Shared mobility for the first and last mile:

Exploring the willingness to share

By

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Executive summary

Over the past decade, the concept of sharing has attracted more and more attention. Although sharing itself is nothing new, the development of ICT and online platforms has provided the infrastructure for new ways of sharing on a scale never seen before, which are causing a shift from ownership to access-based-consumption. This trend offers promising prospects for the case of mobility and a growing body of literature reveals how shared mobility services could help solving transportation problems related to congestion, parking, sustainability, and accessibility. However, the true magnitude of impact that this increasing popularity of shared mobility will have on the total transportation system remains uncertain (Cherry & Pidgeon, 2018; Durand et al., 2018; Standing et al., 2018). Contributing to this uncertainty is, among other things, the under-explored decision-making process of people regarding the use of shared mobility services. This requires for additional research, which is not only relevant from a scientific point of view, but also for companies operating in the transportation sector.

For NS, as largest railway operator in the Netherlands, it is in particular relevant to investigate how these new services can contribute to better first and last mile transportation within the multimodal train trip, as most of these types of shared mobility operate on an urban scale. The goal of this research is therefore:

To explore and measure the factors that affect people's willingness to use shared mobility services as access or egress transport in multimodal train trips.

To achieve this goal, a stated choice survey was conducting among NS customers. Respondents were presented with hypothetical access or egress trip scenarios for which they were asked to choose their most preferred transport mode from a set of four alternatives. Using discrete choice modelling, the effects of the different included factors were measured.

Included shared mobility services in the experiments are the shared bike, shared car and the (standing) shared e-scooter. Shared mobility services can in general be conceptualized as innovative transportation strategies that enable travelers to gain temporary access to transportation modes on an "as-needed" basis. Many different types of shared mobility services exist and when categorizing them, an important split can be made in what the travelers gains access to, a vehicle or a ride. Given the popularity of cycling and walking in the current modal split of access and egress trips and the potential of the shared (standing) e-scooter and bike, shared vehicles (instead of ride sharing) are found to be the most relevant type of shared mobility to investigate in terms of mode choice factors. This results in the included set mentioned above.

To come to set of possible factors that impact travelers' willingness to use shared mobility services as access or egress transport, a conceptual framework was constructed via literature review and experts judgement. Considering general mode choice factors, a common categorization is made by distinguishing factors related to the modes/services available, factors related to the trip, and factors related to the traveler. The factors studied in this research are depicted in Figure 1. The mode related factors such as travel time and costs are included in the experiments as characteristics of the mode alternatives while data on traveler characteristics was collected via separate questions. Trip characteristics of the hypothetical trip were varied among the respondents based on several travel behavior questions asked at the beginning of the survey to characterize the respondents. That way it was possible to present respondents with the type of hypothetical trip that resembles their travel behavior - and thus their perception of reality - as much as possible.

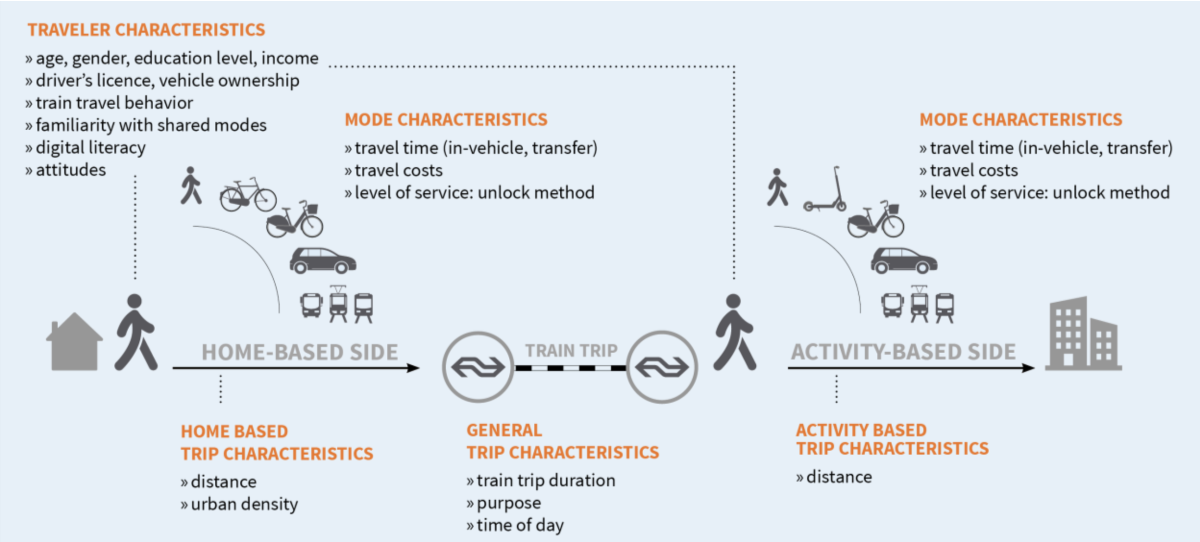

Figure 1 Overview of included factors in the stated choice experiments.

Multiple stated choice experiments were conducted to measure a variety of trade-offs between conventional and shared mode options for access and egress trips. By including multiple distances and limiting the amount of alternatives to four per set, both choice task feasibility and realism of the choice sets are taken into account to ensure validity of the experiments. Table 1 presents the five different experiments. Respondents were assigned to two of these five experiments. In total 1835 respondents filled out the stated choice surveys, which results in a total of 22,020 choice observations that were used to estimate two final choice models, one for the home-based trip and one for the activity-based trip.

Table 1 The four alternative sets (columns): split per distance class and type of trip.

	Mode options	Home based trip experiments		Activity based trip experiments	
		2 km	4 km	1 and 2 km	4 km
conventional options	walk	•		•	
	private bike	•	•		
	private car		•		
	BTM	•	•	•	•
shared options	shared e-scooter			•	
	shared bike	•	•	•	•
	shared car				•

In order to conclude on the importance of the selected mode choice factors, the results from the stated choice experiments are analyzed using descriptive statistics and discrete choice modelling. What stands out from the descriptive statistics is, in the first place, the variety of different modes that respondents switched between in the choice experiments. A large share of respondents (58%) had a fixed preference for one mode in either the home-based or the activity-based trip experiment. This suggests that fixed mode preferences played an important role in the hypothetical choice situations. In total, 41% of the respondents did not switch mode in both experiments. Analysis of this group revealed that especially elderly, lower educated and less frequent train travelers are more likely not to switch to another (shared) mode when transfer time and travel costs are varied.

The second noteworthy result from the descriptive statistics is the degree of familiarity with shared modes among the respondents, which is depicted in Figure 2. Experience with the included shared modes is generally low. Besides, large differences exist between the different modes. Respondents are most familiar with shared bikes: 28% of the respondents has used a shared bike and only 14% has never heard of the concept while only 2% has experience with e-scooters which are new to almost half of the sample (47%). Though these differences are not surprising given the current availability of the different shared modes in the Netherlands, the familiarity distributions provide relevant background information when evaluating the results from the estimated choice models.

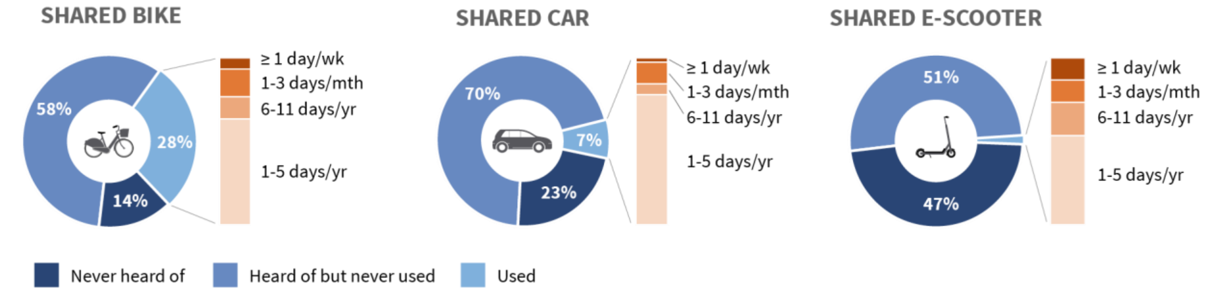

Figure 2 Respondents' familiarity with shared modes.

Results from the discrete choice modelling for the **home-based side** are presented in Figure 3 and reveal that *traveler characteristics* have the largest impact on the willingness to use a shared bike[1] as access mode. Especially whether travelers have previous experience with shared bikes strongly affects the mode choice process.

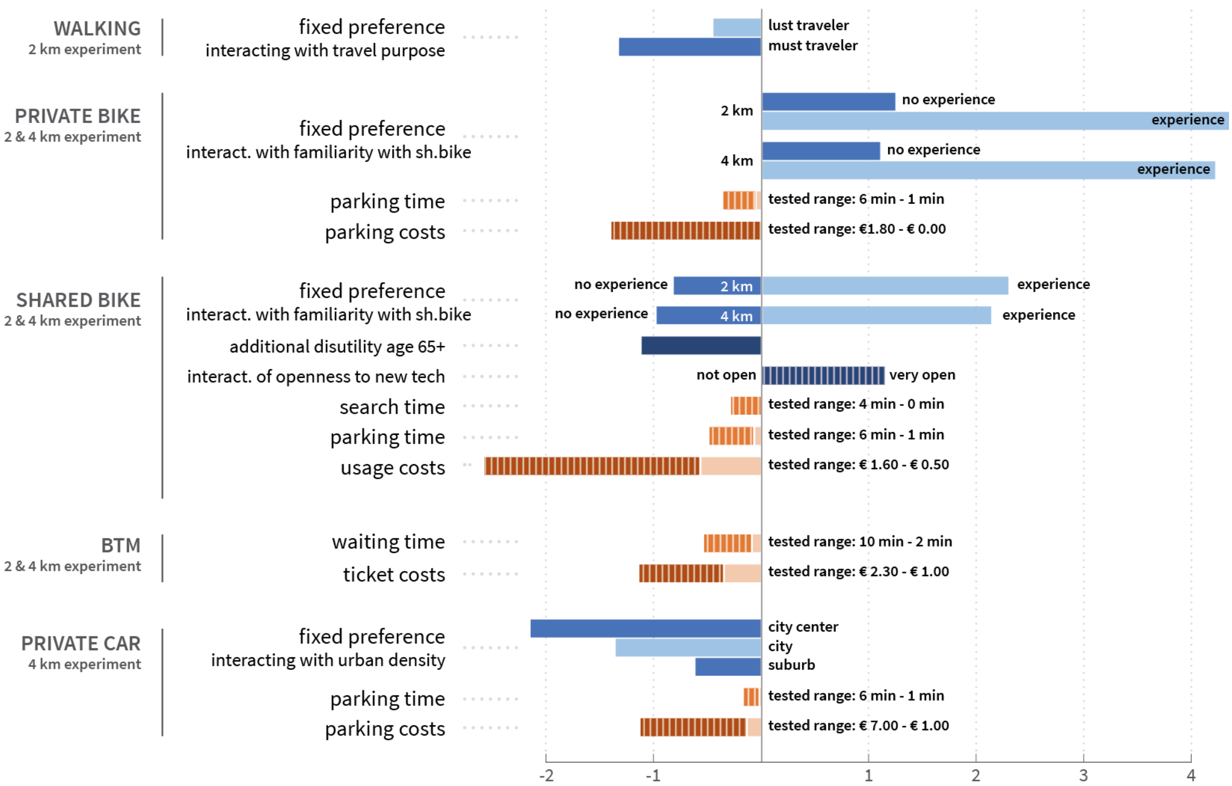

Figure 3 An overview of the relative utility contributions of studied factors. The fixed preference of the BTM alternative is the reference level (0).

