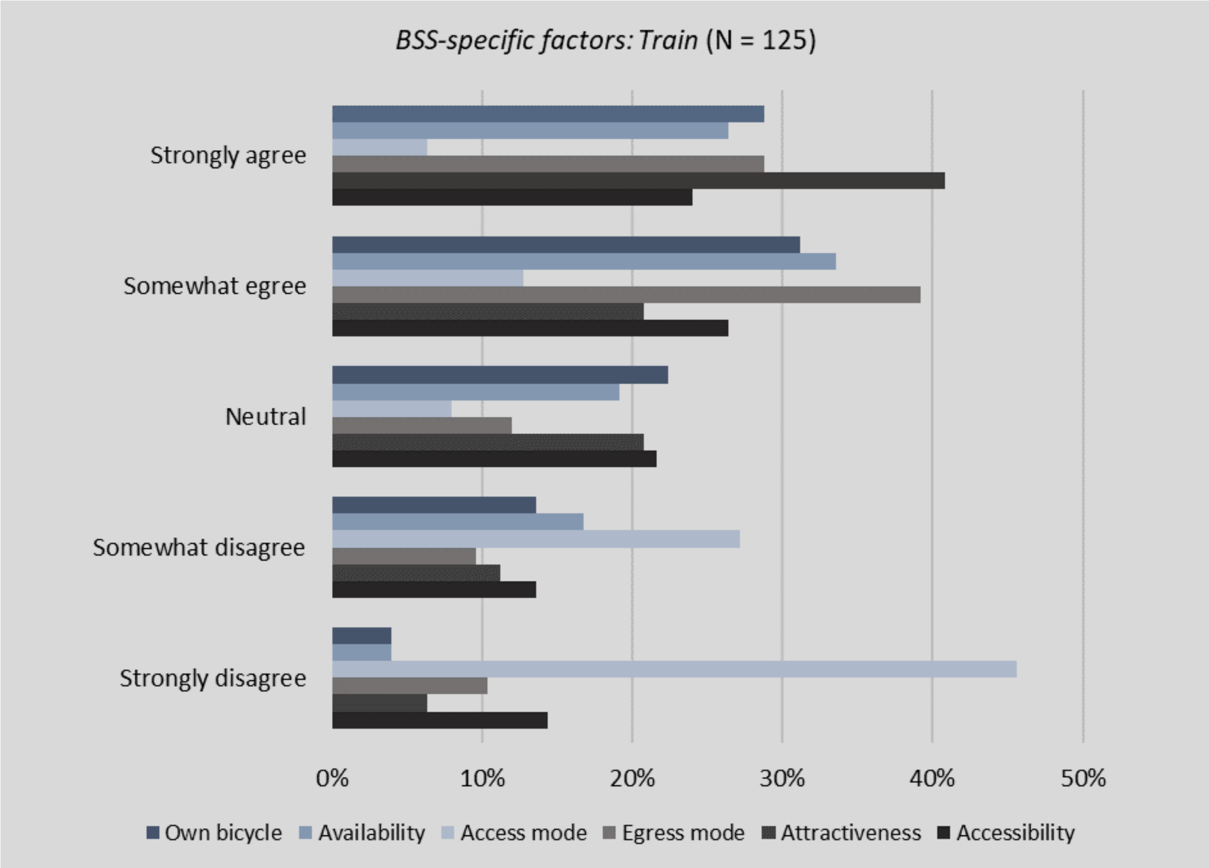


Figure 31. Distribution of BSS-related factors related to the train commuters

4.3 Model Analysis

This section discusses the attribute parameters of the BSS and transportation mode choice models that are estimated using the NLogit 5 software. It is widely assumed that NLogit 5 is a powerful tool for the estimation of discrete choice models among multiple alternatives (Hensher et al., 2005). Considering the research objectives of the study, the estimated models should provide insight into two main subjects:

The attributes that influence the preference of …

i. *Private car commuters* for urban BSSs in relation to the OV-fiets (Model A); and
ii. *Train commuters* for urban BSSs in relation to the OV-fiets (Model B).

And, the attributes that influence the transportation mode choice of …

iii. *Private car commuters* for the train to realize commuting trips (Model C); and
iv. *Train commuters* to realize the egress trip with urban BSSs (Model D).

In fact the BSS attributes represent the characteristics of a BSS, which includes shared bicycles that can be used to realize a part of the commuting trip. The other attributes, such as age and work location, are directly related to the respondents of the sample. Based on the subdivision of the experiment (see Section 3.3.1), the relevant logit models are estimated. A Multinomial

Logit (MNL) model is estimated to analyze the attributes that influence the preference of commuters for an urban BSS (i.e. Model A and Model B), while the influence of attributes on the transportation mode choice is estimated with a Binary Logit (BL) model (i.e. Model C and Model D). The model analysis is structured as follows. Firstly, the MNL models are estimated. Next, the performance of the MNL models is discussed. This is followed by an analysis and interpretation of the model results. Finally, the BL models are estimated and discussed.

To perform the analysis in the NLogit 5 software, some transformations in the dataset have to be realized. The NLogit data format requires that one observation is subdivided into blocks (i.e. choice sets) and represented by several rows of data (i.e. the alternatives). Additionally, the effect coding structure must be applied for the attribute levels. By doing this, a linear relationship to the effects of the levels of the attributes can be avoided (Hensher et al., 2005).

Table 7 shows the setup of the dataset. In the example below, the data of a single respondent is listed, where the experiment comprises three choice sets with three alternatives. An overview of the effect coding of the attribute levels in given in Appendix C.

Table 7. The NLogit 5 Software data format (Example)

Respondent	Block (*choice set)*	Design code	Choice	Effect coding	
				X1	*X2*
1	1	0	1	1	0
1	1	1	0	0	1
1	1	2	0	-1	-1
1	2	0	0	1	0
1	2	1	1	0	1
	2	2	0	-1	-1
1	3	0	0	1	0
1	3	1	0	0	1
1	3	2	1	-1	-1

4.3.1 The influence of BSS attributes on urban BSS preference

This section discusses the BSS models. As the preceding section indicated, two MNL models are estimated, i.e. the MNL model of the *private car* commuters and of the *train* commuters.

Model A: Preference of private car commuters for urban bicycle sharing systems

The first MNL model to be estimated is that of the private car commuters. This model is intended to estimate the parameters that influence the preference of private car commuters for urban BSSs in relation to the OV-fiets. It should be noted that the preference for an alternative is determined by the utility of that alternative.

Depending on the number of respondents recruited (i.e. N = 260) and the number of choice sets presented to each respondent in the SP experiment, the dataset used for model estimation contains in total 2,080 (i.e. 260 x 8) observations. The MNL model statistics are listed in Table 8. The complete output is given in Appendix D-1.

Table 8. Statistics of the Multinomial Logit model of the private car commuters

	Statistics
Number of observations	2,080
Number of estimated parameters	14
Null Log Likelihood	-2285.114
Constants-only Log Likelihood	-2186.268
Optimal Log Likelihood	-2060.527
Rho-squared (ρ^2)	0.098
Chi-square critical	23.685
-2 Log Likelihood	449.174

It is important to determine to what extent the model provides accurate estimates. The first step in this process is to determine the model significance. By doing so, the *Log Likelihood* (LL) values must be compared with each other. The LL values can be obtained from the table above. Considering the LL value of the null model (i.e. -2285.114) and that of the optimal model (i.e. -2060.527), it can be stated that the optimal model performs better than the null model. This is because a LL function closest to zero represents a better model fit (Hensher et al., 2005). Since the LL value of the constants-only model (i.e. -2186.268) is lower than that of the optimal model, this also means that the optimal model performs significantly better compared to the constants-only model.

Following, the *LL ratio-test,* further referred to –2LL, is performed. This test is used to compare the goodness-of-fit between two statistical models (Hensher et al., 2005). For this end, the difference between the logs of the null model and optimal model is multiplied by minus 2, obtaining the *–2 Log Likelihood* (–2LL). In order to perform the LL ratio-test the Equation 8 is used. The level of confidence of the test is defined by 5.0 percent (i.e. $\alpha = 0.05$). To obtain the *Chi-square statistic*, the chi-squared value, the difference in the number of parameters (i.e. degrees of freedom) between the optimal and null model is needed. Since the value of –2LL (i.e. 449.174) does exceed the Chi-square value (i.e. 23.685), it can be concluded that the optimal model is better than the null model. In statistical terms, this means that the null hypothesis can be rejected, because it assumes that the optimal model does not perform better compared to the null model.

The *LL ratio-index*, further referred to *rho-squared* (ρ^2), is a statistical measure that provides insight into the model fit. The exact value can be calculated by using Equation 9Where: . Accordingly, the rho-squared value (i.e. falls always within the range of 0 to 1) of 0.098 has been obtained. It represents the improvement due to all elements of the model (Koppelman & Bhat, 2006). In the literature, a rho-squared value of 0.2 to 0.4 is assumed to represent a decent model fit (Hensher et al., 2005). Since the optimal model has a lower rho-squared value compared to the general guideline, the model fit is questionable. Further analysis is necessary to ascertain the reasons for this low model fit.

Table 9 lists the parameters of the estimated MNL model. In total seven attributes are included to the model (first column). To facilitate the discussion of the output, the attribute levels are named in the table (second column). The part-worth utility (third column) represent the contribution or weight associated with the attribute levels. Based on these values the amount of utility for a specific alternative can be calculated. However, it should be noted that the utility represents the preference for an alternative rather than an actual choice (Hensher et al., 2005). Considering the attributes with three levels, two out of the three utility values were estimated in NLogit. The third utility value, the values shown in *italic front*, has been calculated afterwards. To do this, the utility value of the other two attribute levels was multiplied by minus 1 and then summed (i.e. the sum of the part-worth utility values should be equal to zero). Finally, also the statistical significance (fourth column) of each attribute level and the range of the attributes (fifth column) are shown.

Table 9. The estimated BSS model attributes parameters of the private car commuters

Attribute	Attribute level	Part-worth utility	Significance	Range
Constant (ASC)	-	0.59711	0.0000*	-
Bicycle type	Traditional	0.12435	0.0001*	0.24870
	Electric	*-0.12435*	-	
Reservation option	None	-0.01382	0.7619	-
	OV-chipcard	0.03285	0.5553	
	Application	-0.01903	-	
Rental fare (*per trip*)	0,50 euro	0.39613	0.0000*	0.81676
	1,00 euro	0.02450	0.6262	
	1,50 euro	*-0.42063*	-	
Access time	1 minutes	0.24479	0.0000*	0.47411
	3 minutes	*-0.01547*	-	
	5 minutes	-0.22932	0.0001*	
Egress time	1 minutes	*0.20397*	-	0.45889
	3 minutes	0.05095	0.3267	
	5 minutes	-0.25492	0.0000*	
Reliability starting point	0 minutes	*0.38004*	-	0.78809
	5 minutes	0.02801	0.5367	
	10 minutes	-0.40805	0.0000*	
Reliability endpoint	0 minutes	0.20819	0.0000*	0.46077
	5 minutes	0.04439	0.3206	
	10 minutes	*-0.25258*	-	

* Statistically significant at 5 percent.

Considering the statistical significance, not all attribute levels contribute to the preference of the private car commuters for choosing an urban BSS over the OV-fiets. A confidence level of 95 percent (i.e. $\alpha \leq 0.05$) is used to test the significance of each attribute level. From the attributes, only *reservation option* was observed not to be significant. The other attributes are found to be significant and will be further analyzed below.

The part-worth utility values give an indication of the preference for an urban BSS in relation to the OV-fiets for each attribute level. A positive utility value indicates an increased preference for the use of an urban BSS over the OV-fiets, while a negative value reflects the opposite effect. Considering the utility values of the significant attributes (see Table 9), each attribute includes at least one positive and one negative value. With the exception of the attribute *bicycle type* (i.e. two-level attribute), all the attributes include three levels, which ensures the possibility to observe non-linearity. However, since most of the attribute levels are significant, it would be expected that the gradient of the attributes are rather linear. In order to visualize this, the graphs of the attributes are designed and presented in Appendix E-1. From this analysis, it can be confirmed that the levels of the attributes are linear related.

The relevant BSS attributes were discussed in the literature review (see Section 2.3). As mentioned, the number of stations and bicycles within the network is directly related to the performance of the BSS (Médard De Chardon et al., 2017). On the one hand, the number of stations determines the density of the network, and on the other hand, the number of bicycles influences the reliability of the BSS. The MNL model includes four attributes (i.e. *access time*, *egress time*, *reliability at starting point*, and *reliability at endpoint*) that could be linked to those findings. Since convenience is an important determinant for BSS use (Fishman et al., 2015), the density of stations should be taken into account. In general, a higher density of stations is associated with shorter walking distances (and times) (Gauthier et al., 2013). Both insights support the results of the attributes *access time* and *egress time* whereby a shorter walking time is accompanied with a higher utility value. Similar results were obtained for the attributes *reliability at starting point* and *reliability at endpoint*. Rather than the number of bicycles, the reliability of a BSS is expressed by the plausible waiting time if no shared bicycle is available at the BSS station. In principle, waiting time contradicts the function of BSS introduction, that is, to improve the accessibility and reduce travel time (Jäppinen et al., 2013). Because waiting time affects the total travel utility negatively, the higher the unreliability the lower is the utility value. Furthermore, the *bicycle type* and *rental fare* has been found to be significant. According to the estimated parameters, the traditional bicycle type contributes to the preference for an urban BSS over an OV-fiets. Although this result is not supported by literature, this does apply for the rental fare. The rental fare (i.e. travel costs) is perceived as one of the main benefits of BSS (Fishman et al., 2013). Thus, indicating that increasing travel costs would decrease the attractiveness of BSS use. This is in line with the results, where higher rental costs is associated with a lower utility value. Next, the alternative specific constant (ASC) is also important to consider. The positive value of the ASC indicates that the private car commuters have a preference for urban BSSs in relation to the OV-fiets.

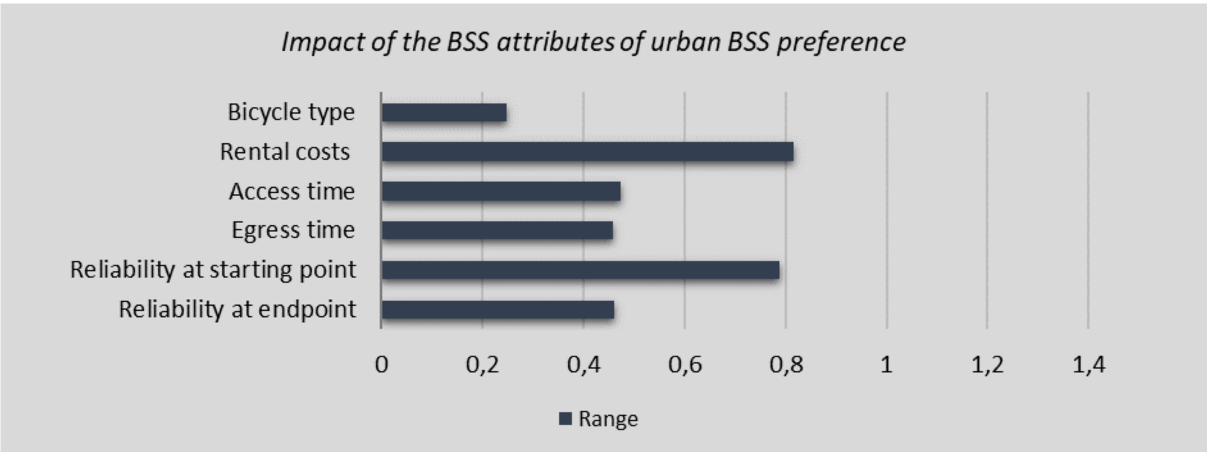


Figure 32. Impact of the BSS attributes related to the preference of private car commuters

Having discussed the statistical significance and utility values of the model, the impact of the attributes will be highlighted. The impact of an attribute is relative to its influence on the preference of an individual for an urban BSS over the OV-fiets. In Figure 32, the impact of the significant attributes is shown. As can be seen, the *rental costs* and *reliability at stating point* have the largest impact on the utility for preferring an urban BSS in relation to the OV-fiets. Because each attribute contains a reference level (i.e. the first), the impact of the other levels should be compared with this level. The following implies, the lower the rental costs (in euros) and reliability at the starting point (in minutes), the higher the probability that an urban BSS is preferred above the OV-fiets. The *access time*, *egress time*, and *reliability at destination* have a lower impact, but both are still considerable. Although the bicycle type is found to be significant, its impact is not high on the preference for an urban BSS.

Model B: Preference of train commuters for urban bicycle sharing systems

The second MNL model to be estimated is that of the *train* commuters. This model is meant to investigate the attributes that influence the preference of train commuters for an urban BSS over the OV-fiets. After the selection of respondents, a sample size of N = 125 was retained. Consequently, in total 1,000 (i.e. 125 x 8) observations have been collected.