Having used a shared bike before massively increases the preference for both the private and the shared bike alternative. In that case, the private bike is still intrinsically preferred over the shared bike, but differences in mode related factors of parking/usage costs and, to a lesser extent, also parking time can cause a substantial amount of disutility to let the shared bike become the preferred option. Overall however, the private bike was strongly preferred over the shared bike (53% of all choices vs. 6%) which can be linked to fact that the majority of the respondents (72%) has no previous experience with using a shared bike.

Besides, compared to the included conventional modes, this relative unpopularity of the shared bike can also be linked to the shared bike in general scoring lowest on intrinsic mode preference. These preferences play a

[1] Shared bike is the only included shared mode in the home-based trip experiments.

substantial role, as was expected based on the discussed large share of respondents with a fixed preference and the fact that the in-vehicle times were not varied in the experiments and therefore load onto the fixed preference scores as well. The effect of *trip characteristics* travel purpose and urban density are found to change this preference order: The private car is least preferred for trips to railway stations in highly dense urban areas and travelers heading towards an important meeting (must-traveler) would quicker turn to using a shared bike compared to walking.

With respect to *mode characteristics*, costs and in particular (transfer) time attributes are found to be less important than the intrinsic mode preference interacting with traveler characteristics. In the case of the shared- and private bike alternatives, costs play a slightly less important role than the mode preferences, while the impact of search- and parking time is approximately five times smaller. Sensitivity to both costs and transfer time is both highest for the shared bike alternative, which could be linked to the familiarity issue: costs and time elements are weighed heavier for never tried alternatives. Lastly, the included qualitative element of accessibility – the unlocking method of the shared bike– appeared not to be a significantly considered factor in the choice process.

In the **activity-based trip** scenario, multiple shared modes were included: the e-scooter, bike and car. The results for this scenario are presented in Figure 4. Similar to the home-based side, familiarity with the shared mode concepts emerged also here as a prominent factor in the mode choice process. Being unknown and therefore unpopular applies in particular to the shared e-scooter and shared car alternative. These alternatives score remarkable low on intrinsic mode preference, which can be linked to the general observed low familiarity with these modes in the sample. The shared bike is a much more common egress mode to the respondents (due to the availability of OVfiets) which correspondents with a much less dominating fixed preference and a larger impact of costs and time attributes compared to the shared e-scooter and car.

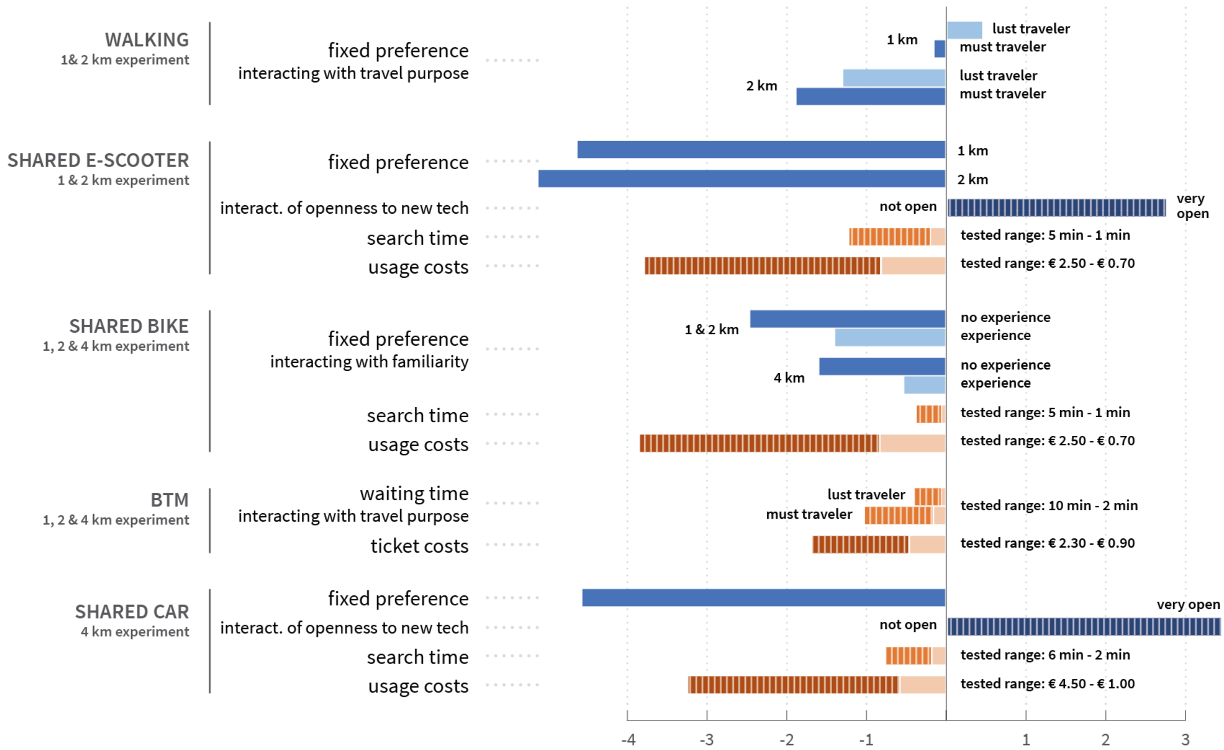

Figure 4 An overview of the relative utility contributions of studied factors. The fixed preference of the BTM alternative is the reference level (0).

Traveler characteristics related to one's openness to trying new technologies and (again) having experience with shared modes emerges as interaction variables that are significantly related with the intrinsic mode preference of the shared modes. The more respondents can be characterized as early adopters (being open to trying new technology), the smaller the difference between the intrinsic mode preferences of shared and conventional modes. Apart from these static preferences, the *trip characteristic* travel purpose is found to affect the sensitivity to travel time in such way that must travelers are more likely to consider a shared bike than lust travelers due to higher sensitivities to walking time and BTM waiting time. However, sensitivity to costs for shared bike usage is much stronger associated with disutility than is the case for costs of a BTM ticket.

All in all, regarding the impact of the tested factors on the willingness to use shared modes, it can be concluded that when the familiarity with the shared mode is too low (e-scooter and car), the role of time and cost attributes is in general too small to play a significant role in travelers' choice process. In case of a more familiar shared mode (shared bike), travel time- and especially costs attributes can make a differences. However, sensitivity to the tested cost attributes among the alternatives was found to be highest for the shared bike (and e-scooter), which means that for equal increase in travel costs, higher disutilities are associated with the shared modes compared to the conventional ones. Lastly, the tested impact of ease of usage (unlocking methods) of the shared modes was – similar to the home-based results – not found to play a role in the mode choice process of the respondents.

When comparing the home-based trip with the activity-trip, similarity can in the first place be noted with respect to the importance of familiarity with shared modes. In both cases having tried before or being willing to try plays an important role in the shared modes' chances of being picked by the respondents. Also the impact of cost and time attributes was in both trip-models found to be higher for the costs attributes. Apart from these similarities, comparison between the willingness to pay for less transfer time (waiting, parking, or search time) revealed that in general slightly more disutility is associated with these transfer times at the home-based side than at the activity-based side.

Based on these findings, it can be concluded that in the first place the chances of shared modes are found in general, to be strongly influenced by travelers' experience and familiarity with these shared modes. This can be linked to the adoption time of these new modes. The less travelers are accustomed to having a particular shared mode in their choice set, the larger the dominance of an intrinsic dislike. Half of the respondents had never heard of e-scooter before and less than 0.01% had used one, which translates into a dominant intrinsic preference factor and also relatively large sensitivities to costs and search time. The shared bike exemplifies a mode that is already a more familiar option, especially for the activity-based trip, which results in a different hierarchy of mode related factors. The intrinsic mode preference become less dominant and other mode characteristics such as search time and usage costs gain more importance.

In this adoption stadium of the shared bike, usage costs become the most decisive factor. Sensitivity to costs of using a shared modes are compared to other modes still high, but this could decrease as the familiarity-burden decreases and the benefits of shared modes in terms of speed increase in valuation. In such future stage, the ease of usage – like the tested unlocking methods – could also become a more relevant factor in the mode choice process, but for now such effect is completely overshadowed by the intrinsic dislike factor.

Naturally, the above made point is generalized and its applicability also depends on the type of traveler and the type of trip. The more that a traveler can be identified as an early adopters of innovations, the smaller the dominance of the found intrinsic mode dislike in his mode choice process. In line with the findings from the presented modal portfolio's, in particular travel purpose and age show to affect the willingness to use shared modes. The type of traveler that is younger and travels often by train (commuting) is more likely to switch to or try a shared mode in his door-to-door trip.

Regarding the *potential role of the different studied shared modes* this research shows clear opportunities for the shared bike, while chances of the shared e-scooter and car are less straightforward to conclude on, which can mainly be attributed to the high degree of unfamiliarity with the modes among the respondents. Via OVfiets, the shared bike is an already proved concept at the activity-based side of the multimodal train trip and results of this study show that when travelers have experience with shared bikes, this mode has potential to compete with the private bike at the home-based side trip. However, that only goes in case of substantial differences in (parking) costs and parking time and would require to move away from the current situation of free bicycle parking at every railway station.

Due to the large impact of the unfamiliarity with shared e-scooter and shared car as egress modes, it is difficult to interpret the estimated effects of the other included attributes on the chances of these modes. Until (private) e-scooters are allowed on the Dutch roads, the familiarity effect will probably not decrease. Besides, the type of trip tested may have been too general to highlight the benefits of the train + shared car combination. Nevertheless, the shared e-scooter and shared car were seriously considered by an early adopter group (5% of all choices e-scooter in 1 and 2 km experiments, 7% shared car in 4 km experiment), which shows that despite the familiarity-burdens there is already a group seriously considering these modes in their choice set.

All in all, this study has contributed to filling the research gap of the underexplored decision-making process regarding the willingness to use shared modes. The results show that in further studying the potential of these new mobility services, it is important to take the adoption-rate of the included services into account. The case of the shared e-scooter shows that unfamiliarity can overshadow the effect of potentially interesting details such as willingness to pay. This advocates for more research based on trials. The case of shared bikes on the other hand showed that in case of a more commonly familiar mode, the role of more detailed attributes such as price and possibly also type of parking systems can be investigated to obtain more concrete and quantitative results on the potential of these shared mobility services.

From the perspective of offering a better door-to-door trip, recommendations to NS based on the findings of this research are in the first place, given the found the importance of familiarity, to provide travelers with opportunities to try a shared bike, e-scooter, or shared car. With respect to the e-scooter and shared car, early adopters can be targeted best as a start. Targeting them via specific channels such as the new NS Lab app could be a reasonable first step. Considering the shared bike, a wider audience can be approached, as this mode is generally heard of, but not often tried (58% of the respondents has heard of shared bike, but never used one). The second recommendation is about shared bike usage on the home-based side. This study shows that cost and parking time benefits can cause the shared bike to be preferred over the private bike, which is highly relevant from the perspective of capacity problems in bicycle parking facilities. Therefore, the recommendation to NS is to experiment with price (parking cost) incentives at the home-based trip side to test into more detail whether travelers would use shared bike over private bike.

Future research could extend this study by zooming in onto the potential role of one shared modality, that way much more factors can be incorporated into a study. Important factors such as availability of a vehicle, which was omitted in this study because of measurability reasons in the stated choice experiment, can that way be studied. Secondly, given the rising number of OVfiets usage and emerging shared bike systems in multiple cities in the Netherlands, research based on revealed preference data becomes an increasingly realistic and interesting option to further explore the role of the shared bike in the multimodal train trip. Related to the found importance of traveler characteristics in the adoption process, collaboration with NS on OVfiets data would be a relevant direction because OVfiets is linked to OV chipcard data, which could provide connections with relevant traveler characteristics like train travel behavior or socio-demographic data.

Table of contents

List of figures

List of tables

1 Introduction

Over the past decade, the concept of sharing has attracted more and more attention. Although sharing itself is nothing new, the development of ICT and online platforms has provided the infrastructure that allows for new ways of sharing while also facilitating older kinds of sharing on a scale never seen before (Belk, 2014b; Cohen & Kietzmann, 2014). This has given rise to what is often referred to as “the sharing economy”: an umbrella concept that covers a wide variety of activities based on “temporary access non-ownership models of utilizing consumer goods and services” (Belk, 2014, p.1595; Hamari, Sjöklint, & Ukkonen, 2016). Examples include *Peerby* for tools, *Airbnb* for accommodation and *SnappCar* for transportation. Research on this phenomenon reveals promising results. Multiple studies show how the sharing economy could provide solutions to a variety of environmental, social, and economic problems (Botsman & Rogers, 2010; Cherry & Pidgeon, 2018; Hawken, Lovins, & Lovins, 2010). Cohen & Kietzmann (2014) even put that the sharing economy may be “the next stage in the evolution of fundamentally restructuring how economies work” (p. 294).

Within the sharing economy, mobility is one of the largest sectors (PwC, 2016). Businesses in this rubric apply the non-ownership model of the sharing economy to transportation by providing people with the opportunity to access mobility without the requirement of owning a vehicle. Various types of sharing can be distinguished (Shaheen & Chan, 2016). Distinctions can be made based on: mode (car, bike, mini-van), whether the vehicle is shared at the same time or not (e.g. car sharing vs ride sharing), who drives the vehicle (ride hailing vs ride sharing), who owns the vehicle (consumer(s), business or public organization), parking (station based sharing vs free-floating sharing), and the time span the vehicle is used (varies from leasing to time needed for a single trip).

Also here, expectations are high (Durand et al., 2018; Wong, Hensher, & Mulley, 2017). As a growing number of shared cars is being used, free floating shared bikes are parked everywhere, and even shared electric scooters emerge as a popular mode of transport (Irfan, 2018; Shaheen & Cohen, 2019), a growing body of literature is exploring how shared mobility services can help solving transportation problems related to congestion, parking, sustainability, and accessibility (Standing et al., 2018). A popular concept within this discourse of shared mobility is the provision of “Mobility-as-a-Service” (MaaS), also called the Netflix of mobility (Hietanen, 2014), in which the consumer is provided with seamless door-to-door mobility without the need of owning a vehicle. Trip options provided by (often combinations of) several modes are offered to the traveler via one platform which also covers ticketing, payment and (real-time) trip information (Hietanen, 2014). Because of the non-ownership based nature of MaaS, shared mobility services play a key role in its provision (Jittrapirom et al., 2017).

Despite an increasing amount of studies devoted to the topics of shared mobility and mobility as a service, the true magnitude of impact that this increasing popularity of shared mobility will have on the total transportation system remains uncertain (Cherry & Pidgeon, 2018; Durand et al., 2018; Standing et al., 2018). Contributing to this uncertainty is, among other things, the under-explored decision-making process of people regarding the use of shared mobility services (Böcker & Meelen, 2017; Cherry & Pidgeon, 2018; Tussyadiah, 2015). To what extent are people willing to use shared mobility services instead of existing options like owning a vehicle or using public transportation? And what about the integration of these new options with existing ones? Although motivations of current users of some shared mobility services have already been studied, there is in particular need for more quantitative oriented research on the decision making process of the wider public (Cherry & Pidgeon, 2018; Durand et al., 2018). To explore how the current transportation system will be impacted by upcoming shared mobility services, it is important to gain additional insight in the decision-making of traveler's with respect to these new services. That is what the contribution of this research will focus on.

1.1 Scope and goal

More insight into the impact of shared mobility and mobility as a service is, in addition to the academic perspective, also relevant from a societal point-of-view. Governments need to understand the development of shared mobility with respect to infrastructure management and regulating the transportation market, potential consumers could alter their decisions regarding vehicle ownership and companies operating in the transportation market are eager to find out how their business will be affected and can adopt to the potential impact of these new developments (Standing et al., 2018).

As this research is conducted for NS, the largest railway operator in the Netherlands, the focus of this research is on exploring the decision-making of travelers with respect to the usage of shared mobility services within the multimodal train trip. Investigating to what extent shared mobility services could be used as access and egress transport to and from train stations aligns with NS's strategy in which improving the door-to-door trip of their travelers is stated as one of the three core activities (NS, 2016).
Given the examined research gap of the under-explored decision making process regarding the use of shared mobility services and this scope of the role of these service as access or egress transport to and from train stations, the goal of this research can be defined as:

To explore and measure the factors that affect people's willingness to use shared mobility services as access or egress transport in multimodal train trips.

Shared mobility services that are included in this research involve the use of existing modes of transportation (e.g. bike, car, scooter, mini-van) that can be accessed as a service. This means that autonomous vehicles, which are often studied as a shared mode due to its self-driving property, will be outside of the scope of this study. As mentioned above, shared mobility services can be categorized according to several dimensions, which are outlined into more detail in Chapter 3. Included types shared mobility services in this study are shared bike systems, shared (standing) e-scooter systems and shared car systems.

The multimodal train trip is interpreted here as a trip consisting of multiple parts as depicted in **Figure 1-1**. In general multimodality in passenger transportation is about trips that are completed by using two or more modes of transport (Van Nes, Hansen, & Winnips, 2014). For train travel however, the multimodal trip is considered to consists of three modes, the main mode being train. The first and last legs of the trip are the access and egress legs, i.e. the trip from the origin of the traveler to the departure train station (access) and the trip from the arrival train station to the destination. As shown in **Figure 1-1** using access and egress to describe the first and last stage of the total trip can be confusing because of their dependence of the trip direction (most trips are made in both direction on the same day). Following (Van Nes et al., 2014) the definitions of home-based and activity-based trip are therefore used.

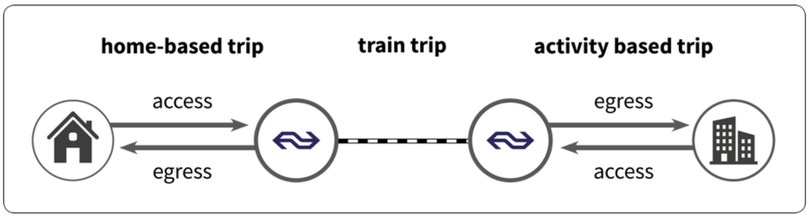

Figure 1-1 Schematic presentation of the multimodal train trip

The current modal split of the home-based and activity-based trip as part of the total multimodal train trip is displayed in **Figure 1-2**. NS distinguishes between walking, bike, car (driver or passenger), bus/tram/metro and taxi (NS, 2018a). Clear differences can be observed between home-based and activity-based side, which can largely be explained by the differences in mode availability between the two trip types. At the home-based side, private modes are available, while this is (often) not the case for the activity-based trip. Besides it can be noted that walking and cycling are dominating modes. The large share of activity based trips covered by foot can be linked to a large share of these trips being nearby train stations, whereas the popularity of the private bike as feeder mode for train trips can be linked to the benefits of bike traveling in urban areas and the fact that the average home-based trip distance[2] is a perfect distance to cover by bike (Jonkeren, Harms, Jorritsma, & Bakker, 2018; Kager, Bertolini, & Te Brömmelstroet, 2016).