In Table 10 the statistics of the MNL model of the train commuters are shown. The complete output is given in Appendix D-2. Because the LL of the optimal model (i.e. -950.432) is lower than the LL of the null model (i.e. -1098.612), the optimal model performs better compared to the null model. The same applies with regard to the constants-only model. In order to determine the overall goodness-of-fit of the optimal model, the –2LL and rho-squared are calculated respectively. The –2LL has a value of 296.360. Based on the statistical significance value of 0.05 and difference in degrees of freedom of the optimal and null model, the Chi-squared value is determined by 23.685. Since this value is exceeded by the –2LL value, it can be stated that the optimal model performs statistically better than the null model. The rho-squared value of 0.135 describes the overall goodness-of-fit of the model.

Table 10. Statistics of the Multinomial Logit model of the train commuters

	Statistics
Number of observations	1,000
Number of estimated parameters	14
Null Log Likelihood	-1098.612
Constants-only Log Likelihood	-1070.118
Optimal Log Likelihood	-950.432
Rho-squared (ρ^2)	0.135
Chi-square critical	23.685
-2 Log Likelihood	296.360

Table 11 shows the estimation results of the MNL model of the train commuters as generated in NLogit. As previously mentioned, the level of confidence of 95 percent is used. Hence, the estimated attributes can be tested. The attributes (i) *bicycle type* and (ii) *reservation option* are found not to be statistically significant (i.e. p-value > 0.05). Since both attributes do not influence the preference for an urban BSS (i.e. utility is equal to zero), none of these are of interest for further discussion. The other five attributes, i.e. (i) rental costs, (ii) access time, (iii), egress time, (iv) reliability at starting point, and (v) reliability at endpoint, have are statistically significant and will be discussed in the next page.

Table 11. Estimated BSS model attributes parameters of the train commuters

Attribute	Attribute level	Part-worth utility	Significance	Range
Constant (ASC)	-	0.32105	0.0000*	-
Bicycle type	Traditional	0.02105	0.6572	-
	Electric	*-0.02105*	-	
Reservation option	None	-0.09999	0.1593	-
	OV-chipcard	0.08815	0.2820	
	Application	*0.01184*	-	
Rental fare (per trip)	0,50 euro	0.62522	0.0000*	1.21472
	1,00 euro	-0.03572	0.6456	
	1,50 euro	*-0.58950*	-	
Access time	1 minutes	0.44587	0.0000*	0.84953
	3 minutes	*-0.04221*	-	
	5 minutes	-0.40366	0.0000*	
Egress time	1 minutes	*0.42317*	-	0.81787
	3 minutes	-0.02847	0.7126	
	5 minutes	-0.39470	0.0000*	
Reliability starting point	0 minutes	*0.56351*	-	1.13949
	5 minutes	0.01247	0.8566	
	10 minutes	-0.57598	0.0000*	
Reliability endpoint	0 minutes	0.23162	0.3350	0.52882
	5 minutes	0.06558	0.0025*	
	10 minutes	*-0.29720*	-	

* Statistically significant at 5 percent.

The utility of each alternative can be calculated by means of the model parameters. Also the ASC of Model B has a positive value, which indicates that the train commuters prefer urban BSSs in relation to the OV-fiets. Looking at the utility values of the remaining significant attributes, it can be concluded that the *higher* the rental fare (i.e. travel costs), access and egress time (i.e. travel time), and unreliability (i.e. waiting time), the lower the preference is for an urban BSS. These results are plausible, since to rent an OV-fiets individuals are not required to walk long distances to reach a pick-up location and wait until a bicycle is available. Moreover, insights from the literature were already mentioned in Model A.

As shown in Figure 33, the attribute *rental costs* (i.e. 1.215) has the largest impact on the preference for an urban BSS, this is followed by *reliability at starting point* (i.e. 1.139). The attributes *access* and *egress time* have also a considerable impact with a value of 0.8450 and 0.818 respectively. In general, it can be stated that the model results of the train commuters are similar to those of the private car commuters. However, except for *reliability at endpoint,* the impact of the BSS attributes on the preference for an urban BSS in relation to the OV-fiets is higher for the MNL model of the train commuters.

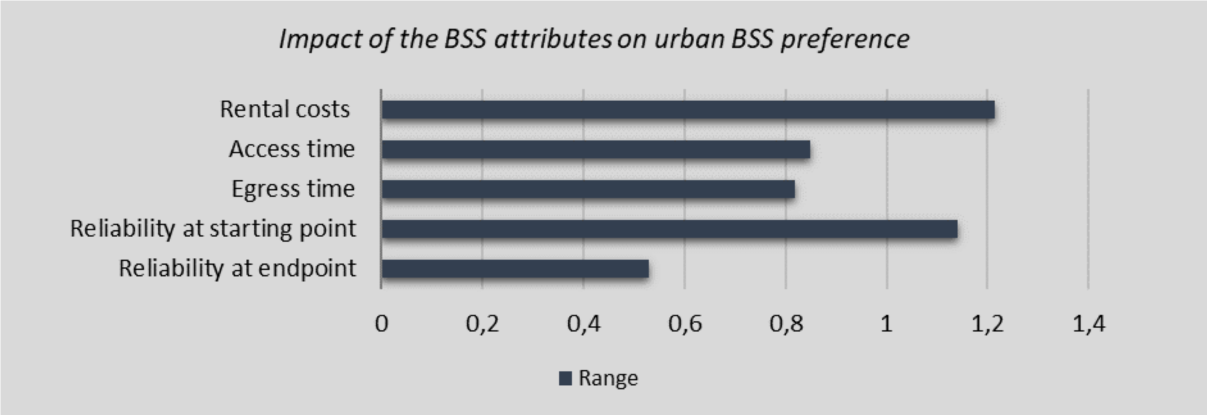


Figure 33. Impact of the BSS attributes related to the preference of train commuters

4.3.2 The influence of BSS attributes on transportation mode preference

The previous section discussed the MNL models that are intended to provide insight into the attributes that influence the preference of both private car commuters and train commuters for an urban BSS in relation to the OV-fiets. This section discusses the transportation mode choice models. Two BL models are estimated on the basis of the collected SP data, i.e. the BL model of the private car commuters and of the train commuters.

Model C: Willingness of private car commuters to commute by train

Firstly, the BL model of the private car commuters is estimated. As mentioned previously, BL models are capable to model only two discrete choices. This implies that an individual has only two alternatives to choose from. In this case, the BL model is used to examine the preference of the private car commuters between the (i) train and (ii) private car for commuting trips.

Table 12. Statistics of the Binary Logit model of the private car commuters

	Statistics
Number of observations	2,080
Number of estimated parameters	14
Null Log Likelihood	-1441.746
Constants-only Log Likelihood	-1078.588
Optimal Log Likelihood	-1051.113
Rho-squared (ρ^2)	0.271
Chi-square critical	23.685
-2 Log Likelihood	781.266

The statistics of the estimated BL model are listed in Table 12. The complete output is given in Appendix D-3. The dataset used to estimate the BL model has 2,080 rows of data (i.e. N = 260). Also for the BL models applies, in total 14 parameters are estimated. Considering the value of the LL of the null model (i.e. -1441.75) and optimal model (i.e. -1051.11), the rho-squared has been calculated. The optimal model has an accuracy rate of 27.1 percent. According to the statistical significance (i.e. p = 0.000), it can be assumed that the model fits the data very well. Comparing the –2LL value (i.e. 781.266) with the Chi-squared value (i.e. 23.685) indicates that the optimal model is statistically better than the null model.

In Table 13 the attribute parameters of the BL model of the private car commuters are shown. The negative value of the ASC indicates that there is the private car commuters prefer traveling by car to work. With respect to the attribute parameters, the willingness of private car commuters for the train as transportation mode for commuting trips can be investigated. The statistically significant (i.e. $p \leq 0.05$) attributes of the optimal BL model include (i) *bicycle type*, (ii) *rental costs*, (iii) *access time*, and (iv) *egress time.* The other attributes are found not to be statistically significant, and therefore not discussed further. Considering the utility values of *access time*, the reference level (i.e. 1 minutes) has a positive value. This means that the longer the access time to reach the urban BSS station the lower the probability of an individual opts for the train for commuting trips. The utility value of *bicycle type* is also positive, indicating that the use of electric shared bicycles affects the willingness for the train negatively. Similar results with the previously estimated models are obtained for the attributes *access* and *egress time*. Increasing walking time to and from an urban BSS station has a negative effect on the willingness to choose for the train over the private car for commuting trips.

Table 13. Binary Logit model attributes parameters related to the transportation mode choice of private car commuters

Attribute	Attribute level	Part-worth utility	Significance	Range
Constant (ASC)	-	-1.65956	-	-
Bicycle type	Traditional	0.13961	0.0387*	0.27922
	Electric	*-0.13961*	-	
Reservation option	None	0.15981	0.08260	-
	OV-chipcard	0.15411	0.13910	
	Application	*-0.31392*	-	
Rental fare (per trip)	0,50 euro	0.20279	0.02840*	0.43437
	1,00 euro	0.02879	0.79500	
	1,50 euro	*-0.23158*	-	
Access time	1 minutes	0.18478	0.04440*	0.48325
	3 minutes	*0.11369*	-	
	5 minutes	-0.29847	0.01420*	
Egress time	1 minutes	*0.31090*	-	0.56803
	3 minutes	-0.05377	0.58250	
	5 minutes	-0.25713	0.00480*	
Reliability starting point	0 minutes	*0.09163*	-	-
	5 minutes	-0.09427	0.30590	
	10 minutes	0.00264	0.98160	
Reliability endpoint	0 minutes	0.04285	0.67950	-
	5 minutes	-0.14489	0.10920	
	10 minutes	*0.10204*	-	

* Statistically significant at 5 percent.

Figure 34 shows the impact of each attribute has on the preference for the train in relation to the private car by the private car commuters. Only the significant attributes are presented. As shown, the *egress time* has the highest impact (i.e. 0.568), followed by *access time* (i.e. 0.483), and the *rental costs* (i.e. 0.434). Although the difference in impact between these attributes is relatively small, it can be assumed that the willingness to shift from the private car to the train is mainly determined by travel costs and walking times (i.e. related to the density of the BSS). In contrast to the estimated MNL models, the influence of the reliability of the urban BSS is neglectable. A plausible explanation for this may be that individuals consider the unreliability of a BSS (i.e. waiting time) as a part of the total travel time by train rather than additional travel time.

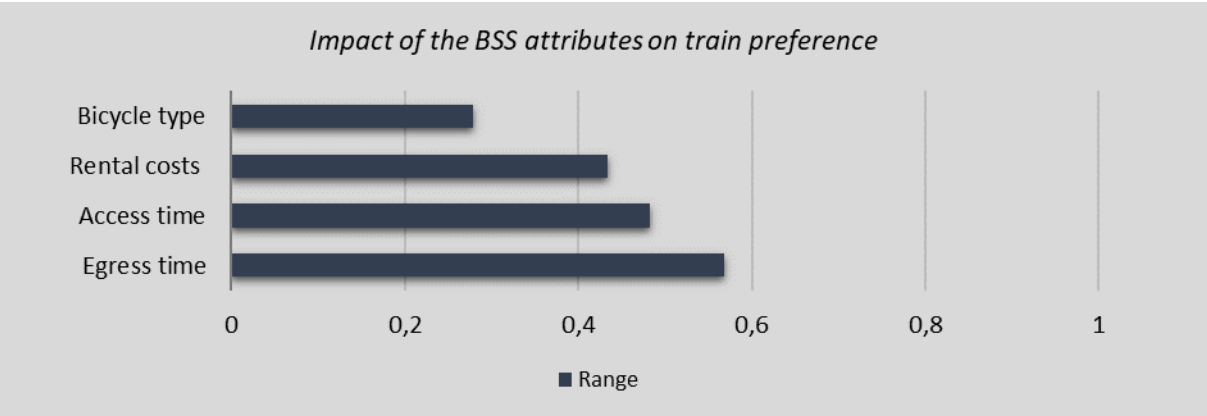


Figure 34. Impact of the attributes on transportation mode choice of private car commuters

Model D: Willingness of train commuters to use shared bicycles as egress mode

Lastly, the BL model of the train commuters is estimated. This model is intended to provide insight into the willingness of train commuters for using a shared bicycle (of the urban BSS) in the egress trip over their current egress mode.

Table 14 provides an overview of the statistics of the estimated BL model of the train commuters. The complete output is given in Appendix D-4. Only a few differences are observed in relation to the BL model of the commuters of the private car. For instance, the optimal model has an accuracy rate of 10.7 percent, indicating that this model has a lower goodness-of-fit. Considering the –2LL value and the chi-squared value, it can be assumed that the optimal model is statistically better compared to the null model.

Table 14. Statistics of the Binary Logit model of the train commuters

	Statistics
Number of observations	1,000
Number of estimated parameters	14
Null Log Likelihood	-693.147
Constants-only Log Likelihood	-632.140
Optimal Log Likelihood	-619.026
Rho-squared (ρ^2)	0.107
Chi-square critical	23.685
-2 Log Likelihood	148.242

The attribute parameters of the optimal BL model can be read directly from the Table 15. As shown, *egress time* is the only statistically significant attribute (i.e. p-value < 0.05). This implies that the other attributes do not influence the willingness of train commuters for using a shared bicycle as egress mode for commuting trips by train. The ASC indicates that the train commuters have a preference for their current egress mode.

Table 15. Binary Logit model attributes parameters related to the transportation mode choice of train commuters

Attribute	Attribute level	Part-worth utility	Significance	Range
Constant (ASC)	-	-0.83659	0.0000	-
Bicycle type	Traditional	0.10910	0.1878	0.21820
	Electric	*-0.10910*	-	
Reservation option	None	-0.05084	0.6599	0.10160
	OV-chipcard	0.00008	0.9995	
	Application	*0.05076*	-	
Rental fare (per trip)	0,50 euro	0.18363	0.1239	0.54105
	1,00 euro	0.17379	0.2154	
	1,50 euro	*-0.35742*	-	
Access time	1 minutes	-0.02896	0.8008	0.04043
	3 minutes	*0.01749*	-	
	5 minutes	0.01147	0.9367	
Egress time	1 minutes	*0.20725*	-	0.63983
	3 minutes	0.22533	0.0601	
	5 minutes	-0.43258	0.0002	
Reliability starting point	0 minutes	*0.20344*	-	0.41322
	5 minutes	-0.20978	0.0673	
	10 minutes	0.00634	0.9655	
Reliability endpoint	0 minutes	0.05801	0.6647	0.10121
	5 minutes	-0.04320	0.7204	
	10 minutes	*-0.01481*	-	

Considering the utility values of *egress time*, the sign of the reference level (i.e. the first) is positive, indicating that the probability of willing to use a shared bicycle in the egress trip decreases as the egress time increases. Since travel costs is mentioned by the train commuters to be the most important factor to realize commuting trips by train (see Figure 27), the *rental costs* was expected to be statistically significant.

4.4 EXTENDED ANALYSIS

In the questionnaire data were collected about the sample regarding their (i) *socioeconomic characteristics*, (ii) *commuting trip characteristics*, (iii) *transportation mode-related attitudinal factors*, and (iv) *BSS-related attitudinal factors*. Each of these attribute categories consists of various attributes that were already been discussed in Section 4.2. In seeking to improve the performance of the estimated logit models the impact of each individual attribute will be determined. For this purpose, the number of levels of each attribute is reduced to 2 or 3, and effect coding is applied. The lowest level is effect coded {-1}, the middle level {0}, and highest level {1}. The distributions are defined by logical thinking, but with the aim of providing an equal distribution across the levels. An overview of the analyzed attributes and related levels is provided in Appendix C.

4.4.1 Correlation analysis

Before measuring what effect the attributes have on the performance of the estimated models, a correlation analysis is performed to investigate whether relationships exist between the various attributes. The results of this analysis are presented in Appendix F. It should be noted that only the statistics per attribute category are presented. The overall table is omitted because no strong relationships were found between attributes of different categories. The significant relationships (i.e. $p = < 0.05$; $r \geq 0.300$) are discussed below.

Private car commuters

There are no significant relationships found between the socioeconomic characteristics of the private car commuters. Regarding the commuting trip characteristics, only the relationship between the province of residence location and province of work location is found to be significant (i.e. r = 0.728). This relationship can be attributed to the fact that many respondents are living and working within the same province, or are working in the provinces that are part of the Randstad (i.e. Noord-Holland, Utrecht, and Zuid-Holland). Also one relationship is found between the transportation mode-related attitudinal factor 3 ("*I am considering to travel less by car because of the environment"*) and 4 (i.e. r = 0.344) ("*I would travel less often by car to my work if the train would be as fast").* This positive relationship may indicate that individuals who are concerned about the environment, may also be willing to travel by train if they are able to do so.

In total, four relationships were found between the BSS-related attitudinal factors. Factor 1 (i.e. "*I prefer to use my own bicycle instead of a shared bicycle"*) and 2 ("*I would use a shared bicycle only if my own bicycle is not available"*) have a positive correlation (i.e. r = 0.531), which may indicate that individuals are not willing to use a shared bicycle when their own bicycle is available. This is mainly in the egress trip of train journeys. More attention deserves the other three correlations, where factor 4 *("A shared bicycle is interesting for me to cycle from the train station to my work location, the egress trip")* is positively correlated with factor 3 (i.e. r = 0.367) *("A shared bicycle is interesting for me to cycle from my home to train station, the access trip")*, factor 5 (i.e. r = 0.552) *("A shared bicycle in the egress trip is more attractive than taking the bus"),* and factor 6 (i.e. r = 0.535) *("A shared bicycle makes my work location more accessible by train")*. It may be possible that the individuals who believe that a shared bicycle is interesting for them in the egress trip (factor 4) are also willing to make use of the system because, for example, they do not feel comfortable with the current bus service (factor 5) or can reach their work location faster by using a shared bicycle (factor 6).