Several studies that address the potency of shared mobility services as access or egress transport can be linked to these observations from the existing modal split. The popularity of the private bike at the home-based side reveals a latent demand for (shared) bike transport at the activity based side (Jonkeren et al., 2018), which seems validated by the growing popularity of OVfiets, NS' own shared bike (NS, 2018b). At the same time shared bicycle solutions are also proposed at the home-based side trip to solve bicycle parking capacity problems at the larger train station in the Netherlands (van Goeverden & Correia, 2018). Apart from shared bikes, also potency of shared standing e-scooters[3] is shown to replace the longer walking distances that are still slightly too short to cycle (Shaheen & Cohen, 2019).

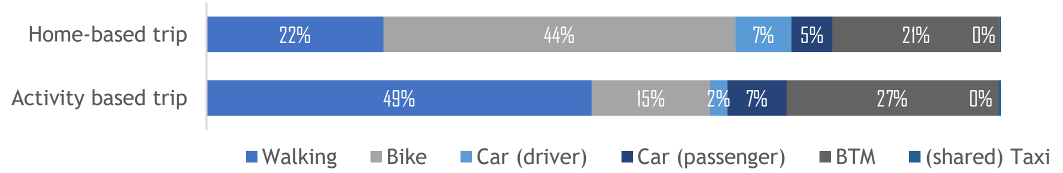

Figure 1-2 Mode distributions of access and egress transport of train trips (NS, 2018a). Note that no distinction is made between private bike and OVfiets at the activity based side.

1.2 Research questions

All in all, given the above elaborated literature gap and the scope and goal of this research, the main question this research seeks to answer then becomes:

What factors determine people's willingness to use shared mobility services as access or egress transport in multimodal train trips, and to what extent?

To structure the process of answering the main research question, several sub questions are formulated:

1. What are shared mobility services, and which ones are most relevant for the case of access and egress transport in multimodal train trips?
2. What factors play a role in (access and egress) mode choice?
3. What are the most relevant factors in case of a choice set with shared and conventional mode options?
4. To what extent to the selected factors play a role in the mode choice process?

Factors is used here as an inclusive term. Factors can be perceptions, personal characteristics, service characteristics and other elements that could possibly affect people's willingness to share.

1.3 Research design

The structure of this research is outlined in **Figure 1-3** and consists of three main phases: conceptualization, data collection, and data analysis.

Conceptualization

As a first step, literature is consulted to ensure a theoretical foundation for this research. Besides conceptualizing the different concepts introduced in this chapter, literature is used to identify general mode choice factors and relevant factors regarding the willingness to use shared mobility services in previous studies.

Using the results of the literature review, a conceptual framework is constructed. Expert judgement (via short interviews) is used to come to a final set of factors that are selected as most relevant to have impact on travelers'

[2] According to research by Kennisinstituut Mobiliteit Nederland (KiM), this average distance is 3.4 km (Jonkeren, Harms, Jorritsma, & Bakker, 2018).

[3] The definition of scooter can be confusing because what seem different modes (standing scooter and moped style scooter) are both called scooters. More detail on the differences is discussed in Section 3.2.2).

decision making process regarding the use of shared mobility services as access or egress transport in multimodal train trips. This final conceptual framework is the input for the stated choice experiments.

Data collection

To gain insight into the trade-offs people make regarding shared mobility as access or egress transport, a stated choice (SC) experiment is conducted. This enables for measuring the effect of different factors on people's decisions (Sanko, 2001). More detail about this research method can be found in Chapter 2. The stated choice experiment consists of a survey in which respondents have to make a mode choice from a set of alternatives for a hypothetical trip scenario. The choice situations are constructed using the factors from the conceptual framework. Additional questions are asked to measure factors that cannot be evaluated within the alternatives. The design process of the stated choice experiments is presented in Chapter 5.

Data analysis

The collected data is analyzed using both descriptive and inferential analyses. Descriptive statistics describe the direct outcomes of the survey, including sample characteristics and choice distributions. Discrete choice modelling is then applied to gain insight in to what extent the proposed factors from the conceptual framework have an effect on people's willingness to use shared mobility services as access and or egress transport. Chapter 2 provides a brief overview of the theoretical background and argumentation for using the applied data analysis techniques.

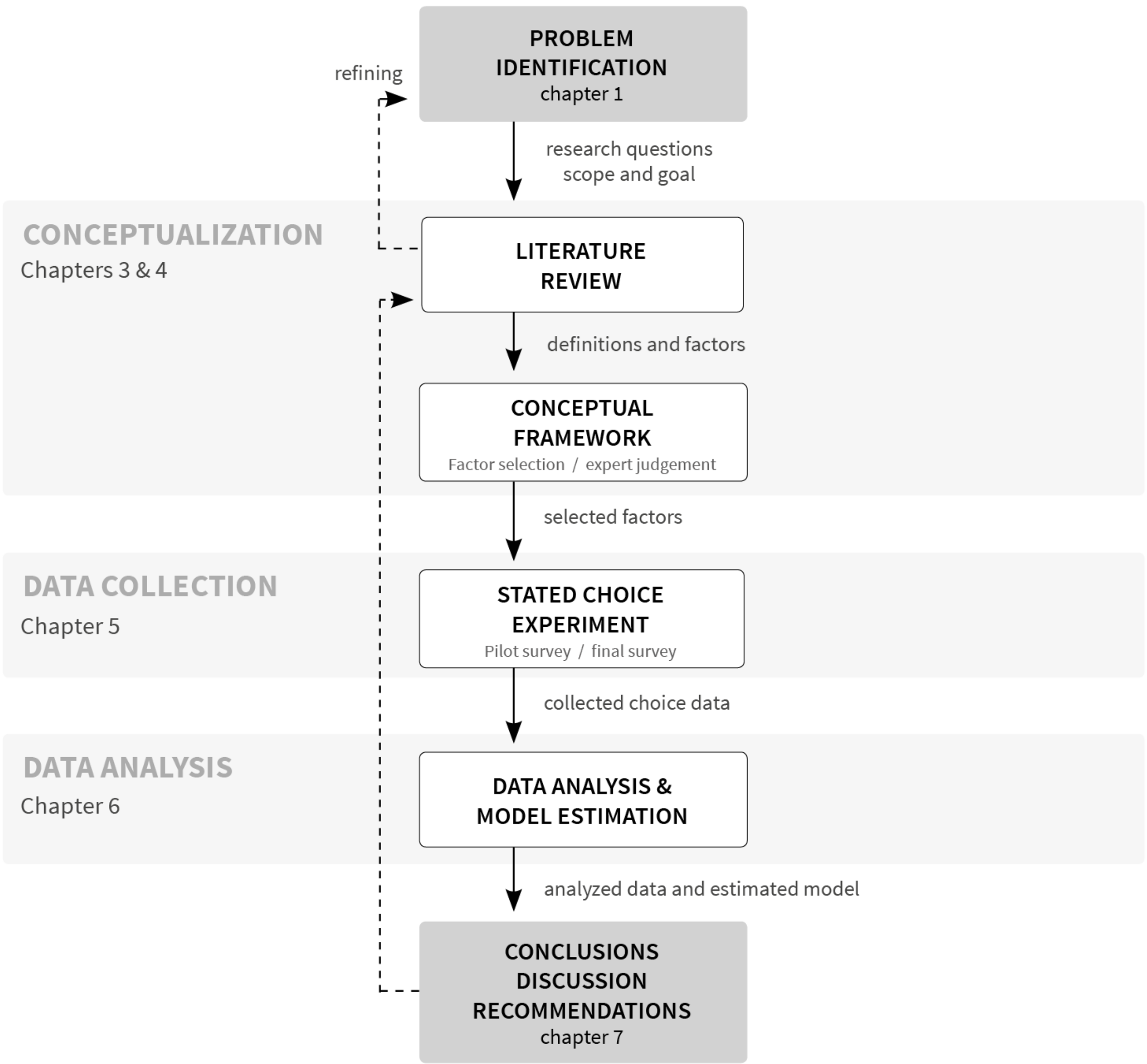

Figure 1-3 Schematic overview of the research design.

2 Methodology

To underpin the research design presented in Section 1.3, this chapter presents a concise overview of the theories behind the applied research methods as well as the argumentation to use them. Section 2.1 deals with the use of stated preference data. The modelling methods applied to analyze the stated choice data are outlined in Section 2.2. Lastly, Section 2.3 explains how measurement and incorporation of attitudinal factors has been conducted in this research.

2.1 Stated preference experiments

In order to study travelers decision making process, it is essential to study their (mode) choices and thus to acquire choice data. Two types of choice data can be distinguished: revealed choices and stated choices (Train, 2009). Revealed preference (RP) data are observations of choices that have been made by travelers in real situations while stated preference (SP) data is collected by asking respondents which option they would prefer in hypothetical choice situations.

Since this study aims at testing the willingness to use shared mobility services of which some are in the majority of cases not (yet) available to train travelers, collection of RP data is no option. Therefore, conducting SP experiments was chosen as research method to collect choice data. An additional benefit of this method is the flexibility and control to construct tailor-made hypothetical choice situations that meet the interests of the study (Hensher, Rose, & Greene, 2015). The design process of this research's SP experiments is explained in Chapter 5.

2.2 Discrete choice modelling

To analyze the collected stated preference data, discrete choice modelling (DCM) is applied. By estimating discrete choice models, the effect of specific components of the alternatives can be evaluated separately (Hensher et al., 2015). This perfectly fits this research's goal of identifying and measuring the role of different factors on travelers willingness to use shared modes. A brief overview of DCM theory and the applied models is presented below. For a more complete overview is referred to Ben-Akiva & Bierlaire (1999) and Train (2009).

2.2.1 Random Utility Maximization

Discrete choice modelling is built upon a framework that consists of four assumptions (Ben-Akiva & Bierlaire, 1999). In the first place, there has to be a (1) *decision-maker* that makes a choice or takes a decision; in this study, the train traveler. Second, the decision-maker can choose from a set of choice options, referred to as (2) *the alternatives.* In this study, these are different transportation-modes to make a trip from home to train station or from train station to activity. Third is the specification of (3) *attributes*, which are variables that describe the alternative and are considered by the decision-maker when choosing. Last assumption is that of the (4) *decision rule*, which describes the process that the decision maker uses to make a choice.

In this research, the decision rule used is that of Random Utility Maximization (RUM), which is the most widely applied decision rule in discrete choice models. RUM assumes that decision-makers aim at maximizing utility when choosing and thus pick the alternative to which he attaches the highest utility. This decision rule can be formulated into a formula which shown in Equation 2.1.

$$U_i = V_i + \varepsilon_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_i \tag{2.1}$$

Where:

U_i = the total utility associated with alternative i

V_i = the observed utility associated with alternative i

ε_i = the random error component

β_m = the estimable parameter associated with attribute x_m
x_{im} = the value of attribute x_m for alternative i

The total utility (U_i) associated with alternative i is a summation of the observed utility (V_i) and an error component (ε_i) that account for randomness in choice behavior: e.g. due to unobserved taste variations, imperfect information, or measurement errors. The observed utility is the sum of attribute levels of attributes (x_{im}) that are each multiplied by their decision weight (β_m), which represent the decision-makers sensitivity to the specific attributes.

2.2.2 Model specifications

Multiple models exist that can estimate the estimate the decision weight parameters and predict choice probabilities. In this study, the three most commonly used models are applied. These are the Multinomial Logit (MNL) model, the Nested Logit (NL) model and the Mixed Logit (ML) model.

Multinomial Logit model

The MNL model is the most widely used discrete choice model (Train, 2009). It assumes that the error components in the RUM decision-rule are independently and identically distributed (i.i.d.). In other words: the error terms of different alternatives are assumed to be uncorrelated and have the same variance. The model formula is a closed form equation (see Equation 2.2) that allows for short computation times, which explains its popularity.

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}} \tag{2.2}$$

Where:

$P_n(i)$ = the choice probability for individual n of alternative i
C_n = Cn is the choice set of j alternatives of individual n

The MNL model is limited in several ways. Two of these are relevant for the application of MNL models in this study: Because of the i.i.d. assumption, the MNL model is not able to account for dependencies between alternatives. To overcome this drawback, Nested Logit models were also estimated in this study, see next subsection. Besides, MNL also assumes that each choice is independent of other choices, and can therefore not deal with panel effects (correlation between multiple choices of one respondent). As a solution to this shortcoming, Mixed Logit models were also applied in this study. They are also discussed below.

Nested Logit model

In case two or more alternatives intuitively have something in common[4], Nested Logit models can be used to account for this in the discrete choice model (Train, 2009). By including a nest-parameter, the model can capture correlations between (unobserved) alternatives that "are within the same nest". Just like the MNL model, NL models are not able to deal with panel effects.

Mixed Logit model

The last and final discrete choice model type that is applied in this study is the Mixed Logit (ML) model. This model can account both for panel effects and nesting (Train, 2009). Panel effect are captured by the ML's ability to consider all (assumed correlated) choices made by one individual as one observation unit. Correlations between the error terms of alternatives (nesting) is captured in the ML model by defining separate shared error components that account for the nesting part of the error-term (Train, 2009).

The formula of the ML model (see equations 2.3 and 2.4) does not take a closed form solution and has to be computed via simulation (Train, 2009). This significantly increases the computation time needed to estimate the

[4] For example: in a choice set with the alternatives: walking, private bike, shared bike, and bus, the two bike alternatives have something in common as they are both bike options.

model. That is the reason why MNL and NL models are used as a start to test different composition of the utility function after which ML models are estimated to account for panel effects and shared error components afterwards. The complete modelling approach is outlined in Section 6.2.1.

$$P_{ni} = \int L_{ni}(\beta) f(\beta)\, d\beta \tag{2.3}$$

$$L_{ni}(\beta) = \frac{e^{V_{ni}(\beta)}}{\sum_{j=1}^{J} e^{V_{nj}(\beta)}} \tag{2.4}$$

Two equations describing the Mixed Logit model, where $L_{ni}(ß)$ is a density function.

2.2.3 Model performance measures

In order to assess the performance of the estimated models, several statistical measurements are available that give information about the goodness of fit. In this study the following measures are used:

McFadden's rho-squared

This statistic compares the performance of the model with that of a 'null-version' of the model (with all ß-values set to zero) and can be calculated as shown in Equation 2.5.

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} \tag{2.5}$$

Where:

LL(β) = final loglikelihood of the model
LL(0) = null loglikelihood

The value of ρ^2 provides information on the percentage of initial uncertainty is explained by the model. When ρ^2 =1, the model has perfect fit (which is impossible), while ρ^2 =0 means that the model is no better than "throwing a dice" (Chorus, 2018).

Likelihood Ratio Test statistic

This test can be used to compare the performances of two nested[5] models[6] and see if one significantly performs better than the other model (Chorus, 2018). To do so, a computed Likelihood Ratio Statistic (LRS) can be checked with the threshold value associated with the applicable significance level. The LRS is computed as shown in Equation 2.4:

$$LRS = -2 * (LL_A - LL_B) \tag{2.6}$$

Where:

LL_A = the loglikelihood of model A
LL_B = the loglikelihood of model B

2.2.4 Model validation

This method is about splitting the sample with choice observations into two (randomly assigned) sets: a training set and a validation set. The training set is used to estimate the models. Next, the performance of the models can

[5] Nested here means that one model is a simpler version of the other model and thus that the models are largely the same. Nested models can be any models and not necessarily Nested Logit models.
[6] In this study, the LRS is in particular used to check if adding parameters to the model causes significant improvement. The model with less parameters is in that case nested in the other model.

be assessed by comparing it’s predictive power on both the training set and the validation set (Larsen, Raymond, Guevara, & Frejinger, 2015).

This process of splitting the data set, estimating the model and comparing can be done multiple times. In this study, only a single cross validation is performed because of workload constraints. Single cross validation is also called the hold-out method because the choice observations assigned to the validation set are not used at all to estimate the models (Arlot & Celisse, 2010). Single cross validation was applied in this study by drawing a random 80% subsample of the choice data which was then used to estimate the models. Validation occurred by comparing the correct choice prediction rate of the estimated model on the 80% sample and the 20% sample (validation set).

2.3 Measuring attitudes

Attitudes are also included in this study as possible factors impact people’s willingness to use shared modes. Attitudes cannot be measured directly, but this can be done by using indicators (Daly, Hess, Patruni, Potoglou, & Rohr, 2012). Several statements were therefore added to the stated preference survey to enable measuring attitudes of interest. To extract these latent attitude factors from the choice data on the statements, exploratory factor analysis is used. This is done by performing the commonly used method of Principal Axis Factoring with varimax rotation (Henson & Roberts, 2006).

The resulting latent factors related to attitudes were then incorporated into the discrete choice models by computing the mean-sum scores of the involved statements for each latent factor. This relative simplistic methods provides an intuitive interpretation of the attitudinal factors (Distefano, Zhu, & Mîndrilă, 2009). A more elegant way would be to construct an integrated choice and latent variable (ICLV) model (Temme, Paulssen, & Dannewald, 2008). That way, the attitudinal factors would not be incorporated directly into the choice model, but rather via their relations with socio-economic variables and the attributes. However, due to the complexity of the ICLV model, this study sticks to computing mean-sum scores. The resulting interpretability of this simpler method is considered sufficient regarding the explorative goal of this research.

3 Literature review

The various concepts mentioned in the introduction are discussed in more depth in this chapter, aiming to construct a theoretical foundation for this research. The main goal of this chapter is to identify factors that could play a role in the decision-making process regarding the use of shared mobility service as access and egress transport. In order to do so, literature from various perspectives is examined and accordingly divides the chapter into three parts: Aiming at constructing a brief understanding of the rise of shared mobility, Section 3.1 shortly addresses the concepts of sharing, sharing economy, and collaborative consumption and additionally presents an overview of factors related to participation in sharing economy practices. Next, Section 3.2 zooms in onto shared mobility by examining definitions, a categorization, and selecting a set of shared mobility business models that are to be included in the stated choice experiments. Section 3.3 then zooms in on the mode choice process and lists relevant factors that this process. Lastly, the chapter is concluded in Section 3.4 by providing the key takeaways, a selected set of the most relevant shared mobility services, and an overview of factors that could affect the willingness to use shared mobility services as access and egress transport. This is used as input for the conceptual framework in Chapter 4.

3.1 Sharing and access based consumption

3.1.1 Different types of sharing activities

"Sharing is the most universal form of human economic behavior, distinct from and more fundamental than reciprocity […] Sharing has probably been the most basic form of economic distribution in hominid societies for several hundred thousand years." (Price, 1975, p.3)

The concept of sharing is not new. Humans have always been sharing, mainly within the context of "intimate economies" such as households or small communes (Price, 1975). Two core characteristics of sharing can be distinguished (Belk, 2010). In the first place, sharing can be seen as an alternative to private ownership. Instead of making a distinction between what is mine and yours, "sharing defines something as ours" (Belk, 2007). Secondly, true sharing is characterized as social and non-reciprocal behavior (Benkler, 2004). One who shares does not expect anything in return.

As the emergence of online platforms has "opened up a new era in sharing" (Belk, 2014c), this interpretation of sharing however, did change to some extent. Most practices associated with what is often called the sharing economy have more in common with economic exchanges than with non-reciprocal social behavior (Hamari et al., 2016). **Figure 3-1** gives a schematic overview of this definitional problem based on a theoretical comparison by (Belk, 2010). True sharing is located bottom left, whereas most sharing economy activities are located more to the right. Participation is often linked to expecting something in return.

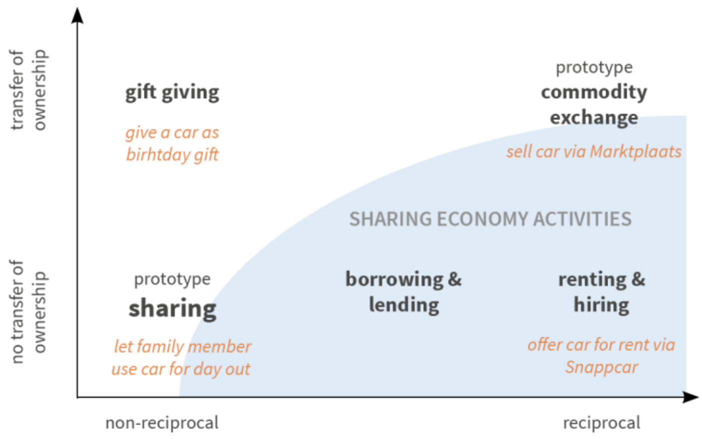

Figure 3-1 Prototype sharing compared to gift giving and commodity exchange, constructed by using the comparisons presented by (Belk, 2010). The grey area indicates the location of sharing economy activities and shows how these activities (from a definition perspective) are different from prototype sharing.