Train commuters

Although most of the relationships between the socioeconomic characteristics are weak, a negative relationship (i.e. r = –0.326) is observed between *age* and *education level*. This relationships indicates that lower age groups are higher educated (i.e. HBO/WO). Considering the transportation mode-related attitudinal factors, in total eight significant relationships are found. Factor 1 *("like traveling by train")* have a positive correlation with factor 4 (i.e. r = 0.398) *("I would travel less often by car to my work if the train would be as fast")*, factor 5 (i.e. r = 0.439) *("would continue traveling to work by train even if traffic jams are resolve"),* and factor 6 (i.e. 0.348) ("*the egress trip is not an obstacle for me to travel by train").* These relationships may indicate that the current train travelers are attracted to the train as commuting mode. Also the strong positive relationship between factor 4 and 5 (i.e. r = 0.522), and 4 and 6 (i.e. r= 0.427) support this assumption. In addition, it seems that the train travelers are also more concerned about the environment, based on the sample data. The positive relationship between factor 3 *("I try to travel as often as possible by train because of the environment")* and factor 4 (i.e. r = 0.519), and with factor 5 (i.e. r = 0.383) provide an explanation to this. The last two relationships found are between factor 4 and 8 (i.e. r = 0.311) *("I would travel by train to work more often if more people would do this")*, and factor 5 and 6 (i.e. r = 0.482).

Lastly, the bicycle sharing system-related attitudinal factors. Similar relationships are found as for the private car commuters. The relationship between factor 4 and 6 (i.e. 0.632) is higher than that of the private car commuters. This may indicate that the train commuters think more positive about the implementation and contribution of bicycle sharing systems in the egress trip of train journeys in general.

No significant relationships (i.e. r ≥ 0.300) were found between the attributes of different categories with respect to the private car commuters. Regarding the train commuters, some relationships are explored. These correlations are shown in Appendix F-3. Two correlations are worthwhile to be appointed. The first correlation is between age and transportation mode-related attitudinal factor 5 (i.e. r = 0.313), and states that older age groups are more likely to be willing to travel to work by train, even if the congestion problems are solved. The second relationship is between the province of work location and the mode choice factor (i.e. r = – 0.357), indicating that other factors, such as travel time and comfort are more likely to be decisive for choosing the train to commute in the provinces that shape the Randstad.

The relationship between attributes is important to consider during model estimation. This is because high relationships can influence the model performance and reliability of estimates. For this reason, high correlations between attributes must be avoided in the model and this analysis helps to achieve this.

4.4.2 Interaction effects

In seeking to improve the performance of the estimated models, the *interaction effects* of 23 attributes are investigated on the private car commuter related models (i.e. Model A and Model C), and 26 attributes on the train commuter related models (i.e. Model B and Model D). The attributes can be assigned to the following four categories:

i. Socioeconomic characteristics (see Section 4.2.1);
ii. Commuting trip characteristics (see Section 4.2.2);
iii. Transportation mode-related factors (see Section 4.2.3.); and
iv. BSS-related factors (see Section 4.2.4).

This section discusses the most significant interaction effects to the estimated models. The analysis is carried out in a number of steps. Firstly, the impact of each attribute category is determined to the model. Secondly, the attributes are individually included in the model and tested for significance. Finally, the set of significant attributes is further analyzed.

Interaction effects in MNL model of private car commuters (Model A)

The analysis of interaction effects of the MNL model of the private car commuters indicated in total eight attributes with a significant impact on the preference for urban bicycle sharing systems. The following attributes are found to be significant at a 95 percent level (i.e. $p < 0.05$):

i. Education level;
ii. Household type;
iii. Province of work location;
iv. Travel time;

The transportation mode-related attitudinal factors,

v. Expensive (factor 2);
vi. Environment (Factor 3);
vii. Unreliability (Factor 6); and
viii. Social norms (Factor 8).

The interaction effect with the attribute *education level* should be interpreted with caution, because the sample is not equally distributed over the two levels. Table 16 shows the results of the model estimate. Model A1 represents the model with all (eight) significant attributes. The complete output of the model is presented in Appendix G-1. As shown, Model A1 has a higher goodness of fit compared to the basic Model A. This is because the included attributes reduce the Log Likelihood function. In order to determine whether Model A performs significantly better in relation to Model A, the -2LL test is performed. The level of confidence is defined by five percent. Since the -2LL value is higher than the chi-square statistic, Model A1 performs actually better compared to Model A.

Table 16. Statistics of the Multinomial Logit model of the private car commuters with interaction effects

	Model A (*basic*)	Model A1	*Test*
Attribute(s) included	BSS (only)	Selection	
Number of observations	2,080	2,080	
Number of parameters	14	22	
Null Log Likelihood	-2285.114	-2285.114	
Constants-only Log Likelihood	-2186.268	-2186.268	
Optimal Log Likelihood	-2060.527	-2011.586	
ρ^2	0.098	0.120	
Chi-square critical			15.507
-2 Log Likelihood			97.882

The attribute parameters are shown in Table 17. The positive value of the ASC indicates that there is a preference for urban BSSs in relation to the OV-fiets. The negative sign of *education level* indicates that high educated individuals (i.e. with university and higher professional education) have a lower utility and preference for an urban BSS. Also having a *child(ren)* in the household, a *work location* in the provinces of Noord-Holland, Utrecht, and Zuid-Holland, and higher *travel times* affect the preference for urban BSSs. The factor *expensive* has the expected positive sign, indicating that individuals who perceive traveling by private car as expensive, prefer an urban BSS (which is cheaper) in relation to the OV-fiets. Factor 3 has a positive sign, indicating that individuals who travel less due to environmental concern prefer urban BSSs. The *unreliability* of egress transportation affects the utility of private car commuters for the urban BSS alternatives. Lastly, social norm has a positive impact on the utility for urban BSSs.

Table 17. Estimated attributes parameters of Model A (Extended analysis)

Attribute	*Part-worth utilities*	*Significance*	Range
Constant (ASC)	0.7325	0.0000	-
Education level	-0.2536	0.0004	0.5072
Household type	-0.1549	0.0078	0.3098
Province of work location	-0.2374	0.0001	0.4748
Travel time by car	-0.1813	0.0109	0.3626
Expensive (factor 2)	0.1705	0.0044	0.3411
Environment (factor 3)	0.1385	0.0194	0.2770
Unreliability (factor 6)	-0.2008	0.0006	0.4015
Social norms (factor 8)	0.1476	0.0154	0.2951

The impact of the interaction effects are shown in Figure 35. The impact of *education level* and *province of work location* is highest on the total utility of private car commuters for the preference of urban BSSs. The other attributes have a similar impact on the total utility.

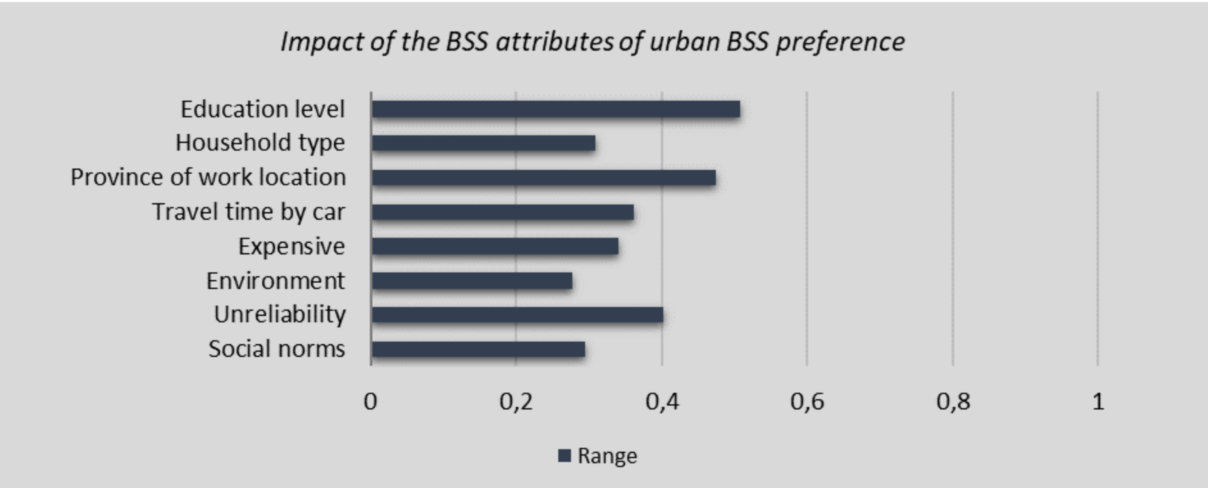


Figure 35. Impact of interactions effects on urban BSS preference by private car commuters

Interaction effects in MNL model of train commuters (Model B)

The analysis conducted in order to investigate the interaction effects to the MNL model of the train commuters, found to attributes to be significant:

The transportation mode-related attitudinal factors,

i. Attachment (factor 4); and

The bicycle sharing system-related attitudinal factor,

ii. Access trip (factor 3).

The model results are shown in Table 18. Both attributes are included in Model B1. The complete output of the model estimate is given in Appendix G-2. As listed, also for this model applies that the goodness of fit is improved. In addition, the -2LL test indicates that Model B1 performs significantly better in relation to Model B.

Table 18. Statistics of the Multinomial Logit model of the train commuters with interaction effects

	Model B (*basic*)	Model B1	*Test*
Attribute(s) included	BSS (only)	Selection	
Number of observations	1,000	1,000	
Number of parameters	14	16	
Null Log Likelihood	-1098.612	-1098.612	
Constants-only Log Likelihood	-1070.118	-1070.118	
Optimal Log Likelihood	-950.432	-920.448	
ρ^2	0.135	0.162	
Chi-square critical			5.991
-2 Log Likelihood			59.968

The parameters of the attributes are shown in Table 19. The positive value of the ASC indicates that there is a preference for urban BSSs in relation to the OV-fiets by the train commuters. The negative sign of *attachment* indicates a reduced utility on the preference for urban BSSs for individuals who *would preferably travel by train when changing to a new job*. It may be possible that this group of commuters are satisfied with the current public transportation service, or are not willing to use shared bicycles as egress mode. The factor *access trip* has a positive sign. This indicates that individuals who confirmed that a shared bicycle is interesting for them in their access trip, have an increased utility for the preference of urban BSSs.

Table 19. Estimated attributes parameters of Model B (Extended analysis)

Attribute	Part-worth utilities	Significance	Range
Constant (ASC)	0.7653	0.0000	-
Attachment (factor 4)	-0.4113	0.0001	0.8223
Access trip (BSS factor 3)	0.63815	0.0000	1.2763

The impact of *attachment* and *access trip* is presented in Figure 36. The factor *access trip* have an extreme high impact of the utility for the preference of urban BSSs. Although the attributes are statistically significant in the model, the question arises to what extent these results are reliable. Further analysis should provide more insight into this factor. The factor *attachment* is also found to have a great impact on the utility, however, lower than the *egress trip.*

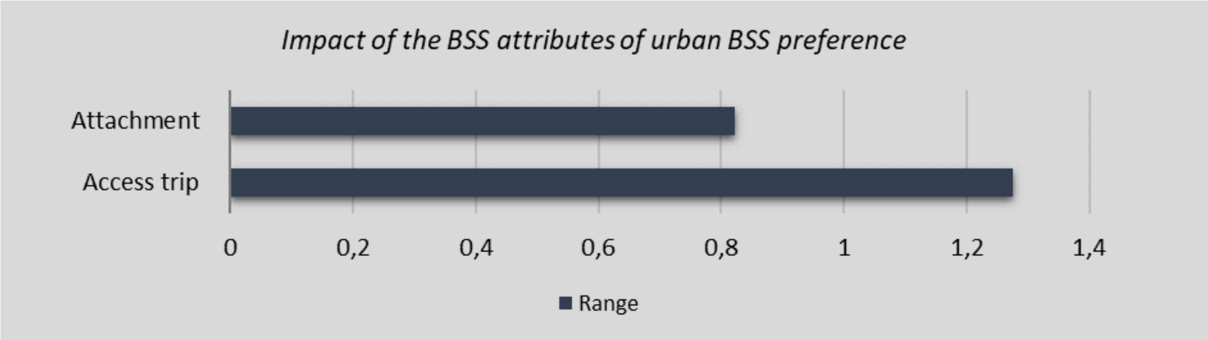


Figure 36. Impact of interactions effects on urban BSS preference by train commuters

Interaction effects in BL model of private car commuters (Model C)

Considering the BL model of the private car commuters, in total 8 attributes are found to be significant. The interaction effects of the following attributes are analyzed:

i. Age;
ii. Travel time by private car;

The transportation mode-related attitudinal factors,

iii. Environment (factor 3);
iv. Attachment (factor 4);
v. Unreliability (factor 6);
vi. Captivity (factor 7);

The bicycle sharing system-related attitudinal factors,

vii. Own bicycle preference (factor 1); and
viii. Egress trip (factor 4).

The results of the model estimate are shown in Table 20. The complete output of the model is presented in Appendix G-3. Model C1 has a considerable higher rho-squared value, indicating an improvement in the goodness of fit of the model compared to Mode C. In addition, when testing the -2LL function with the chi-squared value, it can be stated that Model C1 performs significantly better in relation to Model C.

Table 20. Statistics of the Binary Logit model of the private car commuters with interaction effects

	Model C (*basic*)	Model C1	*Test*
Attribute(s) included	BSS (only)	Selection	
Number of observations	2,080	2,080	
Number of parameters	14	22	
Null Log Likelihood	-1441.746	-1441.746	
Constants-only Log Likelihood	-1078.588	-1078.588	
Optimal Log Likelihood	-1051.113	-927.1415	
ρ^2	0.271	0.3569	
Chi-square critical			15.507
-2 Log Likelihood			247.943

Referring to Table 21, the negative value of the ASC indicates that there is a preference for the car by the private car commuters. In order to cause a modal shift this utility has to be undo by other attributes. *Age* has a positive sign which indicates that older age groups may be more willing to shift to the train. Increasing *travel time* has a positive effect on the preference for the train instead of the private car. The mode choice-related attitudinal factors *environment* and *attachment* have both a positive utility value. *Captivity* by private car commuters decreases the utility for the shift to the train. In addition, individuals who prefer to use their own bicycle instead of a shared bicycle, this also have a negative impact on the utility for the train. The results of the factor *egress trip* is interesting. Individuals who perceive shared bicycles as an suitable or interesting egress mode to reach their work location, have an increased utility for the shift from the private car to the train.

Table 21. Estimated attributes parameters of Model C (Extended analysis)

Attribute	*Part-worth utilities*	*Significance*	Range
Constant (ASC)	-1.94613	0.0000	-
Age	0.4441	0.0000	0.8882
Travel time by car	0.2042	0.0197	0.4084
Environment	0.3275	0.0000	0.6550
Attachment	0.2616	0.0009	0.5231
Unreliability	-0.3068	0.0000	0.6137
Captivity	-0.2142	0.0037	0.4284
Own bicycle	-0.2666	0.0002	0.5332
Egress trip	0.7336	0.0000	1.4671

In Figure 35 the impact of interactions effects of the attributes are shown. The BSS-related attitudinal factor *egress trip* has by far the greatest impact on the total utility. In order to increase the willingness to shift from the private car to the train, this factor has an important role and should be therefore be satisfied. Next, *age* has also a high impact on the total utility. The other attributes have similar impacts around 0,5.

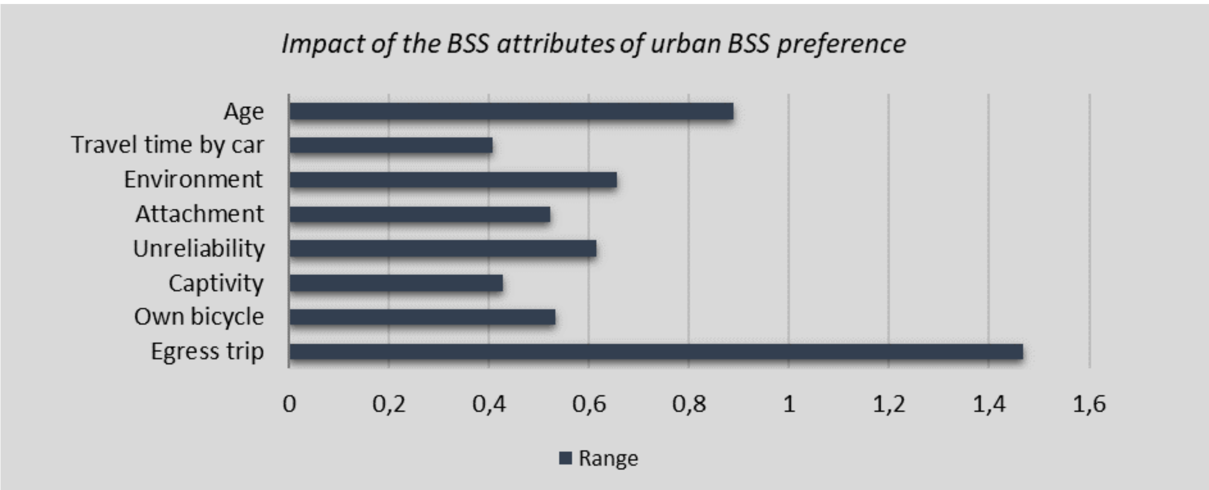


Figure 37. Impact of interactions effects on transportation mode choice by private car commuters

Interaction effects in BL model of train commuters (Model D)

Finally, the analysis of the BL model of train commuters is discussed. In total nine attributes are found to be statistically significant. Based on the correlation analysis and different model estimations, only the most clear relationships are remained for further analysis. This relates to the following attributes:

i. Commute trip frequency;
ii. Access mode;
iii. Egress mode;

The transportation mode-related attitudinal factors,

iv. Expensive (factor 2);
v. Unreliability (factor 6);
vi. Social norms (factor 8);

The bicycle sharing system-related attitudinal factors,

vii. Availability (factor 2);
viii. Access trip (factor 3); and
ix. Bus preference (factor 5).