The misplaced used of the concept of sharing is one of the reasons why defining the sharing economy has been controversial so far (Cherry & Pidgeon, 2018). Proposed alternatives include: "pseudo-sharing" (Belk, 2014a), "access-based consumption" (Bardhi & Eckhardt, 2012), and "collaborative consumption" (Botsman & Rogers, 2010).

Additionally, the dispute is also caused by the fact that many different types of activities are assigned to the sharing economy (Frenken & Schor, 2017). Distinctions can, for example, be made based on peer-to-peer activities vs. business-to-consumer or profit vs. non-profit (Cherry & Pidgeon, 2018). In order to conceptualize the position of shared mobility within these mix of activities, the framework by Frenken, Meelen, Arets, & Glind (2015) is used and presented in Figure 3-2.

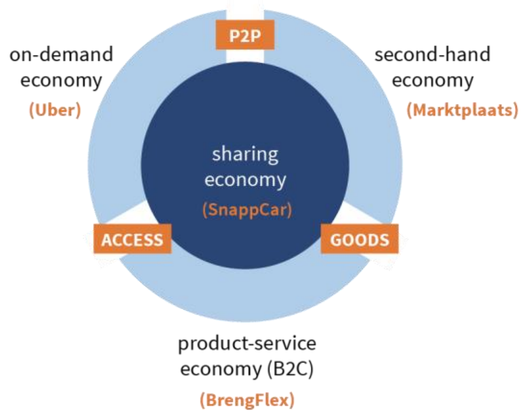

Figure 3-2 Sharing economy and related sectors in the platform economy. The total can be referred to as collaborative consumption. Shared mobility examples in the different sectors are indicated in yellow. Adopted from Frenken et al. (2015).

In this framework, the sharing economy refers to "consumers granting each other temporary access to under-utilized physical assets ("idle capacity"), possibly for money" (Frenken & Schor, 2017, p.4-5). Consumers offering services instead of access to assets to other consumers via online platforms, are part of the on-demand economy. When such services are operated by companies (B2C), they are part of the product-service economy. As an example, several sharing related mobility services and platforms can be linked to these different categories. P2P car rental platform SnappCar perfectly fits within the definition of the sharing economy. People can give other people access to their underutilized asset: their car. When instead of offering access to one's car, a consumer is offering the service of mobility (a ride), that type of activity belongs to the on-demand economy. Ride service platform Uber can be categorized here. In case such ride service is being operated professionally, it is part of the product-service economy. Flexible bus-service BrengFlex is an example of such activity. Lastly, a bit further apart Frenken et al. distinguish the second hand economy, which is what takes place at online platform Marktplaats. Different types and business models of shared mobility are further looked into in Section 3.2.

The group of different related platform economies are referred to by Frenken et al. (2015) as collaborative consumption or when excluding the second-hand economy sector, as access-based consumption. Given the controversy of using the concept of sharing economy, in this research *access-based consumption* will be used as an 'umbrella term' (Hamari et al., 2016) to refer to consumption activities that are based on obtaining (shared) access to a (mobility) service instead of ownership (of in this case, a vehicle).

3.1.2 Participation in access based consumption

In order to identify factors that influence the willingness to use shared mobility services, it is useful to include a brief overview of the key drivers for participation in access based consumption in general. Mainly due to a rising awareness of the potential of sharing economy practices as solutions to a range of environmental, social, and economic problems, a growing number of studies is investigating the decision making process regarding consumption based on sharing and shared access (Cherry & Pidgeon, 2018). The resulting list of factors found in these studies can be split into three parts: motives, socio-demographic factors, and (general) attitudes.

Motives

The majority of studies addresses consumers' motivations for participating in access based consumption (Böcker & Meelen, 2017). Drawing upon the motivation theory of Self Determination (Deci & Ryan, 2000), these studies make a distinction between intrinsic and extrinsic motivations. In general, three motives are discussed:

1. **Personal utility maximization** (extrinsic), in particular economic benefit, is found in most studies as key driver for participation in, for example, studies on the sharing activities of product rental (Moeller & Wittkowski, 2010), car sharing (Bardhi & Eckhardt, 2012), and accommodation sharing (Tussyadiah, 2015).
2. **Reputation and social benefits** (extrinsic) are also mentioned as important drivers for participation (Botsman & Rogers, 2010; Ozanne & Ballantine, 2010), though be it in a less general way as utility maximization (Böcker & Meelen, 2017). Besides, social benefits as in sense of community are more often found to be drivers in peer-to-peer activities compared to business-to-consumer services (Tussyadiah, 2016).
3. **Environmental motives** (intrinsic). Also repeatedly mentioned are motivations with respect to sustainability and the environment. However, literature presents mixed findings on the effect of this motive. Studies by Gansky (2010), Lawson (2010), and Piscicelli, Cooper, & Fisher, (2015) find concern for sustainability and environmental issues as an important motive for a significant amount of users. On the other hand, no relationship between environmental concern and motivation to use shared services was found in studies by Bardhi & Eckhardt (2012), Hamari et al. (2016), Möhlmann (2015) and Tussyadiah (2016). Apart from these mixed findings, sustainability motives appear to be perceived as a positive side effects of participation rather than being main drivers (Hamari et al., 2016; Hartl, Sabitzer, Hofmann, & Penz, 2018).

As a brief reflection on these motives, two comments can be made. In the first place, it is useful to note the chronological link among these studies. Identified motivators that are more about altruistic values like involvement in a community and sustainability were found as important drivers in earlier studies, whereas the economic driver seems to have taken over as main reason why people join. Several of the above mentioned studies refer to the "crowding-out" effect (Frey & Jegen, 2002) as a possible explanation. As the amount of sharing economy practices grew bigger and became more diverse, extrinsic motivations took over from intrinsic ones (Hamari et al., 2016; Martin, 2016).

Secondly, it is important to note that the relative importance of these motivations significantly differ across the various types of sharing and access based consumption. The study by Böcker & Meelen (2017) showed that economic drivers are dominant in car- and accommodation sharing while social motive dominated meal sharing and ride sharing.

Socio demographic characteristics
Differences in reasons to participate also applies for population categories (Hellwig, Morhart, Girardin, & Hauser, 2015; Lutz & Newlands, 2018). Therefore, socio-demographic characteristics are also relevant to include.

1. **Age.** The appeal of sharing activities was found to differ per age group (Olson, 2013).
2. **Gender.** Diamantopoulos, Schlegelmilch, Sinkovics, & Bohlen (2003) for example propose that women are more environmentally aware than men, which can be linked to the above mentioned motivations, this was confirmed by Böcker & Meelen (2017).
3. **Income**. A relationship exists for example between environmental awareness and income (Shen & Saijo, 2008), which can also be linked to the Maslow's theory of hierarchical needs. On the other hand, Fraiberger & Sundararajan (2017) claim that income can also affect participation the other way around, as for lower incomes, the economic gains of obtaining shared access instead of ownership could be higher than for higher incomes.
4. **Digital literacy** refers to individual knowledge on how to move around in the digital world. As sharing activities predominantly occur via online platforms and smartphones, having digital skills is an important requirement to be able to participate in access based consumption practices .

Attitudes
Apart from the concrete motives and socio-demographic characteristics, some underlying general attitudes also affect the willingness to participate in sharing based consumption (Belk, 2014; Schreiner, Pick, & Kenning, 2018).

1. **Social distance** towards "the stranger". Degree of intimacy is an important factor related to one's willingness to share (Belk, 2010). Due to the growth of communication via online platforms, the social distance that people perceive between them and strangers has decreased (Schreiner et al., 2018; Van Dijk, 2012), which has also affected the attitude towards materialism.
2. **Materialism**. Belk (2010) states people's willingness to share is strongly linked with the degree of attachment to possessions, both in general as well as to the specific type of product. As the perceived social distance is changing, Botsman and Rogers (2010) note a paradigm shift in this degree of attachment, being one of the triggers for the rise of sharing and access based consumption.

To conclude this section, this literature review so far can be summarized by noting that trying to define practices related to sharing or the sharing economy is a complex process. A wide variety of practices can (to some extent) be linked to the umbrella term 'sharing economy'. Likewise, different reasons for participation exist. This first general structuring provides a basis to understand the rise of shared mobility services within the wider trend of shifting to access-based consumption. The next step is to zoom in on shared mobility.

3.2 Shared mobility

Mobility has grown to one of the largest sectors within access based consumption in the last decade and is expected to keep growing (Franckx & Mayeres, 2016; PwC, 2016). The global car sharing fleet increased between 2006 and 2014 from 0.35 million to 4.82 million (Shaheen & Cohen, 2016). Last year in the Netherlands, the fleet size increased with 25% (CROW-KpVV, 2018). Besides cars, also shared usage of other modes is increasing in popularity. The amount of trips made with NS's OVfiets for instance, increased with 33% over the last year (NS, 2018) and scooters emerge as a popular new transportation mode for urban areas (Irfan, 2018).

As mentioned in the previous section, different kinds of shared mobility exist. Some can be assigned to the sharing economy whereas others are about providing on-demand services on a peer-to-peer (P2P) or business-to-consumer (B2C) basis. In a whitepaper on shared mobility, (Shaheen, Chan, Bansal, & Cohen, 2015) define the concept as:

"an innovative transportation strategy that enables users to gain short-term access to transportation modes on an "as-needed" basis" (p.4).

Important to note here is that sharing thus refers in particular to the fact that travelers can use modes without the necessity to own a vehicle: access based consumption of mobility. Directly sharing a ride or a vehicle with other travelers is not necessarily the case and depends on the type of shared mobility (see next subsection). The label of innovative strategy refers to the role of smartphones and online platforms in facilitating shared mobility (Cohen & Kietzmann, 2014). Online platforms for example, allow consumers not only to access mobility, but also to supply others with access to their vehicle or offer a ride service. Smartphones, at the same time, enable for on-demand access to mobility via internet connectivity and smart locks.

3.2.1 Shared mobility business models

Different names are used in both academic and non-academic literature to describe the different kinds of shared mobility (Standing, Standing, & Biermann, 2018). One of the first and most often cited categorizations is the overview by Shaheen and Chan (2016), seeFigure 3-3. As the overview depicts, the first important split that can be made is about what is shared, a vehicle or a passenger ride. The left side of the figure then further distinguishes between modes, vehicle owner, and how parking and payment are arranged. The categories on the right side of the figure are more diverse, separating different forms of peer-to-peer pooling (ride sharing) from ride services that offer passengers a ride on an individual or collective basis. Interesting to note is amount of car-related shared mobility types.