Table 22 shows the results of the model estimate. Model D1 represents the model with all (nine) significant attributes. The complete output of the model is given in Appendix G-4. Model D1 has a higher goodness of fit in relation to the basic Model D. In order to determine whether Model D performs significantly better in relation to Model D, the -2LL test is conducted. Because -2LL value exceeds the chi-square statistic, it can be stated that Model D1 performs better compared to Model D.

Table 22. Statistics of the Binary Logit model of the train commuters with interaction effects

	Model D(*basic*)	Model D1	*Test*
Attribute(s) included	BSS (only)	Selection	
Number of observations	1,000	1,000	
Number of parameters	14	23	
Null Log Likelihood	-693.147	-693.147	
Constants-only Log Likelihood	-632.140	-632.140	
Optimal Log Likelihood	-619.026	-560.127	
ρ^2	0.107	0.192	
Chi-square critical			16.919
-2 Log Likelihood			117.798

The parameters of the attributes are shown in **Fout! Verwijzingsbron niet gevonden.**Table 19. The negative value of the ASC indicates that preference for the current egress mode instead of urban BSSs. The *commuting trip frequency* has a positive sign indicating that a higher frequency contributes to the total utility. The results of is *access* and *egress mode* are interesting. A bicycle as access mode provides a positive impact on the total utility, while walking have a negative impact on the total utility. A possible explanation may be that if individuals use the bicycle as access mode they are willing to use it as also as egress mode. *Expensive* has the expected positive sign, which may indicate that individuals are willing cheaper transportation alternatives. The *unreliability* has a negative sign indicating that individuals who do not perceive the egress trip as unreliable have a decreased utility. *Social norms, access trip,* and *bus preference* increase the total utility, while the *availability* decreases.

Table 23. Estimated attributes parameters of Model B (Extended analysis)

Attribute	Part-worth utilities	Significance	Range
Constant (ASC)	-1.03992	0.0000	-
Commuting trip frequency	0.1973	0.0379	0.39462
Access mode	0.6269	0.0000	1.25378
Egress mode	-0.3626	0.0002	0.7251
Expensive	0.4706	0.0000	0.9412
Unreliability	-0.3519	0.0010	0.7038
Social norms	0.2482	0.0161	0.4963
Availability	-0.64528	0.0000	1.2906
Access trip	0.35537	0.0006	0.71074
Bus preference	.53922	0.0000	1.07844

The impact of the interaction effects are presented in Figure 36. The factor *access mode* and *availability* have the greatest impact on the total utility. Both attributes have determine to a large extent the preference for urban BSS as egress mode. Other attributes that have also a high impact of the total utility are *bus preference* and *expensive.*

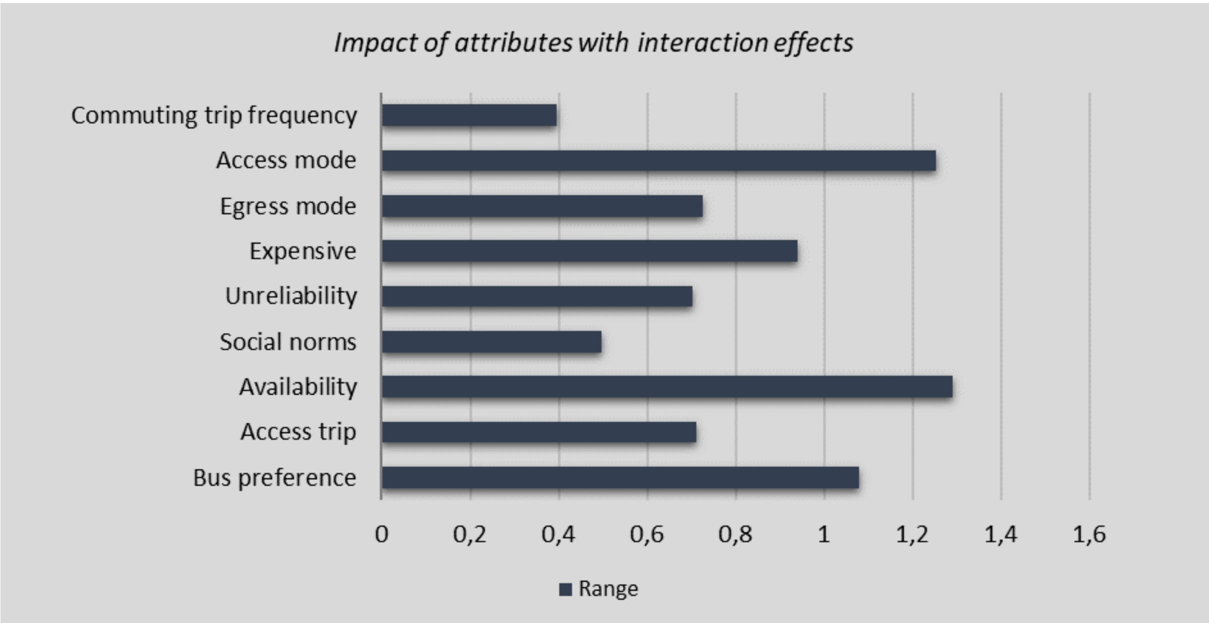


Figure 38. Impact of interactions effects on transportation mode choice by train commuters

4.4 CONCLUSIONS

The aim of this chapter was to provide insight into two main subjects, i.e. the (i) bicycle sharing system (BSS) attributes that influence the preference for an urban BSS in relation to the OV-fiets and the (ii) BSS attributes that influence the transportation mode choice of individuals. A distinction is made between two types of respondents, i.e. the (i) *private car* and (ii) *train commuters*. The relevant attributes that have been used for designing the stated preference experiment were explored from the literature, as discussed in Chapter 2.

The descriptive statistics indicated similar distributions between the sample with the Dutch target population. To reach the target group, two questions were formulated in the questionnaire for selection. As a result, the sample represents all individuals, the *commuters*, in the Netherlands who make at least one commuting trip per week by private car or train. A large variety in travel behavior patterns have been observed in the sample. However, since the representativeness of the sample has been proven, the results can be useful for parties who intend to use the insights provided for specific purposes.

In total, four discrete choice models were estimated in which each pursuing a different study aim. The Multinomial Logit (ML) models provide insight into the attributes that influence the preference for an urban BSS in relation to the OV-fiets for private car and train commuters. Regarding the Binary Logit (BL) models, the attributes that influence the willingness of private car commuters to commuting by train, and the willingness of train commuters to use urban BSSs as egress mode is investigated.

The statistical significance of the models was determined by using the Log Likelihood ratio-test. The results have shown that the MNL and BL models perform significantly better compared to the null models. Three out of the four models generated a low rho-squared value, indicating a relatively low goodness of fit. However, several authors emphasized that there is no "good" value for the rho-squared, because it can be improved by adding more attributes to the model (Abdel-Aal, 2017; Koppelman & Bhat, 2006).

Considering the MNL models, similar results were obtained for both private car and train commuters. The most important attributes that influence the preference for an urban BSS in relation to the OV-fiets are (i) *rental fare* and (ii) *reliability at stating point*. The utility of an urban BSS increases as the rental fare and unreliability at the BSS station at starting point are lower. The density of BSSs is an often recurring measure of BSS performance in the literature (Médard de Chardon *et al*., 2017). To a limited extent, the influence of *access* and *egress time* (related to walking distance) is also found significantly. The BL model of the private car commuters, i.e. Model C, indicates the (i) *rental fare,* (ii) *access time*, and (iii) *egress time* as the most important attributes on the preference for the train as transportation mode in relation to the private car for commuting trips. As a result, it can be assumed the density of BSS is the most important factor of transportation mode choice of private car commuters in order to encourage them to shift to the train. Model D indicates only the *egress time* that influences the preference for an urban BSS in relation to the current egress transportation mode. This result reflects the important of door-to-door journeys, since the train commuters are not willing to walk longer distances after the (shared) bicycle trip.

The extended analysis provided interesting results. Model A is extended with eight attributes of which *education level* and *province of work location* have the greatest impact on the utility of private car commuters for the preference of urban BSSs. Model B is extended with the attitudinal factors *attachment* and *egress trip*. The factor *attachment* is found to affect the utility for preference of urban BSSs of train commuters, while *egress trip* has a strong positive impact. In total, eight attributes were found with a significant interaction effect with Model C. The utility of private car commuters for their willingness to commute by train is most positively influenced by *age* and *egress trip*. Lastly, Model D is extended with nine attributes, where the attitudinal factors *availability* and *bus preference*, and the commute access mode have the largest impact on the utility for urban BSS preference as egress mode by train commuters.

The value of the alternative specific constant increased for Model A and B, indicating a higher preference for urban BSSs by both private car and train commuters. The opposite effect is found for Model C and D. This indicates that the willingness to commute by train and use urban BSS as egress mode decreased for the private car and train commuters respectively based on the constant.

5 CONCLUSIONS AND DISCUSSION

5.1 INTRODUCTION

This chapter discusses the conclusions drawn based on the literature review and the research carried out. The following section presents the main finding of the study and provides an answer to the research questions (Section 5.2). This is followed by a discussion of the research findings (Section 5.3). Finally, recommendations are made for further research.

5.2 RESEARCH FINDINGS

A stated preference experiment was conducted. The bicycle sharing system attributes of the stated preference experiment were explored in the literature review. The stated preference data is collected through an online questionnaire where respondents are recruited by Panel Inzicht, which is an online fieldwork organization in the Netherlands. Two questions are formulated for the selection of respondents. Only the respondents who commute more than once a week by private car or train were guided further by the questionnaire. In total, 385 respondents completed the questionnaire completely, of which 260 private car commuters and 125 train commuters. Four discrete choice analysis are performed: the attributes that influence the preference of (1) private car commuters and (2) train commuters for urban bicycle sharing systems; the (3) attributes that influence the willingness of private car users to shift to the train for commuting trips; and the (4) attributes that influence the willingness of train commuters to use urban bicycle sharing systems as egress mode instead of the current transportation mode. The preference of individuals for urban bicycle sharing systems is analyzed by Multinomial Logit models, and Binary Logit models are estimated for the analysis of transportation mode choice.

The aim of this study was to provide insight into the attributes that influence the preference of individuals with regard to the design of urban bicycle sharing systems, and the influence of urban bicycle sharing systems in the egress trip of multimodal train journeys on individuals' transportation mode choice regarding commuting trips. In order to reduce the complexity of the study and the experiment as well, two main research questions were formulated:

Research question 1:

How should urban bicycle sharing systems be designed in accordance with the preferences of individuals in the Netherlands?

Research question 2:

What is the influence of urban bicycle sharing systems in the egress trip of multimodal train journeys on individuals' transportation mode choice relating commuting trips?

A total of six research sub-questions were formulated to provide an answer to the main research questions. Research sub-question 1 to 3 relates to the literature review (Chapter 2) and research sub-questions 4 to 6 relates to the results of the experiment (Chapter 4).

Research sub-question 1:
What is multimodal (train) transportation?

In order to provide a comprehensive answer to this question, two perspectives of multimodal transportation are considered. First, the concept of multimodality refers to the integration of private and public transportation alternatives in a single transportation system that ensures that the strengths of the individual systems are utilized. The main idea of this concept is that the private transportation alternatives can be used to serve the main transportation system. Second, the concept of multimodality refers to the different phases accompanied. In order to reach the main transportation system, access transportation is needed, and to reach the final destination, egress transportation is needed. In short, multimodal transportation involves the use of private and public transportation modes in a transportation system to travel from origin to final destination, where two or more different transportation modes are used for the access to, and egress from the main service.

Research sub-question 2:
What are the most relevant attributes of existing (urban) bicycle sharing systems?

Four representative bicycle sharing systems were discussed in the literature review. These systems differ by *bicycle type*, *return option*, *system access*, *user registration*, *pricing structure*, *network type*, and *area type*. Based on existing literature, the most important attributes were further selected. Insights revealed that individuals' bicycle sharing system mode choice can be influenced mainly by seven attributes regarding the system characteristics mentioned above. The concerning attributes are : *bicycle type*, *reservation option*, *rental fare*, *access time*, *egress time*, *reliability at starting point*, and *reliability at endpoint*. In general, the defined seven attributes are related to travel time, convenience, travel costs, and reliability which are key factors in predicting transportation mode choice behavior of individuals. A factor that influences the performance of bicycle sharing systems is *density of the system,* which is related to access and egress (walking) times.

Research sub-question 3:
What attributes influence the transportation mode choice of commuters?

The decision of individuals for choosing one transportation mode alternative over another depends on various aspects. The *Theory of Planned Behavior* was used as underlayer in this study, including the intrapersonal attributes *attitudes, social norms, perceived behavioral control,* and *habits*; which all have a strong and direct influence on the transportation mode choice of individuals. In the literature it is assumed that this theory applies for all *human beings*. At a lower level, the *context attributes* were defined that influence the transportation mode choice of commuters specifically, including *travel time, monetary costs*, *affective motives (experiences), effort minimization (reliability),* and *need for personal space (freedom).* The third level of attributes have an indirect influence of the transportation mode choice of individuals, and relates to the *socioeconomic attributes, gender, age, education level, and household type;* and *knowledge of commuters* regarding transportation mode alternatives.

Research sub-question 4:
What attributes influence the preference for urban bicycle sharing systems?

The design of urban bicycle sharing systems is important to attract and retain users. Regarding the analysis of the urban bicycle sharing system's preferences of private car commuters, two attributes were found most influential, the rental fare costs and reliability at starting point. To a lesser extent, the access time, egress time, and reliability at endpoint were also found to influence the preference of individuals. Less decisive, however still significant, is the influence of bicycle type.

Almost identical results were obtained with regard to the attributes that influence the preference of train commuters for urban bicycle sharing systems. The reliability at endpoint has a lower influence on the preference compared to the access and egress time to the system. Furthermore, the results have shown that the bicycle type does not influence the preference of train commuters. Based on the positive value of the alternative specific constant of both models, it can be concluded that urban bicycle sharing systems are preferred by both private car and train commuters in relation to the OV-fiets.

Research sub-question 5:
How should urban bicycle sharing systems be designed in the egress trip of train journeys in order to attract the current private car commuters for commuting by train?

The willingness to shift from the car to the train by the private car commuters was found to be influenced mainly by the egress time to the urban bicycle sharing system, followed by access time, rental fare, and finally bicycle type. As expected, the alternative specific constant shows that the private car is preferred as commuting mode for this group of respondents. For this reason, the urban bicycle sharing system must be made attractive in order to encourage a modal shift by the private car commuters. The design of urban bicycle sharing systems that provides the highest willingness to shift from the private car to the train, should lower access and egress times as much as possible. The travel costs should also be minimized. Furthermore, the system should operate with traditional bicycles. In general, it can be concluded that urban bicycle sharing systems offer potential to encourage current private car commuters to shift to the train, only in case of minimized rental fare, access time, and egress time as described above.

Research sub-question 6:
How should urban bicycle sharing systems be designed in the egress trip of train journeys in order to attract the current train commuters to make use of shared bicycles?

The willingness to shift from the current egress mode to urban bicycle sharing systems by the train commuters was only found to be influenced by egress time from the urban bicycle sharing system station to the final destination. The alternative specific constant indicates that the current mode is preferred as egress mode regarding commuting train journeys instead of urban bicycle sharing systems. The design of urban bicycle sharing systems should focus on providing a network of stations that ensure an egress trip equal or lower than 3 minutes. By ensuring this, urban bicycle sharing systems have the potential to encourage train commuters to make use of the shared bicycles as egress mode.

In short, based on the answers provided to the research sub-questions, it can be concluded that urban bicycle sharing systems in the egress trip of train journeys can influence the transportation mode choice of both private car and train commuters in the Netherlands. The most important attribute to realize this is egress time to the final destination.

The extended analysis provided interesting results. Model A is extended with eight attributes of which *education level* and *province of work location* have the greatest impact on the utility of private car commuters for the preference of urban BSSs. Model B is extended with the attitudinal factors *attachment* and *egress trip*. The factor *attachment* is found to affect the utility for preference of urban BSSs of train commuters, while *egress trip* has a strong positive impact. In total, eight attributes were found with a significant interaction effect with Model C. The utility of private car commuters for their willingness to commute by train is most positively influenced by *age* and *egress trip*. Lastly, Model D is extended with nine attributes, where the attitudinal factors *availability* and *bus preference*, and the commute access mode have the largest impact on the utility for urban BSS preference as egress mode by train commuters.