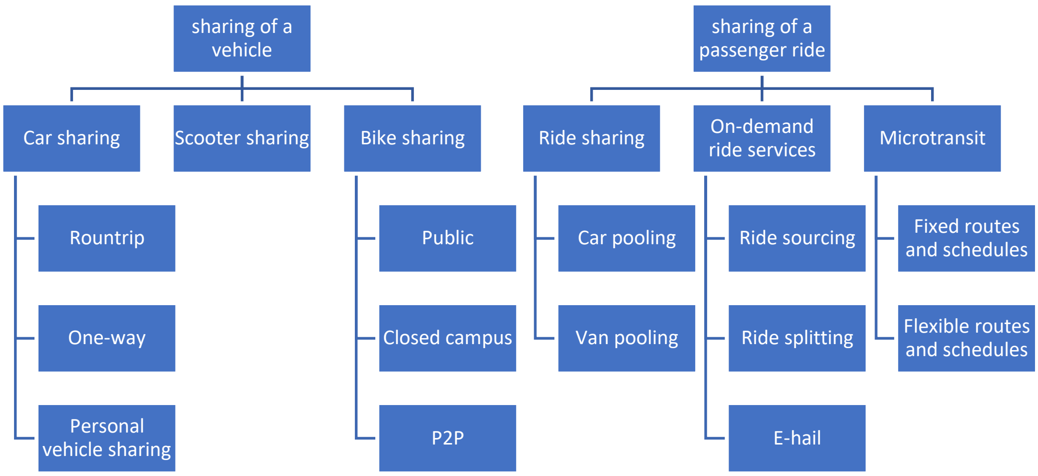

Figure 3-3 Key areas of shared mobility as presented by Shaheen & Chan (2016).

Given the goal and scope of this research, the structuring by Shaheen & Cohen was adapted by using Cohen & Kietzmann (2014), CROW-KpVV (2017), Franckx & Mayeres (2016), and Durand et al., (2018). Details were added and removed to make the overview fit better to the Dutch context and focus on access and egress transport of train travel. This provides a more useful overview that can be used to assess which type of mobility services examine into more detail and incorporate in the stated preference experiments.

This adapted overview is presented in Figure 3-4. As can be noted, the vehicle sharing side is structured into more detail by separating the distinction between P2P vs B2C and distinction in parking system. On the passenger ride sharing side, more structure and detail is added to the on-demand service category which is considered the most relevant passenger ride service from the perspective of access and egress transport. Flexible micro transit in incorporated into this category, while fixed micro transit is not taken into account. To clarify the different categories, examples of present services/modes in the Netherlands[7] are added including costs. By using

[7] This is not the case for the standing e-scooter mode is not yet legally allowed to be used in public. More on this scooter is also discussed in Section 3.2.2.

this overview, the next section discusses the selection of the most relevant types of shared mobility services that are to be incorporated into the stated choice experiments conducted in this study.

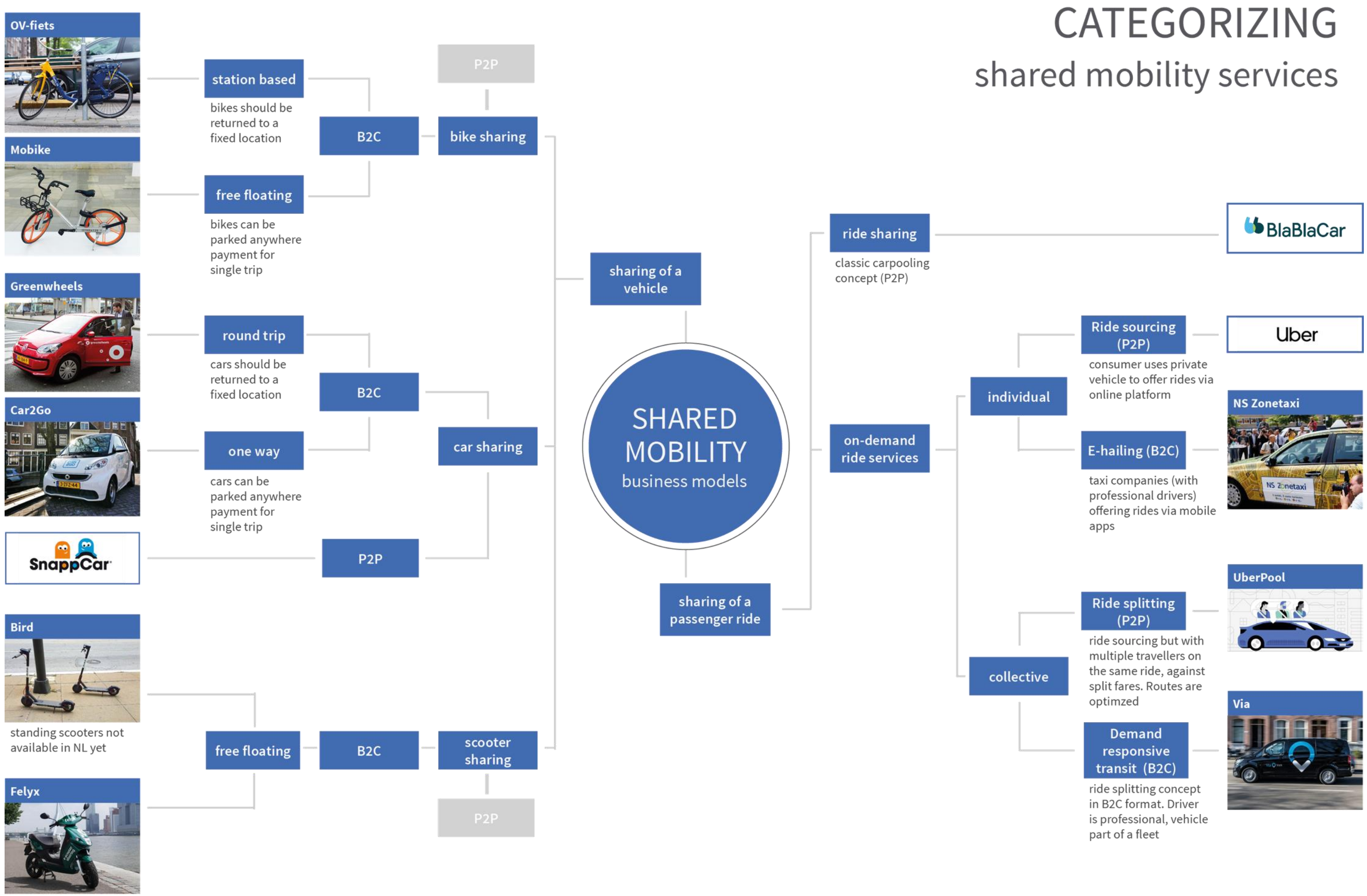

Figure 3-4 Overview of shared mobility business models.

3.2.2 Selecting shared mobility services

Given the scope and feasibility of this research, only a selected set of shared mobility services can be included in the stated preference experiments. Included services are selected based on (i) their relevance as access or egress transport within the multimodal train trip, (ii) their presence within the current Dutch transportation market, and (iii) the likeliness of becoming a successful mobility service in the next decade.

As a first step, the scope is narrowed down to sharing vehicles. The popularity of OVfiets already proves the benefits of grab-and-go vehicles at the egress side of the trip. From here, is also assumed relevant to explore the willingness to use other shared vehicles. Although on-demand ride services also show to have potential as access and egress transportation, they are not included in this research because of feasibility reasons.

As a second step, the scope is narrowed down further to the following three types of shared mobility:

Bike sharing (business to consumer (b2c) models), both free floating and station based type of services. Multiple studies show that bike and public transport, especially train, are a powerful mode combination because they complement each other's core qualities (flexibility and spatial reach) (Brand, Hoogendoorn, Oort, & Schalkwijk, 2017; Kager et al., 2016; Shelat, Huisman, & van Oort, 2017). In the Netherlands, the private bike is the most popular access mode for train travel (NS, 2018) and shared bike systems are found to have a large potential of facilitating the bike as egress mode at the activity side of the multi-modal train trip (Jonkeren et al., 2018), which is also proved by the rapid growth of OVfiets usage. Including shared bike services here, is thus highly relevant.

Only b2c services are taken into account, also because peer-to-peer bike sharing services do not exist in the Netherlands (Jonkeren et al., 2018; van Goeverden & Correia, 2018). Electric bikes are also excluded because of the differences in the relation between preference and distance compared to regular bikes. Including both regular bike and e-bikes introduces additional complexity due to the fact that having e-bike as mode option effects station choice[8] (Jonkeren et al., 2018).

Car sharing (b2c), though the private car is not used a lot as access- and egress transport (7% of total (NS, 2018)), car sharing in general is steadily growing in the Netherlands. Besides, research shows that people who switch to shared car usage instead of private car ownership make more use of public transport including the train (Oldenburg, Olde Kalter, & Timmermans, 2018). Therefore car sharing as access egress mode is included in this research. With respect to feasibility of the choice experiment, only b2c business models are included.

Scooter sharing (b2c, free floating, standing version). As also shown in **Figure 3-4**, scooter in English can refer to two types of transportation modes: the more common moped-style scooter and the electric standing scooter, which more recently emerged as an promising new type of shared mobility in urban areas (Shaheen & Cohen, 2019). In the Netherlands these vehicles are not legally allowed to be used in public yet (Boot, 2018). However, combining these expectations with its promising fit between walking and cycling in the modal split (as discussed in Chapter 1) and qualities like a small parking space footprint (Boot, 2018), the standing e-scooter is considered a relevant additional shared mode to include into this research.

[8] E-bike as access or egress mode option impacts the entire multimodal trip: the combination e-bike to intercity station + intercity train could become more attractive than regular bike to suburban station + sprinter train + intercity train (Jonkeren et al., 2018). This type of additional choice complexity is out of this research's scope.

Figure 3-5 Two different types of scooters. The moped style scooter (left) and the electric standing variant (right).

This selection of further to be included shared mobility services closes this section. So far this chapter has moved from general concepts of sharing and access based consumption to examining and categorizing shared mobility which has resulted into a concise set of shared modes that can be incorporated in the stated choice experiments. In the second part of this chapter the focus shifts towards factors that play a role in the mode choice process.

3.3 Mode choice factors

In order to identify relevant mode choice factors that can be studies into more detail using discrete choice modelling later in this research, literature is consulted to come to a first set of factors. This set is then evaluated in the next chapter to come to a final and feasible number of factors that is to be incorporated in the stated choice experiments.