The value of the alternative specific constant increased for Model A and B, indicating a higher preference for urban BSSs by both private car and train commuters. The opposite effect is found for Model C and D. This indicates that the willingness to commute by train and use urban BSS as egress mode decreased for the private car and train commuters respectively based on the constant.

5.3 Discussion

Recently, research into the integration of bicycle sharing and train has received increasing attention. This integration is considered as potential to achieve more complete door-to-door journeys by train and cause a modal shift from the private car. However, the scarcity of existing literature on this topic limits new insights and developments. Especially in the Dutch context, insights into the implementation of bicycle sharing systems and the integration with the train system is still limited. The aim of this study was to contribute and provide insights into the attributes that influence the preference of individuals for urban bicycle sharing systems, and to determine the influence of urban bicycle sharing systems in the egress trip of train journeys on the transportation mode choice of individuals regarding commuting trips.

With respect to the design of urban bicycle sharing systems, this study provides interesting insights. For instance, in the literature, access and egress times are often referred as the most important attributes of bicycle sharing system performance. However, this study found that rental fare and reliability at starting point are even more important on the urban bicycle sharing system mode choice. Where many systems abroad are confronted with lacking infrastructure that, for example, can impede access to systems, this is hardly the case in the Netherlands due to the high-quality pedestrian and bicycle infrastructure. Another interesting result, is the high impact of reliability at starting point. Apparently, commuters are less willing to wait before working time comparing to after working time. In order to avoid disutility by users, urban bicycle sharing systems must have enough capacity to meet demand, and especially during the morning and evening peak hours. Based on the results, it can be stated that urban bicycle sharing systems are preferred over the existing public transportation-related bicycle sharing system in the Netherlands, the OV-fiets. A possible explanation for this, may be that users experience the OV-fiets as too expensive (travel costs) , and the lack of supply in larger cities of the Netherlands there is not enough supply (increasing of unreliability).

Considering the integration of urban bicycle sharing system and train, it is assumed that urban bicycle sharing systems have the potential to contribute in achieving a modal shift from the private car to the train. However, for a modal shift to be achieved the design of urban bicycle sharing systems must be made attractive enough and three main design aspects must be considered. Firstly, the rental fare must be lower than 1.00 euro per trip. This is considerably cheaper compared to the OV-fiets (3.85 euro per day). Secondly, an equilibrium must be created between demand and supply of the system to avoid the unreliability of availability of shared bicycles at stations. Thirdly, the urban bicycle sharing system stations should ensure connectivity between locations to reduce walking access and egress time. The general guideline for this is 3 to 4 minutes (approximately 300 meters), however, lower access times from train stations and egress times to final destinations are desirable. Although the reservation option is not found to have a significant influence on the transportation mode choice of commuters, providing a system which enables travelers to travel by train and rent a shared bicycle with, for example, a public transportation card (OV-chipcard), can increase the convenience of travelers during the travel.

The reason that (urban) bicycle sharing systems still have not broken though in the Netherlands can be mainly attributed to the fact that the Dutch population has a high bicycle ownership. The existing literature has appointed that individuals add value to property, which implies that a shared bicycle will only be used when the own bicycle is not at hand. This is especially the case in the egress trip of train journeys. The results of the study are in line with this assumption. For this reason, several considerations have to be made when implementing an urban bicycle sharing systems in the Netherlands that aims to serve commuters in the egress trip of train journeys. In contrast to many urban bicycle sharing systems abroad, increasing the cycling population is not the main goal itself of the Dutch government. However, this relates to creating healthier urban environments by decreasing congestion levels and increasing the accessibility of urban areas that has been negatively affected by increasing private car use. Implementing urban bicycle sharing systems should be therefore mainly focus on the egress trip, at specific locations of demand. It is of key importance that both transportation systems are integrated in order to provide travelers more complete door-to-door journeys, where the network of urban bicycle sharing systems should increases the accessibility from train stations to work locations.

The findings in this thesis can be used by several parties, such as municipalities, bicycle sharing system organizations, and public transportation facilitators as starting point for the design of urban bicycle sharing systems that can serve as extension of the existing public transportation system. The discrete choice models proved to be significant, however, it should be noted that relative low rho-squared values were obtained, which reflects a low goodness-of-fit. On the other hand, the estimated models provided realistic outcomes, where the travel time and costs shown to have the largest impact of the urban bicycle sharing system preference and influence on transportation mode choice of commuters.

Although the questionnaire data provided interesting insights, the length of the questionnaire was perceived by the respondents as being too long. For this reason, it is expected that many respondents did not answered the questionnaire completely. In addition, the number of tasks, in total nine, presented was also perceived as too high. Many respondents entered the questionnaire, however, only a small proportion of respondents has been used in the analysis. In the next research, the length of questionnaire should be considered in more detail.

5.4 Directions for Further Research

Further research can be conducted on the integration between urban bicycle sharing and train in order to offer both systems as an integrated system or service to travelers. This study proposed the integration between urban bicycle sharing system and train as hypothetical situation in the Netherlands, however no clear assumptions have been made regarding how both systems have to be integrated. In the literature, this is referred to "seamless" integration of systems. Since the main trip is characterized by a high quality in the Netherlands, attention should be mainly paid to the egress trip and the implementation of urban bicycle sharing systems. A possible direction of research is investigating how the access to urban bicycle sharing system stations can be facilitated from train station to travelers and how systems can improve the accessibility or connectivity between the train station and final destination (work location) of travelers. In addition, research on (potential) travel time reductions can be carried out by this integration.

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A APPENDIX

Overview of Treatment Combinations

TC	*Attribute*							Score* (0 to 10)
	A	B	C	D	E	F	G	
1	Traditional	None	0.50 euro	1 minutes	5 minutes	5 minutes	5 minutes	4
2	Traditional	None	0.50 euro	1 minutes	5 minutes	0 minutes	0 minutes	2
3	Traditional	None	0.50 euro	3 minutes	3 minutes	10 minutes	5 minutes	5
4	Traditional	None	0.50 euro	3 minutes	1 minutes	5 minutes	10 minutes	4
5	Traditional	None	1.00 euro	1 minutes	1 minutes	5 minutes	5 minutes	3
6	Traditional	None	1.00 euro	5 minutes	5 minutes	5 minutes	10 minutes	8
7	Traditional	None	1.50 euro	1 minutes	3 minutes	0 minutes	0 minutes	3
8	Traditional	None	1.50 euro	5 minutes	5 minutes	10 minutes	5 minutes	9
9	Traditional	OV-chipcard	1.00 euro	1 minutes	1 minutes	10 minutes	0 minutes	3
10	Traditional	OV-chipcard	1.00 euro	3 minutes	5 minutes	0 minutes	5 minutes	5
11	Traditional	OV-chipcard	1.50 euro	1 minutes	3 minutes	5 minutes	5 minutes	5
12	Traditional	OV-chipcard	1.50 euro	3 minutes	5 minutes	5 minutes	10 minutes	8
13	Traditional	Application	0.50 euro	1 minutes	5 minutes	5 minutes	5 minutes	4
14	Traditional	Application	0.50 euro	1 minutes	5 minutes	10 minutes	0 minutes	4
15	Traditional	Application	0.50 euro	5 minutes	3 minutes	5 minutes	10 minutes	6
16	Traditional	Application	0.50 euro	5 minutes	1 minutes	0 minutes	5 minutes	3
17	Electric	None	0.50 euro	1 minutes	3 minutes	5 minutes	5 minutes	3
18	Electric	None	0.50 euro	1 minutes	1 minutes	0 minutes	10 minutes	2
19	Electric	None	0.50 euro	3 minutes	5 minutes	5 minutes	0 minutes	4
20	Electric	None	0.50 euro	3 minutes	5 minutes	10 minutes	5 minutes	6
21	Electric	None	1.00 euro	1 minutes	5 minutes	5 minutes	5 minutes	5
22	Electric	None	1.00 euro	5 minutes	3 minutes	5 minutes	0 minutes	5
23	Electric	None	1.50 euro	1 minutes	5 minutes	0 minutes	10 minutes	6
24	Electric	None	1.50 euro	5 minutes	1 minutes	10 minutes	5 minutes	7
25	Electric	OV-chipcard	0.50 euro	1 minutes	3 minutes	10 minutes	10 minutes	5
26	Electric	OV-chipcard	0.50 euro	1 minutes	1 minutes	5 minutes	5 minutes	2
27	Electric	OV-chipcard	0.50 euro	5 minutes	5 minutes	5 minutes	0 minutes	5
28	Electric	OV-chipcard	0.50 euro	5 minutes	5 minutes	0 minutes	5 minutes	5
29	Electric	Application	1.00 euro	1 minutes	5 minutes	10 minutes	10 minutes	7
30	Electric	Application	1.00 euro	3 minutes	3 minutes	0 minutes	5 minutes	4
31	Electric	Application	1.50 euro	1 minutes	5 minutes	5 minutes	5 minutes	6
32	Electric	Application	1.50 euro	3 minutes	1 minutes	5 minutes	0 minutes	4

* Score assigned to attribute level: [0] = *lowest*; [1] = *middle*; and [2] = *highest*.

B APPENDIX

Choice set Generation: Overview of Alternatives

Alternative	*Treatment combination*	*Attribute* A	B	C	D	E	F	G
1	31	Electric	Application	1.50 euro	1 minutes	5 minutes	5 minutes	5 minutes
	18	Electric	None	0.50 euro	1 minutes	1 minutes	0 minutes	10 minutes
2	15	Traditional	Application	0.50 euro	5 minutes	3 minutes	5 minutes	10 minutes
	22	Electric	None	1.00 euro	5 minutes	3 minutes	5 minutes	0 minutes
3	32	Electric	Application	1.50 euro	3 minutes	1 minutes	5 minutes	0 minutes
	13	Traditional	Application	0.50 euro	1 minutes	5 minutes	5 minutes	5 minutes
4	5	Traditional	None	1.00 euro	1 minutes	1 minutes	5 minutes	5 minutes
	27	Electric	OV-chipcard	0.50 euro	5 minutes	5 minutes	5 minutes	0 minutes
5	1	Traditional	None	0.50 euro	1 minutes	5 minutes	5 minutes	5 minutes
	3	Traditional	None	0.50 euro	3 minutes	3 minutes	10 minutes	5 minutes
6	30	Electric	Application	1.00 euro	3 minutes	3 minutes	0 minutes	5 minutes
	2	Traditional	None	0.50 euro	1 minutes	5 minutes	0 minutes	0 minutes
7	21	Electric	None	1.00 euro	1 minutes	5 minutes	5 minutes	5 minutes
	24	Electric	None	1.50 euro	5 minutes	1 minutes	10 minutes	5 minutes
8	11	Traditional	OV-chipcard	1.00 euro	3 minutes	5 minutes	0 minutes	5 minutes
	10	Traditional	OV-chipcard	1.00 euro	3 minutes	5 minutes	0 minutes	5 minutes
9	28	Electric	OV-chipcard	0.50 euro	5 minutes	5 minutes	0 minutes	5 minutes
	14	Traditional	Application	0.50 euro	1 minutes	5 minutes	10 minutes	0 minutes
10	4	Traditional	None	0.50 euro	3 minutes	1 minutes	5 minutes	10 minutes
	17	Electric	None	0.50 euro	1 minutes	3 minutes	5 minutes	5 minutes
11	9	Traditional	OV-chipcard	1.00 euro	1 minutes	1 minutes	10 minutes	0 minutes
	26	Electric	OV-chipcard	0.50 euro	1 minutes	1 minutes	5 minutes	5 minutes
12	6	Traditional	None	1.00 euro	5 minutes	5 minutes	5 minutes	10 minutes
	25	Electric	OV-chipcard	0.50 euro	1 minutes	3 minutes	10 minutes	10 minutes
13	7	Traditional	None	1.50 euro	1 minutes	3 minutes	0 minutes	0 minutes
	20	Electric	None	0.50 euro	3 minutes	5 minutes	10 minutes	5 minutes
14	12	Traditional	OV-chipcard	1.50 euro	3 minutes	5 minutes	5 minutes	10 minutes
	23	Electric	None	1.50 euro	1 minutes	5 minutes	0 minutes	10 minutes
15	29	Electric	Application	1.00 euro	1 minutes	5 minutes	10 minutes	10 minutes
	8	Traditional	None	1.50 euro	5 minutes	5 minutes	10 minutes	5 minutes
16	19	Electric	None	0.50 euro	3 minutes	5 minutes	5 minutes	0 minutes
	16	Traditional	Application	0.50 euro	5 minutes	1 minutes	0 minutes	5 minutes

C APPENDIX

Effect Coding Used For Attribute Levels

Attribute	Attribute level	Indicator 1	Indicator 2
Bicycle sharing system			
Bicycle type	Traditional	-1	
	Electric	1	
Reservation option	None	1	0
	OV-chipcard	0	1
	Application	-1	-1
Rental fare	0.50 euro	1	0
	1.00 euro	0	1
	1.50 euro	-1	-1
Access time	1 minutes	1	0
	3 minutes	-1	-1
	5 minutes	0	1
Egress time	1 minutes	-1	-1
	3 minutes	0	1
	5 minutes	1	0
Reliability at starting point	0 minutes	-1	-1
	5 minutes	1	0
	10 minutes	0	1
Reliability at endpoint	0 minutes	0	1
	5 minutes	1	0
	10 minutes	-1	-1
Socioeconomic characteristics			
Gender	Man	-1	
	Female	1	
Age	Younger than 35 years	-1	
	35 till 49 years	0	
	Older than 49 years	1	
Education level	Others	-1	
	WO/HBO	1	
Household	Others	-1	
	With child(ren)	1	

(Table previous page continued)

Attribute	Attribute level	Indicator 1	Indicator 2
Trip characteristics			
Commute trip frequency	4 days or less	-1	
	More than 4 days	1	
Province of home location[1]	Others	-1	
	N-H/N-Z/UT	1	
Province of work location[1]	Others	-1	
	N-H/Z-H/UT	1	
Travel time of private car	1 till 25 minutes	-1	
	26 till 40 minutes	0	
	More than 40 minutes	1	
Travel time of train	1 till 45 minutes	-1	
	46 till 60 minutes	0	
	More than 60 minutes	1	
Access mode[2]	Others	-1	
	Bicycle	1	
Egress mode[2]	Others	-1	
	Walking	1	
Egress time[2]	10 minutes or less	-1	
	More than 10 minutes	1	
Transportation Mode-related attitudinal factors (train)			
Mode choice factor	Others	-1	
	Travel time	1	
Enjoyment (factor 1)	Disagree/Neutral	-1	
	Agree	1	
Expensive (factor 2)	Disagree/Neutral	-1	
	Agree	1	
Environment (factor 3)	Disagree	-1	
	Agree/Neutral	1	
Attachment (factor 4)	Disagree/Neutral	-1	
	Agree	1	
Congestion (factor 5)	Disagree	-1	
	Agree/Neutral	1	
Unreliability (factor 6)	Disagree/Neutral	-1	
	Agree	1	

[1] Provinces of the Netherlands: N-H = Noord-Holland, Z-H = Zuid-Holland, and UT = Utrecht.
[2] This attribute relates to train transportation only.

(Table previous page continued)

Attribute	Attribute level	Indicator 1	Indicator 2
Captivity (factor 7)	Disagree	-1	
	Agree/ Neutral	1	
Social norms (factor 8)	Disagree	-1	
	Agree/Neutral	1	
Transportation Mode-related attitudinal factors (train)			
Mode choice factor	Others	-1	
	Travel costs	1	
Enjoyment (factor 1)	Disagree/Neutral	-1	
	Agree	1	
Expensive (factor 2)	Disagree/Neutral	-1	
	Agree	1	
Environment (factor 3)	Disagree/ Neutral	-1	
	Agree	1	
Attachment (factor 4)	Disagree/Neutral	-1	
	Agree	1	
Congestion (factor 5)	Disagree/Neutral	-1	
	Agree	1	
Unreliability (factor 6)	Disagree/Neutral	-1	
	Agree	1	
Captivity (factor 7)	Disagree/ Neutral	-1	
	Agree	1	
Social norms (factor 8)	Disagree	-1	
	Agree/Neutral	1	
BSS-related attitudinal factors			
Own bicycle (factor 1)	Disagree/Neutral	-1	
	Agree	1	
Availability (factor 2)	Disagree/Neutral	-1	
	Agree	1	
Access trip (factor 3)	Disagree	-1	
	Agree/Neutral	1	
Egress trip (factor 4)	Disagree/Neutral	-1	
	Agree	1	
Attractiveness (factor 5)	Disagree/Neutral	-1	
	Agree	1	
Bus preference (factor 6)	Disagree/Neutral	-1	
	Agree	1	

D APPENDIX

DISCRETE CHOICE MODEL OUTPUT (BASIC MODELS)

Description of attributes:

ICON	=	Alternative-specific constant;
ITYP	=	Type of bicycle (2 levels);
IRES	=	Reservation option (3 levels);
ITAR1	=	Rental fare (3 levels);
IWDS1	=	Access (walking) time to BSS station (3 levels);
IWB1	=	Egress (walking) time to work location (3 levels);
ITDS1	=	Waiting time at BSS station at starting point (3 levels); and
ITB1	=	Waiting time at BSS station at endpoint (3 levels).

APPENDIX D-1 | NLogit output 1: Multinomial Logit model of the private car commuters.

```
--------------------------------------------------------------------------------

|-> SAMPLE ; All $
|-> DISCRETECHOICE;Lhs = icho
    ;Choices = 1,2,3
    ;Rhs     = icon,
    ityp,ires1,ires2,itar1,itar2,itds1,itds2,itb1,itb2,
    iwds1,iwds2,iwb1,iwb2$
Normal exit:   5 iterations. Status=0, F=    2060.527

--------------------------------------------------------------------------------
```

```
-----------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -2060.52740
Estimation based on N =    2080, K =  14
Inf.Cr.AIC  =    4149.1 AIC/N =    1.995
Model estimated: May 02, 2018, 21:08:34
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -2186.2684  .0575 .0543
Response data are given as ind. choices
Number of obs.=  2080, skipped    0 obs
--------+--------------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
    ICHO|  Coefficient     Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------------
    ICON|      .59711***    .06149     9.71  .0000      .47658     .71763
    ITYP|      .12435***    .03216     3.87  .0001      .06132     .18737
   IRES1|    -.01382        .04562     -.30  .7619    -.10323     .07558
   IRES2|     .03285        .05568      .59  .5553    -.07629     .14198
   ITAR1|      .39613***    .04796     8.26  .0000      .30213     .49013
   ITAR2|     .02450        .05030      .49  .6262    -.07409     .12308
   ITDS1|      .24479***    .04098     5.97  .0000      .16447     .32512
   ITDS2|    -.22932***     .05907    -3.88  .0001    -.34509    -.11354
    ITB1|    -.25492***     .04213    -6.05  .0000    -.33750    -.17234
    ITB2|     .05095        .05195      .98  .3267    -.05088     .15278
   IWDS1|     .02801        .04535      .62  .5367    -.06086     .11689
   IWDS2|    -.40805***     .05255    -7.76  .0000    -.51106    -.30505
    IWB1|     .04439        .04470      .99  .3206    -.04321     .13200
    IWB2|      .20819***    .05081     4.10  .0000      .10860     .30779
--------+--------------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------------
```

APPENDIX D-2 | NLogit output 2: Multinomial Logit model of the train commuters.

```
--------------------------------------------------------------------------------
|-> SAMPLE ; All $
|-> DISCRETECHOICE;Lhs = icho
    ;Choices = 1,2,3
    ;Rhs     = icon,
    ityp,ires1,ires2,itar1,itar2,itds1,itds2,itb1,itb2,
    iwds1,iwds2,iwb1,iwb2$
Normal exit:   5 iterations. Status=0, F=    950.4323
--------------------------------------------------------------------------------
```

```
--------------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -950.43231
Estimation based on N =   1000, K =  14
Inf.Cr.AIC  =   1928.9 AIC/N =    1.929
Model estimated: May 05, 2018, 16:21:05
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1070.1181  .1118 .1056
Response data are given as ind. choices
Number of obs.=  1000, skipped    0 obs
--------+-----------------------------------------------------------------------
        |                 Standard            Prob.       95% Confidence
    ICHO|  Coefficient      Error       z    |z|>Z*          Interval
--------+-----------------------------------------------------------------------
    ICON|     .32105***     .08752     3.67  .0002      .14952     .49258
    ITYP|     .02166        .04882      .44  .6572     -.07401     .11734
   IRES1|    -.09999        .07104    -1.41  .1593     -.23922     .03925
   IRES2|     .08815        .08194     1.08  .2820     -.07244     .24875
   ITAR1|     .62522***     .07360     8.49  .0000      .48097     .76947
   ITAR2|    -.03572        .07767     -.46  .6456     -.18794     .11651
   ITDS1|     .44587***     .06312     7.06  .0000      .32215     .56959
   ITDS2|    -.40366***     .09014    -4.48  .0000     -.58033    -.22699
    ITB1|    -.39470***     .06478    -6.09  .0000     -.52167    -.26773
    ITB2|    -.02847        .07730     -.37  .7126     -.17998     .12303
   IWDS1|     .01247        .06902      .18  .8566     -.12279     .14774
   IWDS2|    -.57598***     .08320    -6.92  .0000     -.73904    -.41291
    IWB1|     .06558        .06802      .96  .3350     -.06773     .19889
    IWB2|     .23162***     .07676     3.02  .0025      .08117     .38207
--------+-----------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------------------
```

APPENDIX D-3 | NLogit output 3: Binary Logit model of the private car commuters.

```
--------------------------------------------------------------------------------

|-> SAMPLE ; All $
|-> Rejecting all observations with choice = 1
    reject; icho = 0$
|-> create; if (icho2 = 1) icho3=0$
|-> create; if (icho2 = 2) icho3=1$
|-> LOGIT;Lhs=ICHO3
    ;Rhs=ICON,ITYP,IRES1,IRES2,ITAR1,ITAR2,ITDS1,ITDS2,ITB1,ITB2
    ,IWDS1,IWDS2,IWB1,IWB2$
Normal exit:   6 iterations. Status=0, F=    1051.113

--------------------------------------------------------------------------------
```

```
--------------------------------------------------------------------------------
Binary Logit Model for Binary Choice
Dependent variable                 ICHO3
Log likelihood function     -1051.11284
Estimation based on N =    2080, K =  14
Inf.Cr.AIC  =    2130.2 AIC/N =    1.024
Model estimated: May 05, 2018, 17:21:52
Hosmer-Lemeshow chi-squared = 339.61834
P-value=  .00000 with deg.fr. =       8
--------+-----------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
   ICHO3|  Coefficient       Error       z    |z|>Z*         Interval
--------+-----------------------------------------------------------------------
    ICON|   -1.65956***      .09350   -17.75  .0000    -1.84282  -1.47630
    ITYP|     .13961**       .06752     2.07  .0387      .00726    .27195
   IRES1|     .15981*        .09207     1.74  .0826    -.02065    .34027
   IRES2|     .15411         .10420     1.48  .1391    -.05012    .35834
   ITAR1|     .20279**       .09253     2.19  .0284      .02144    .38414
   ITAR2|     .02879         .11079      .26  .7950    -.18836    .24593
   ITDS1|     .18478**       .09192     2.01  .0444      .00462    .36495
   ITDS2|    -.29847**       .12168    -2.45  .0142    -.53696   -.05998
    ITB1|    -.25713***      .09111    -2.82  .0048    -.43570   -.07857
    ITB2|    -.05377         .09782     -.55  .5825    -.24549    .13795
   IWDS1|    -.09427         .09208    -1.02  .3059    -.27473    .08620
   IWDS2|     .00264         .11455      .02  .9816    -.22187    .22716
    IWB1|    -.14489         .09046    -1.60  .1092    -.32218    .03240
    IWB2|     .04285         .10373      .41  .6795    -.16044    .24615
--------+-----------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------------------
```

APPENDIX D-4 | NLogit output 4: Binary Logit model of the train commuters.

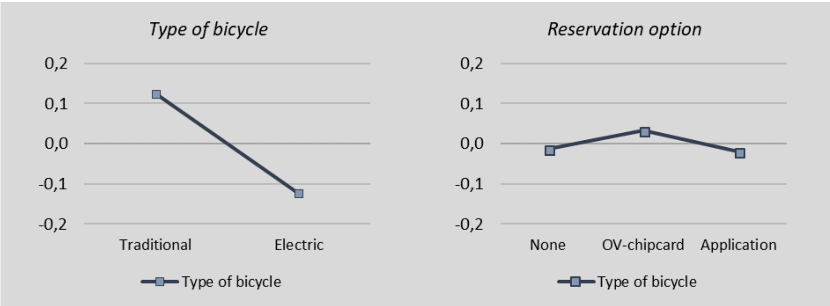
```
--------------------------------------------------------------------------------

|-> SAMPLE ; All $
|-> Rejecting all observations with choice = 1
    reject; icho = 0$
|-> create; if (icho2 = 1) icho3=0$
|-> create; if (icho2 = 2) icho3=1$
|-> LOGIT;Lhs=ICHO3
    ;Rhs=ICON,ITYP,IRES1,IRES2,ITAR1,ITAR2,ITDS1,ITDS2,ITB1,ITB2
    ,IWDS1,IWDS2,IWB1,IWB2$
Normal exit:   5 iterations. Status=0, F=    619.0263

--------------------------------------------------------------------------------
```

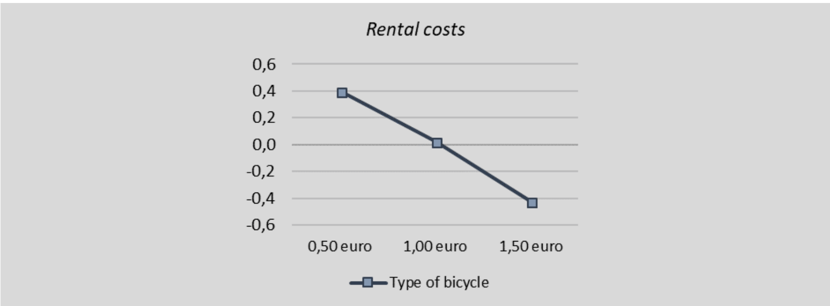
```
--------------------------------------------------------------------------------
Binary Logit Model for Binary Choice
Dependent variable                ICHO3
Log likelihood function      -619.02626
Estimation based on N =   1000, K =  14
Inf.Cr.AIC  =    1266.1 AIC/N =    1.266
Model estimated: May 05, 2018, 17:38:09
Hosmer-Lemeshow chi-squared = 161.81942
P-value=  .00000 with deg.fr. =       8
--------+-----------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
   ICHO3|  Coefficient     Error       z    |z|>Z*         Interval
--------+-----------------------------------------------------------------------
    ICON|    -.83659***    .11616    -7.20  .0000    -1.06425    -.60892
    ITYP|     .10910       .08283     1.32  .1878     -.05323     .27144
   IRES1|    -.05084       .11554     -.44  .6599     -.27728     .17561
   IRES2| .79413D-04       .12614      .00  .9995 -.24716D+00  .24732D+00
   ITAR1|     .18363       .11933     1.54  .1239     -.05026     .41753
   ITAR2|     .17379       .14027     1.24  .2154     -.10114     .44872
   ITDS1|    -.02896       .11475     -.25  .8008     -.25385     .19594
   ITDS2|     .01147       .14439      .08  .9367     -.27154     .29448
    ITB1|    -.43258***    .11583    -3.73  .0002     -.65962    -.20555
    ITB2|     .22533*      .11984     1.88  .0601     -.00954     .46021
   IWDS1|    -.20978*      .11464    -1.83  .0673     -.43447     .01491
   IWDS2|     .00634       .14659      .04  .9655     -.28097     .29364
    IWB1|    -.04032       .11266     -.36  .7204     -.26112     .18049
    IWB2|     .05801       .13386      .43  .6647     -.20435     .32038
--------+-----------------------------------------------------------------------
Note: nnnnn.D-xx or D+xx => multiply by 10 to -xx or +xx.
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------------------
```

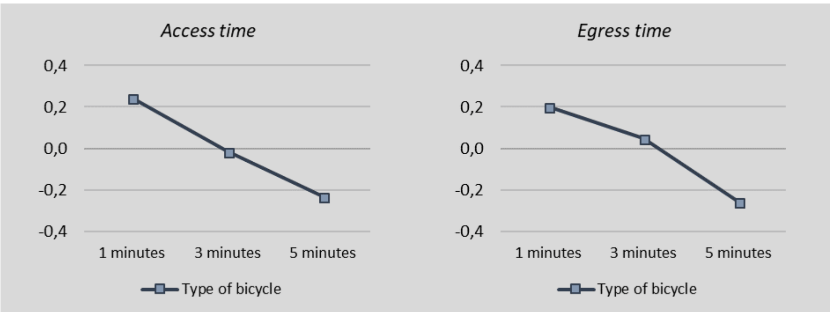
E | APPENDIX

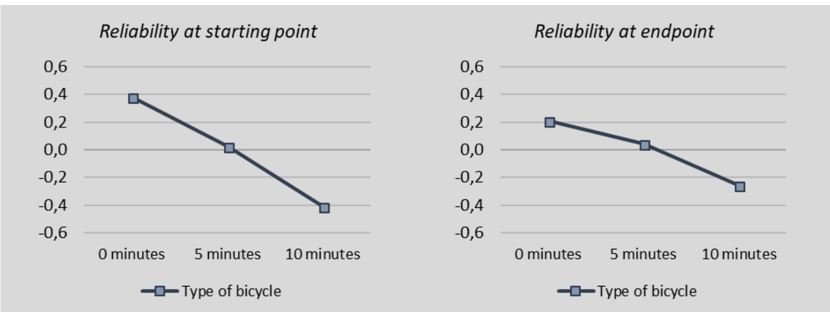
Bicycle Sharing System Utilities

APPENDIX E-1 | Utilities of Multinomial Logit Model A (private car commuters)

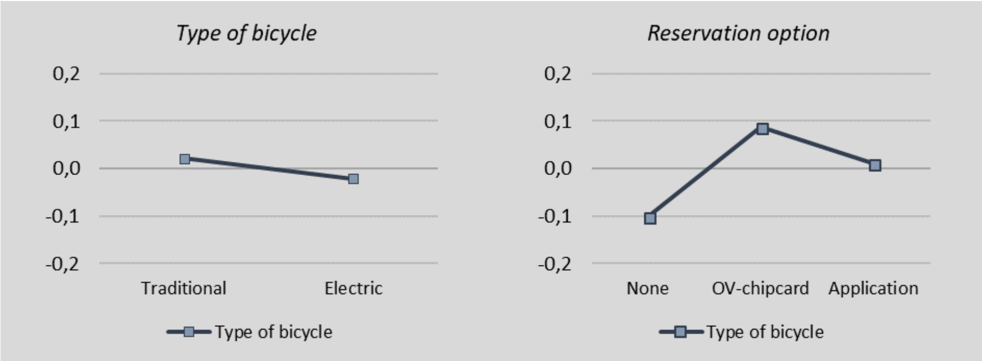


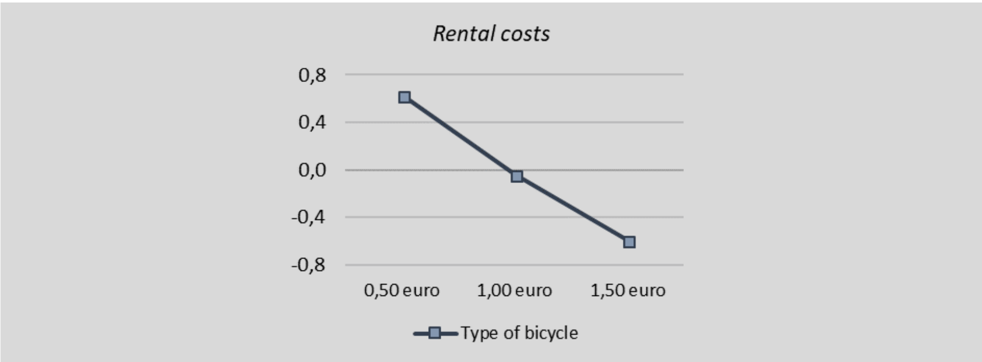


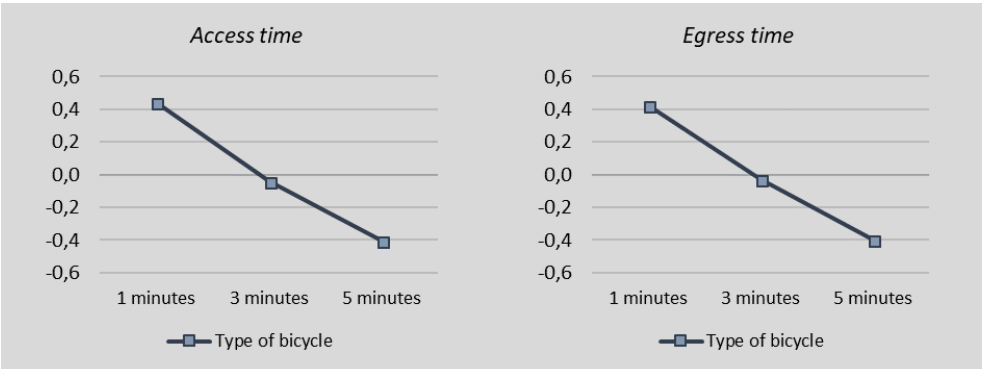


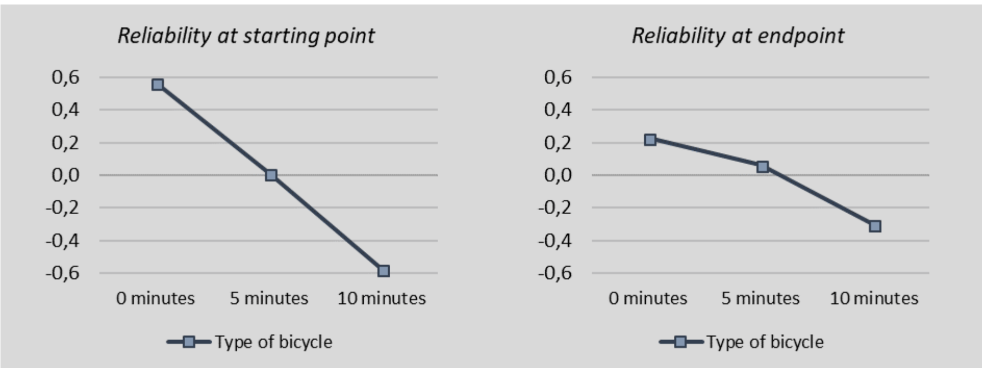


APPENDIX E-2 | Utilities of Multinomial Logit Model B (train commuters)

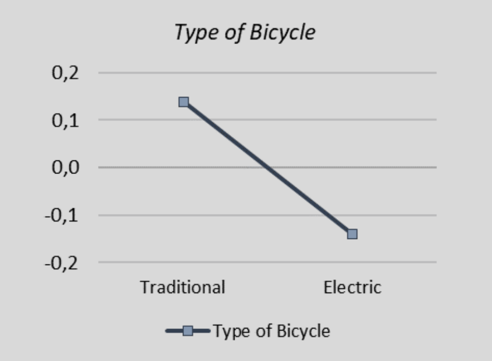


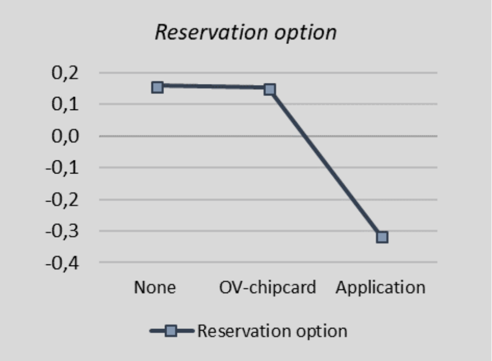


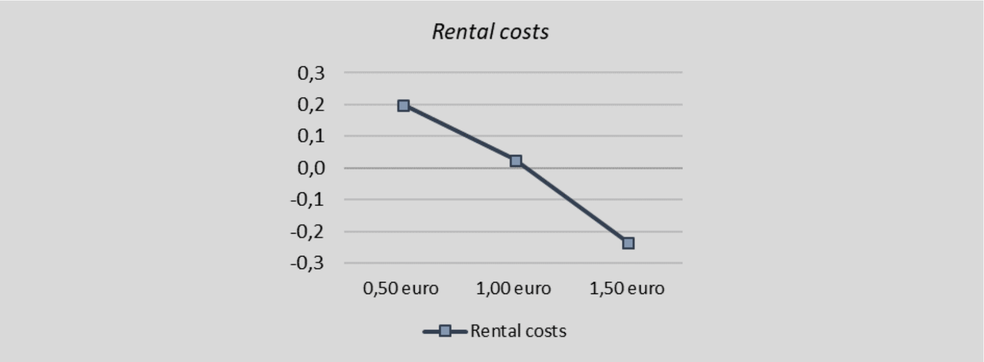


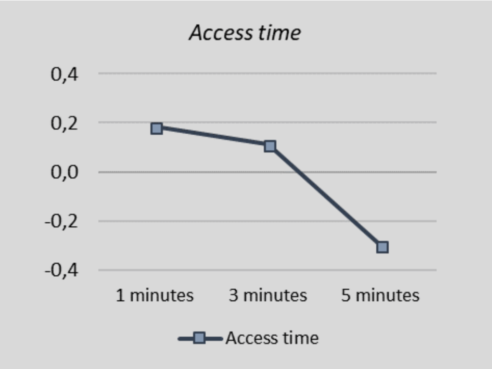


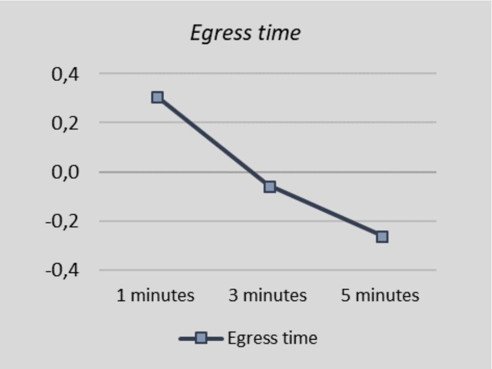
APPENDIX E-3 | Utilities of Binary Logit Model C (private car commuters)

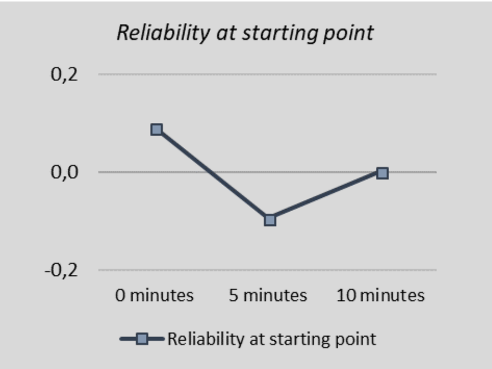


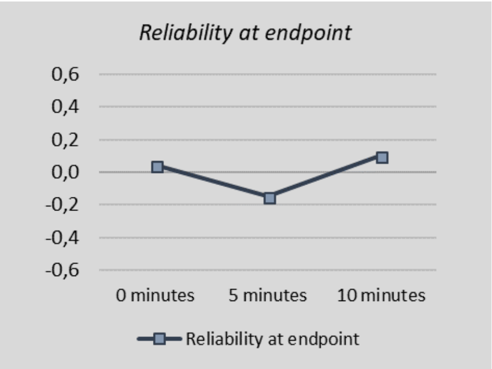




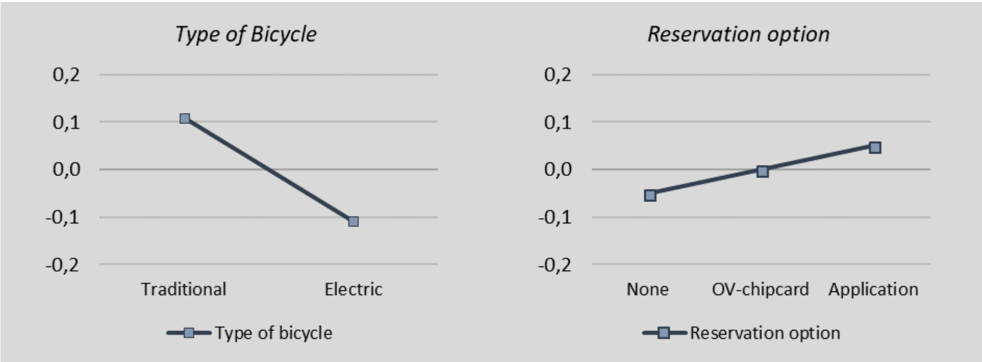


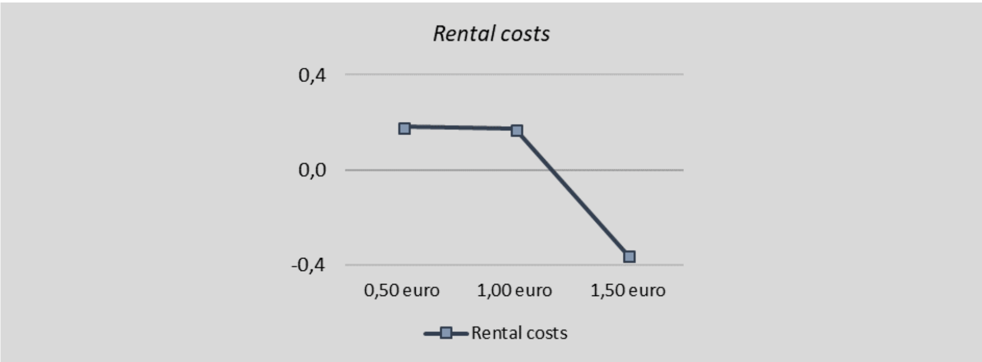


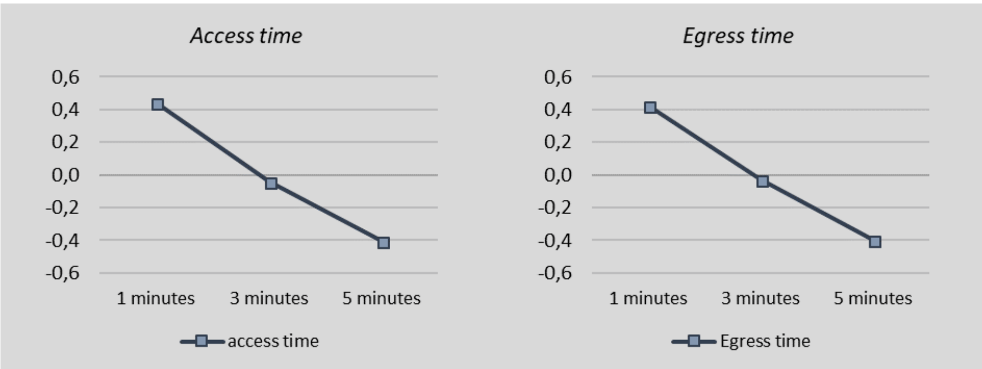


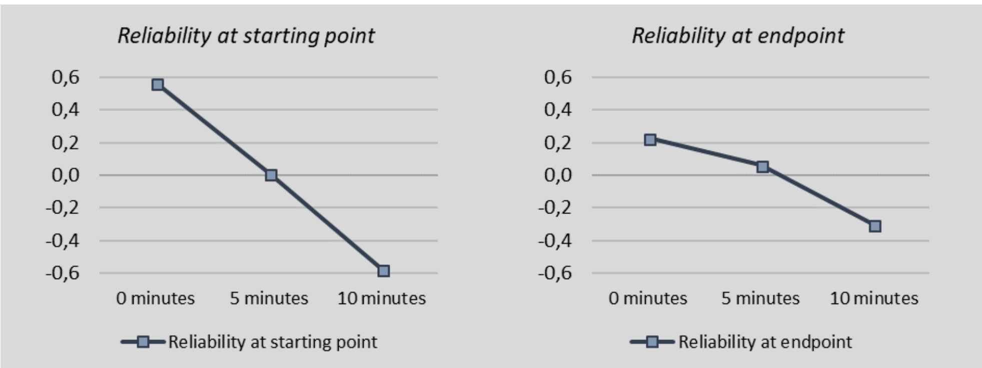


APPENDIX E-4 | Utilities of Binary Logit Model D (train commuters)









F | APPENDIX

CORRELATION STATISTICS OF ATTRIBUTES

APPENDIX F-1 | Private car commuters

(Table 1 out of 4)

Correlations

		GENDER	AGE	EDUCATION	HOUSEHOLD
GENDER	Pearson Correlation	1	-,147*	-,101	-,045
	Sig. (2-tailed)		,018	,105	,468
	N	260	260	260	260
AGE	Pearson Correlation	-,147*	1	-,127*	,234**
	Sig. (2-tailed)	,018		,042	,000
	N	260	260	260	260
EDUCATION	Pearson Correlation	-,101	-,127*	1	-,035
	Sig. (2-tailed)	,105	,042		,577
	N	260	260	260	260
HOUSEHOLD	Pearson Correlation	-,045	,234**	-,035	1
	Sig. (2-tailed)	,468	,000	,577	
	N	260	260	260	260

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

(Table 2 out of 4)

Correlations

		FREQUENCY	HOME	WORK	TIMECAR
FREQUENCY	Pearson Correlation	1	,087	-,044	-,035
	Sig. (2-tailed)		,162	,477	,573
	N	260	260	260	260
HOME	Pearson Correlation	,087	1	,728**	,022
	Sig. (2-tailed)	,162		,000	,729
	N	260	260	260	260
WORK	Pearson Correlation	-,044	,728**	1	,151*
	Sig. (2-tailed)	,477	,000		,015
	N	260	260	260	260
TIMECAR	Pearson Correlation	-,035	,022	,151*	1
	Sig. (2-tailed)	,573	,729	,015	
	N	260	260	260	260

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

(Table 3 out of 4)

Correlations

		FACTORCHOICE	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5	FACTOR6	FACTOR7	FACTOR8
FACTORCHOICE	Pearson Correlation	1	,022	,094	-,019	,175**	-,005	,142*	,100	,032
	Sig. (2-tailed)		,728	,129	,765	,005	,932	,022	,108	,604
	N	260	260	260	260	260	260	260	260	260
FACTOR1	Pearson Correlation	,022	1	-,015	-,136*	-,008	-,005	,016	-,024	-,112
	Sig. (2-tailed)	,728		,815	,028	,902	,936	,796	,696	,071
	N	260	260	260	260	260	260	260	260	260
FACTOR2	Pearson Correlation	,094	-,015	1	,149*	,186**	,046	,020	,257**	,166**
	Sig. (2-tailed)	,129	,815		,016	,003	,459	,746	,000	,007
	N	260	260	260	260	260	260	260	260	260
FACTOR3	Pearson Correlation	-,019	-,136*	,149*	1	,344**	,040	,003	,046	,257**
	Sig. (2-tailed)	,765	,028	,016		,000	,516	,966	,458	,000
	N	260	260	260	260	260	260	260	260	260
FACTOR4	Pearson Correlation	,175**	-,008	,186**	,344**	1	-,063	,123*	,020	,238**
	Sig. (2-tailed)	,005	,902	,003	,000		,309	,047	,750	,000
	N	260	260	260	260	260	260	260	260	260
FACTOR5	Pearson Correlation	-,005	-,005	,046	,040	-,063	1	,024	,221**	,288**
	Sig. (2-tailed)	,932	,936	,459	,516	,309		,695	,000	,000
	N	260	260	260	260	260	260	260	260	260
FACTOR6	Pearson Correlation	,142*	,016	,020	,003	,123*	,024	1	,122*	,070
	Sig. (2-tailed)	,022	,796	,746	,966	,047	,695		,049	,258
	N	260	260	260	260	260	260	260	260	260
FACTOR7	Pearson Correlation	,100	-,024	,257**	,046	,020	,221**	,122*	1	,089
	Sig. (2-tailed)	,108	,696	,000	,458	,750	,000	,049		,153
	N	260	260	260	260	260	260	260	260	260
FACTOR8	Pearson Correlation	,032	-,112	,166**	,257**	,238**	,288**	,070	,089	1
	Sig. (2-tailed)	,604	,071	,007	,000	,000	,000	,258	,153	
	N	260	260	260	260	260	260	260	260	260

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

(Table 4 out of 4)

Correlations

		BSS1	BSS2	BSS3	BSS4	BSS5	BSS6
BSS1	Pearson Correlation	1	,531**	-,110	-,182**	-,129*	-,166**
	Sig. (2-tailed)		,000	,077	,003	,038	,007
	N	260	260	260	260	260	260
BSS2	Pearson Correlation	,531**	1	,010	,086	,111	,067
	Sig. (2-tailed)	,000		,877	,169	,073	,279
	N	260	260	260	260	260	260
BSS3	Pearson Correlation	-,110	,010	1	,367**	,163**	,113
	Sig. (2-tailed)	,077	,877		,000	,008	,068
	N	260	260	260	260	260	260
BSS4	Pearson Correlation	-,182**	,086	,367**	1	,522**	,535**
	Sig. (2-tailed)	,003	,169	,000		,000	,000
	N	260	260	260	260	260	260
BSS5	Pearson Correlation	-,129*	,111	,163**	,522**	1	,514**
	Sig. (2-tailed)	,038	,073	,008	,000		,000
	N	260	260	260	260	260	260
BSS6	Pearson Correlation	-,166**	,067	,113	,535**	,514**	1
	Sig. (2-tailed)	,007	,279	,068	,000	,000	
	N	260	260	260	260	260	260

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX F-2 | Train commuters

(Table 1 out of 4)

Correlations

		GENDER	AGE	EDUCATION	HOUSEHOLD
GENDER	Pearson Correlation	1	,101	-,157	,088
	Sig. (2-tailed)		,262	,080	,327
	N	125	125	125	125
AGE	Pearson Correlation	,101	1	-,326**	,171
	Sig. (2-tailed)	,262		,000	,057
	N	125	125	125	125
EDUCATION	Pearson Correlation	-,157	-,326**	1	-,091
	Sig. (2-tailed)	,080	,000		,311
	N	125	125	125	125
HOUSEHOLD	Pearson Correlation	,088	,171	-,091	1
	Sig. (2-tailed)	,327	,057	,311	
	N	125	125	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

(Table 2 out of 4)

Correlations

		FREQUENCY	HOME	WORK	TIMETRAIN	ACCESSMODE	EGRESSMODE	EGRESSTIME
FREQUENCY	Pearson Correlation	1	-,207*	-,094	-,167	,115	-,147	-,056
	Sig. (2-tailed)		,021	,295	,063	,203	,102	,537
	N	125	125	125	125	125	125	125
HOME	Pearson Correlation	-,207*	1	,612**	-,219*	,065	,002	-,134
	Sig. (2-tailed)	,021		,000	,014	,474	,979	,138
	N	125	125	125	125	125	125	125
WORK	Pearson Correlation	-,094	,612**	1	,070	-,001	-,054	-,099
	Sig. (2-tailed)	,295	,000		,437	,989	,553	,270
	N	125	125	125	125	125	125	125
TIMETRAIN	Pearson Correlation	-,167	-,219*	,070	1	-,208*	-,189*	,182*
	Sig. (2-tailed)	,063	,014	,437		,020	,035	,042
	N	125	125	125	125	125	125	125
ACCESSMODE	Pearson Correlation	,115	,065	-,001	-,208*	1	-,114	,035
	Sig. (2-tailed)	,203	,474	,989	,020		,204	,701
	N	125	125	125	125	125	125	125
EGRESSMODE	Pearson Correlation	-,147	,002	-,054	-,189*	-,114	1	-,098
	Sig. (2-tailed)	,102	,979	,553	,035	,204		,278
	N	125	125	125	125	125	125	125
EGRESSTIME	Pearson Correlation	-,056	-,134	-,099	,182*	,035	-,098	1
	Sig. (2-tailed)	,537	,138	,270	,042	,701	,278	
	N	125	125	125	125	125	125	125

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

(Table 3 out of 4)

Correlations

		FACTORCHOICE	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5	FACTOR6	FACTOR7	FACTOR8
FACTORCHOICE	Pearson Correlation	1	-,019	-,074	-,061	-,189*	-,160	-,087	,196*	-,006
	Sig. (2-tailed)		,830	,411	,501	,035	,074	,332	,028	,949
	N	125	125	125	125	125	125	125	125	125
FACTOR1	Pearson Correlation	-,019	1	-,133	,204*	,398**	,439**	,348**	,018	,271**
	Sig. (2-tailed)	,830		,139	,022	,000	,000	,000	,840	,002
	N	125	125	125	125	125	125	125	125	125
FACTOR2	Pearson Correlation	-,074	-,133	1	-,014	-,050	,036	-,143	,158	,125
	Sig. (2-tailed)	,411	,139		,881	,577	,690	,112	,078	,163
	N	125	125	125	125	125	125	125	125	125
FACTOR3	Pearson Correlation	-,061	,204*	-,014	1	,519**	,383**	,264**	-,170	,242**
	Sig. (2-tailed)	,501	,022	,881		,000	,000	,003	,058	,007
	N	125	125	125	125	125	125	125	125	125
FACTOR4	Pearson Correlation	-,189*	,398**	-,050	,519**	1	,522**	,427**	-,159	,311**
	Sig. (2-tailed)	,035	,000	,577	,000		,000	,000	,077	,000
	N	125	125	125	125	125	125	125	125	125
FACTOR5	Pearson Correlation	-,160	,439**	,036	,383**	,522**	1	,482**	-,093	,235**
	Sig. (2-tailed)	,074	,000	,690	,000	,000		,000	,303	,008
	N	125	125	125	125	125	125	125	125	125
FACTOR6	Pearson Correlation	-,087	,348**	-,143	,264**	,427**	,482**	1	,026	,233**
	Sig. (2-tailed)	,332	,000	,112	,003	,000	,000		,772	,009
	N	125	125	125	125	125	125	125	125	125
FACTOR7	Pearson Correlation	,196*	,018	,158	-,170	-,159	-,093	,026	1	,056
	Sig. (2-tailed)	,028	,840	,078	,058	,077	,303	,772		,535
	N	125	125	125	125	125	125	125	125	125
FACTOR8	Pearson Correlation	-,006	,271**	,125	,242**	,311**	,235**	,233**	,056	1
	Sig. (2-tailed)	,949	,002	,163	,007	,000	,008	,009	,535	
	N	125	125	125	125	125	125	125	125	125

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

(Table 4 out of 4)

Correlations

		BSS1	BSS2	BSS3	BSS4	BSS5	BSS6
BSS1	Pearson Correlation	1	,592**	-,034	-,121	-,058	-,119
	Sig. (2-tailed)		,000	,709	,178	,522	,185
	N	125	125	125	125	125	125
BSS2	Pearson Correlation	,592**	1	-,022	-,154	,006	-,115
	Sig. (2-tailed)	,000		,811	,087	,950	,201
	N	125	125	125	125	125	125
BSS3	Pearson Correlation	-,034	-,022	1	,227*	,136	,176*
	Sig. (2-tailed)	,709	,811		,011	,130	,049
	N	125	125	125	125	125	125
BSS4	Pearson Correlation	-,121	-,154	,227*	1	,521**	,632**
	Sig. (2-tailed)	,178	,087	,011		,000	,000
	N	125	125	125	125	125	125
BSS5	Pearson Correlation	-,058	,006	,136	,521**	1	,648**
	Sig. (2-tailed)	,522	,950	,130	,000		,000
	N	125	125	125	125	125	125
BSS6	Pearson Correlation	-,119	-,115	,176*	,632**	,648**	1
	Sig. (2-tailed)	,185	,201	,049	,000	,000	
	N	125	125	125	125	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

APPENDIX F-3 | Correlations between attributes of different categories

(Note: The following (5) correlations are found for the train commuters only)

Correlations

		AGE	FACTOR5
AGE	Pearson Correlation	1	,313**
	Sig. (2-tailed)		,000
	N	125	125
FACTOR5	Pearson Correlation	,313**	1
	Sig. (2-tailed)	,000	
	N	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		WORK	FACTORCHOICE
WORK	Pearson Correlation	1	-,356**
	Sig. (2-tailed)		,000
	N	125	125
FACTORCHOICE	Pearson Correlation	-,356**	1
	Sig. (2-tailed)	,000	
	N	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		ACCESSMODE	FACTOR4
ACCESSMODE	Pearson Correlation	1	,346**
	Sig. (2-tailed)		,000
	N	125	125
FACTOR4	Pearson Correlation	,346**	1
	Sig. (2-tailed)	,000	
	N	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		FACTOR3	BSS5
FACTOR3	Pearson Correlation	1	,300**
	Sig. (2-tailed)		,001
	N	125	125
BSS5	Pearson Correlation	,300**	1
	Sig. (2-tailed)	,001	
	N	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		FACTOR8	BSS3
FACTOR8	Pearson Correlation	1	,318**
	Sig. (2-tailed)		,000
	N	125	125
BSS3	Pearson Correlation	,318**	1
	Sig. (2-tailed)	,000	
	N	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

G APPENDIX

EFFECT OF ATTRIBUTES ON ESTIMATED MODELS

***APPENDIX G-1* | Extended analysis Multinomial Logit model of private car commuters**

```
-----------------------------------------------------------------------------
|-> DISCRETECHOICE;Lhs = icho
    ;Choices = 1,2,3
    ;Rhs     = icon,
    ityp,ires1,ires2,itar1,itar2,itds1,itds2,itb1,itb2,
    iwds1,iwds2,iwb1,iwb2,

                                             A_edc,A_houc,
                                             A_worc,A_timc,
                                             A_fac2,A_fac3,A_fac6,A_fac8$
Normal exit:   5 iterations. Status=0, F=    2011.586

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -2011.58617
Estimation based on N =    2080, K =  22
Inf.Cr.AIC  =   4067.2 AIC/N =    1.955
Model estimated: Jun 12, 2018, 23:06:56
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -2186.2684  .0799  .0750
Response data are given as ind. choices
Number of obs.=  2080, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.      95% Confidence
    ICHO|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    ICON|     .73249***     .07570     9.68  .0000      .58412     .88087
    ITYP|     .12896***     .03236     3.99  .0001      .06554     .19238
   IRES1|    -.00831        .04583     -.18  .8561    -.09813     .08151
   IRES2|     .03377        .05614      .60  .5475    -.07626     .14381
   ITAR1|     .40354***     .04848     8.32  .0000      .30852     .49857
   ITAR2|     .02067        .05067      .41  .6833    -.07864     .11997
   ITDS1|     .24769***     .04118     6.02  .0000      .16699     .32839
   ITDS2|    -.23912***     .05962    -4.01  .0001    -.35596    -.12227
    ITB1|    -.25861***     .04240    -6.10  .0000    -.34171    -.17550
    ITB2|     .04447        .05223      .85  .3946    -.05791     .14685
   IWDS1|     .02806        .04554      .62  .5378    -.06120     .11732
   IWDS2|    -.41506***     .05283    -7.86  .0000    -.51860    -.31151
    IWB1|     .04874        .04508     1.08  .2796    -.03961     .13709
    IWB2|     .21552***     .05127     4.20  .0000      .11504     .31601
   A_EDC|    -.25358***     .07135    -3.55  .0004    -.39343    -.11374
  A_HOUC|    -.15493***     .05819    -2.66  .0078    -.26897    -.04089
  A_WORC|    -.23737***     .05973    -3.97  .0001    -.35443    -.12030
  A_TIMC|    -.18128**      .07122    -2.55  .0109    -.32087    -.04168
  A_FAC2|     .17053***     .05980     2.85  .0044      .05331     .28774
  A_FAC3|     .13852**      .05923     2.34  .0194      .02243     .25460
  A_FAC6|    -.20075***     .05886    -3.41  .0006    -.31610    -.08539
  A_FAC8|     .14755**      .06093     2.42  .0154      .02813     .26696
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
```

***APPENDIX G-2* | Extended analysis of Multinomial Logit model of train commuters**

```
-----------------------------------------------------------------------------
|-> DISCRETECHOICE;Lhs = icho
    ;Choices = 1,2,3
    ;Rhs     = icon,
    ityp,ires1,ires2,itar1,itar2,itds1,itds2,itb1,itb2,
    iwds1,iwds2,iwb1,iwb2,
                                            A_fat4,A_bt3$
Normal exit:   6 iterations. Status=0, F=    920.4484

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable                 Choice
Log likelihood function       -920.44837
Estimation based on N =    1000, K =  16
Inf.Cr.AIC  =   1872.9 AIC/N =     1.873
Model estimated: Jun 13, 2018, 02:17:05
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only  -1070.1181  .1399 .1329
Response data are given as ind. choices
Number of obs.=  1000, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
    ICHO|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
    ICON|    .76534***    .12036     6.36  .0000      .52945    1.00123
    ITYP|    .02240       .04919      .46  .6488    -.07401     .11881
   IRES1|   -.09223       .07177    -1.29  .1988    -.23289     .04844
   IRES2|    .08642       .08331     1.04  .2996    -.07686     .24970
   ITAR1|    .64887***    .07471     8.69  .0000      .50244     .79530
   ITAR2|   -.04988       .07874     -.63  .5265    -.20421     .10446
   ITDS1|    .44904***    .06337     7.09  .0000      .32483     .57325
   ITDS2|   -.42442***    .09146    -4.64  .0000    -.60367    -.24517
    ITB1|   -.40027***    .06524    -6.14  .0000    -.52815    -.27240
    ITB2|   -.04039       .07822     -.52  .6056    -.19370     .11292
   IWDS1|    .01413       .06917      .20  .8382    -.12145     .14971
   IWDS2|   -.58856***    .08367    -7.03  .0000    -.75255    -.42457
    IWB1|    .07545       .06897     1.09  .2740    -.05974     .21063
    IWB2|    .24881***    .07805     3.19  .0014      .09584     .40178
  A_FAT4|   -.41129***    .08475    -4.85  .0000    -.57740    -.24519
   A_BT3|    .63815***    .11043     5.78  .0000      .42172     .85458
--------+--------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
-----------------------------------------------------------------------------
```

***APPENDIX G-3* |** Extended analysis of Binary Logit model of private car commuters

```
--------------------------------------------------------------------------------
|-> LOGIT;Lhs=ICHO3
    ;Rhs=ICON,ITYP,IRES1,IRES2,ITAR1,ITAR2,ITDS1,ITDS2,ITB1,ITB2
    ,IWDS1,IWDS2,IWB1,IWB2,
    A_fac3,A_fac4,A_fac6,A_fac7,A_agec,A_timc,A_bc1,A_bc4$
Normal exit:   6 iterations. Status=0, F=    927.1415

--------------------------------------------------------------------------------
Binary Logit Model for Binary Choice
Dependent variable                 ICHO3
Log likelihood function       -927.14154
Estimation based on N =    2080, K =  22
Inf.Cr.AIC  =    1898.3 AIC/N =     .913
Model estimated: Jun 13, 2018, 00:45:05
Hosmer-Lemeshow chi-squared = 268.67553
P-value=  .00000 with deg.fr. =        8
--------+-----------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
   ICHO3|  Coefficient     Error        z    |z|>Z*        Interval
--------+-----------------------------------------------------------------------
    ICON|  -1.94613***     .11257    -17.29  .0000    -2.16675   -1.72550
    ITYP|    .21469***     .07400      2.90  .0037      .06966     .35972
   IRES1|    .11472        .09996      1.15  .2511     -.08119     .31064
   IRES2|    .15898        .11258      1.41  .1579     -.06167     .37963
   ITAR1|    .17105*       .10070      1.70  .0894     -.02632     .36841
   ITAR2|    .03216        .12050       .27  .7895     -.20402     .26835
   ITDS1|    .28262***     .10073      2.81  .0050      .08520     .48004
   ITDS2|   -.37043***     .13214     -2.80  .0051     -.62941    -.11145
    ITB1|   -.29129***     .09993     -2.91  .0036     -.48715    -.09543
    ITB2|   -.07071        .10680      -.66  .5079     -.28003     .13861
   IWDS1|   -.06666        .10031      -.66  .5063     -.26326     .12994
   IWDS2|   -.05150        .12452      -.41  .6792     -.29555     .19256
    IWB1|   -.10777        .09888     -1.09  .2758     -.30157     .08604
    IWB2|    .03665        .11329       .32  .7463     -.18539     .25869
  A_FAC3|    .32749***     .07884      4.15  .0000      .17296     .48201
  A_FAC4|    .26155***     .07849      3.33  .0009      .10771     .41540
  A_FAC6|   -.30683***     .07314     -4.20  .0000     -.45018    -.16349
  A_FAC7|   -.21421***     .07381     -2.90  .0037     -.35887    -.06955
  A_AGEC|    .44411***     .09293      4.78  .0000      .26197     .62624
  A_TIMC|    .20419**      .08752      2.33  .0197      .03265     .37574
   A_BC1|   -.26659***     .07241     -3.68  .0002     -.40850    -.12468
   A_BC4|    .73355***     .08225      8.92  .0000      .57233     .89476
--------+-----------------------------------------------------------------------
Note: ***, **, * ==>  Significance at 1%, 5%, 10% level.
--------------------------------------------------------------------------------
```

***APPENDIX G-4* | **Extended analysis of Binary Logit model of train commuters

```
|-> LOGIT;Lhs=ICHO3
    ;Rhs=ICON,ITYP,IRES1,IRES2,ITAR1,ITAR2,ITDS1,ITDS2,ITB1,ITB2
    ,IWDS1,IWDS2,IWB1,IWB2,
    A_fret,A_acct,A_eggt,
    A_fat2,A_fat6,A_fat8,
    A_bt2,A_bt3,A_bt5$
Normal exit:   6 iterations. Status=0, F=    523.3752

Binary Logit Model for Binary Choice
Dependent variable                ICHO3
Log likelihood function      -523.37523
Restricted log likelihood    -560.12723
Chi squared [  22 d.f.]        73.50401
Significance level               .00000
McFadden Pseudo R-squared      .0656137
Estimation based on N =    1000, K =  23
Inf.Cr.AIC  =   1092.8 AIC/N =    1.093
Model estimated: Jun 13, 2018, 07:43:34
Hosmer-Lemeshow chi-squared = 164.01859
P-value=  .00000 with deg.fr. =       8
```

ICHO3	Coefficient	Standard Error	z	Prob. |z|>Z*	95% Confidence Interval	
ICON	-1.03992***	.16184	-6.43	.0000	-1.35712	-.72272
ITYP	.17886*	.09592	1.86	.0622	-.00914	.36686
IRES1	-.11888	.13365	-.89	.3737	-.38084	.14307
IRES2	.02797	.14535	.19	.8474	-.25691	.31285
ITAR1	.33540**	.13724	2.44	.0145	.06643	.60438
ITAR2	.10854	.16000	.68	.4975	-.20505	.42213
ITDS1	.01718	.13132	.13	.8959	-.24020	.27455
ITDS2	-.10237	.16569	-.62	.5367	-.42711	.22237
ITB1	-.46309***	.13402	-3.46	.0005	-.72578	-.20041
ITB2	.23213*	.13849	1.68	.0937	-.03930	.50357
IWDS1	-.21434	.13095	-1.64	.1017	-.47099	.04231
IWDS2	-.07114	.16942	-.42	.6746	-.40320	.26092
IWB1	-.07179	.12868	-.56	.5769	-.32400	.18041
IWB2	.08641	.15311	.56	.5725	-.21368	.38650
A_FRET	.19731**	.09507	2.08	.0379	.01098	.38365
A_ACCT	.62689***	.10563	5.94	.0000	.41987	.83391
A_EGGT	-.36255***	.09750	-3.72	.0002	-.55365	-.17146
A_FAT2	.47060***	.10899	4.32	.0000	.25698	.68421
A_FAT6	-.35191***	.10671	-3.30	.0010	-.56106	-.14276
A_FAT8	.24817**	.10313	2.41	.0161	.04604	.45030
A_BT2	-.64528***	.10486	-6.15	.0000	-.85080	-.43976
A_BT3	.35537***	.10395	3.42	.0006	.15163	.55910
A_BT5	.53922***	.10663	5.06	.0000	.33023	.74822

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.