3.3.1 The mode choice process

Before identifying relevant mode choice factors that can be used to construct choice models, it is useful to examine how these factors relate to the bigger picture of (modelling) mode choice in general, see Figure 3-6. This schematic overview of transport modelling shows how assumptions linked to several aspects need to be made in order to formulate a (choice) model. Only a selected set of choice determining factors can be included as variables. Some factors cannot be included because they cannot be controlled, other could be irrelevant with respect to the scope of the study or are not part of the assumed (choice) behavior theory (Ortuzar & Willumsen, 2011).

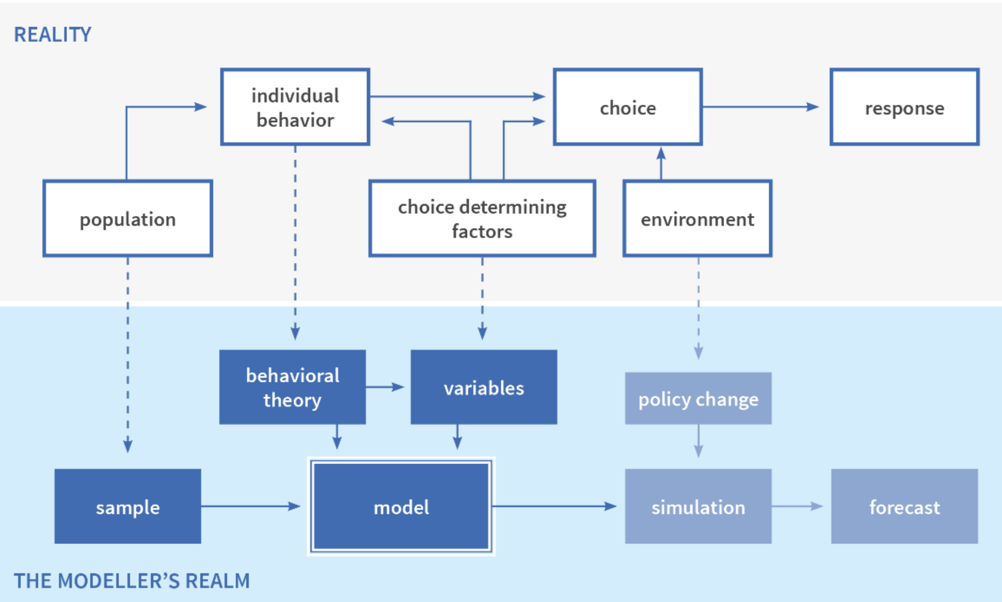

Figure 3-6 Generic conceptual overview of modelling in transport as presented in Ortuzar & Willumsen (2011). The right side of the modeler's realm (lighter blue) is not considered in this study.

The assumed behavioral theory thus plays an important role in the selection of choice determining factors to include in the model. In general, three major approaches of analyzing the mode choice process can be distinguished: the rationalist approach, the socio-geographical approach and the socio-psychological approach (De Witte, Hollevoet, Dobruszkes, Hubert, and Macharis, 2013). The rationalist approach takes the microeconomic perspective and assumes that individuals make a rational decision based on the available information. In the socio-geographical approach, the activity schedule of the individual (in space and time) is assumed as a starting point to model mode choice. Lastly, the socio-psychological seeks to explain mode choice by including psychological variables such as individuals' attitudes and habits (Donald, Cooper, & Conchie, 2014).

The rationalist approach is the mainstream method to conceptualize the mode choice process and is also used in this study as a basis to model the choice of access- and egress mode. That way, the underexplored quantitative side of the mode choice process (Chapter 1) can be explored by applying discrete choice modeling (Chapter 2). This behavioral theory framework is, together with the focus on access and egress transport, used as a scope in the process of identifying relevant mode choice factors in existing literature. Though the assumed theoretical focus is the rationalist approach, this does not mean that spatial or psychological factors are not included in this study. They are not assumed the basis of the choice process, but can still be included (to some extent) in the discrete choice models.

3.3.2 Selecting mode choice factors

Though factors linked to choice of a shared mobility option is the focus of this research, choice is always about comparing alternatives and therefore factors with respect to general mode choice access egress are examined here. Mode choice is an extensively studied topic and depends on many factors. Even though there is no generic way of identifying and structuring these factors, some universal rough categories can be distinguished (De Witte et al., 2013; Ortuzar & Willumsen, 2011). These are factors related to the available *transport service/modes*, factors related to the *trip*, and factors related to the *traveler*. Relevant factors for this study are listed below using these three categories. Selection occurred based on the assumed behavioral theory and relevance with respect to the scope of this research (access- egress transport of train trips).

Mode characteristics

Traditionally, the rationalist view on mode choice is the trade-off between **travel time** and **travel costs**, which are also the most widely studied mode choice factors (De Witte et al., 2013). With respect to both travel time and costs it is important to consider that different travel time components are perceived differently for different reasons. For example, different types of travel time are perceived differently (Arentze & Molin, 2013). In general travelers are found to be more sensitive to out-of-vehicle time than in-vehicle time (Bhat, 1998; Halldórsdóttir, Nielsen, & Prato, 2017). Also travel purpose affects the perception of travel time and costs (Kouwenhoven et al., 2014; Litman, 2004) and above all, perception of travel time and costs is affected by characteristics related to the traveler (Arentze & Molin, 2013; Molin & Timmermans, 2010; Yap, Correia, & van Arem, 2016).

Apart from these qualitative factors, also qualitative mode characteristics that define the **level of service** can be relevant mode choice factors (Ortuzar & Willumsen, 2011). Van Hagen & Kieft (1998) make distinction between the impact of comfort and convenience. A large drawback of these qualitative factors is that they are hard to measure compared to travel time and costs.

Trip characteristics

Mode choice factors related to the characteristics of the trip make up a broad category of factors and their relative impact differs substantially. The first and most important trip characteristic is **trip distance**. It has a strong effect on the attractiveness of modes because of its link with travel time. Multiple studies show the effect of trip distance on the modal split (Givoni & Rietveld, 2007; Krygsman, Dijst, & Arentze, 2004; Molin & Timmermans, 2010). As trip distance increases, faster modes are preferred (De Witte et al., 2013). A study by (Rietveld, 2000) on mode preferences for the access and egress trips finds walking to be the preferred mode for distances up to 1.2 km. Between 1.2 and 3.7 km, bike is the most preferred mode, while public transport is most preferred for trips longer than 3.7 km.

Next to trip distance, **trip motive** is also a factor to include. The reason to travel in particular affects the perception of other mode factors such as sensitivity to travel time and costs. Studies by for example Van Hagen & Kieft (1998), Molin & Timmermans (2010), and Kouwenhoven et al. (2014) show how travelers travelling for business purposes often have a higher willingness to pay for less travel time and are likelier to opt for the car alternative when available.

A more spatial oriented mode choice factor is the **urban context** of the access- or egress trip. In a study on access- and egress mode preference for train travel in Copenhagen Halldórsdóttir, Nielsen, & Prato (2017) find for example that the higher the *urban density* in which an access or egress trip takes place, the higher the share of walking and public transport as chosen mode. Also the *availability of convenient infrastructure* (both quality and quantity) was found to be a relevant factor, in particular for bike usage, in studies by Faghih-Imani, Eluru, El-Geneidy, Rabbat, & Haq (2014) and Van Mil, Leferink, Annema, & van Oort (2018).

Besides characteristics related to the access of egress trip itself, also **characteristics of the train journey** can be listed a factor that affects mode choice. As concluded by Van Mil et al. (2018) in a study on the factors influencing the combined use of bicycle and public transport, the *duration of the train trip* should be of a significant length to compensate for the inconvenience required to "collect, park or board a bicycle". Also the *type of transfer station*, including *the quality and quantity of parking and transfer facilities* is mentioned by multiple studies affect mode choice (Halldórsdóttir et al., 2017; Van Jonkeren et al., 2018; Puello & Geurs, 2015).

Lastly, context related factors **weather**, carrying **luggage**, and **time of day** were tested via stated choice experiments and all found significant by Molin and Timmermans (2010) in a study on train egress mode choice. They are also included in the selected set of factors resulting from this chapter.

Traveler characteristics

The found effects of the above listed factors are always dependent on the type of traveler (De Witte et al., 2013). To select factors that describe the type of traveler a distinction can be made between socio-demographic characteristics that are simple measurable indicators, and socio-psychological factors which include experiences, familiarity, habits, lifestyle, perceptions, affect, motives, and attitudes (Ben-Akiva & Bierlaire, 1999).

Socio-demographic characteristics

Many socio-demographic characteristics can be included with respect to mode choice. Given the focus on shared mobility as access and egress transport, the amount of factors lists is limited to the "basis" factors **age**, **gender**, **education level**, **income** and **vehicle ownership** and **driver's license** holding because of their high relevance given the topic of shared mobility. Although there is no general agreement on the role of age in (general) mode choice (De Witte et al., 2013), it is included as a factor because of the found relationship between willingness to use Mobility-as-a-Service and age in a recent study by Zijlstra et al. (2019). Younger people are found to be more likely to adopt MaaS (including shared mobility services). With respect to vehicle ownership, literature presents mixed findings. Givoni & Rietveld (2007) find no relationship between owning a car and access- egress mode choice whereas such relationship is found in studies by Halldórsdóttir, Nielsen, & Prato (2017) and Puello & Geurs (2015).

In addition to these general socio-demographic factors, **familiarity with shared modes** is added given the specific testing of these (new) modes in this study. Previous studies by for example Brown, Werner, & Kim (2003) and De Witte et al. (2006) show how being familiar with a transport system reduces barriers to use it in the future.

Lastly, also **digital literacy** is added as a relevant mode choice factor, given the focus on shared mobility services. Digital literacy was discussed in Section 3.1.2 as a socio-demographic characteristic linked to participants of access-based consumption practices in general. It refers to individual knowledge on how to move around in the digital world. Usage of shared mobility services heavily depends on smartphone usages, which makes digital literacy a relevant traveler characteristics to include.

Socio-psychological factors

These factors are hard to measure because of their subjectivity and the fact that they often do not have a scale of measurement (Ortuzar & Willumsen, 2011), which is also the reason why they are commonly not included or found significant in mode choice studies (De Witte et al., 2013). However, using statement questions as separate survey next to the choice experiments, some of these latent variables can be measured (Ortuzar & Willumsen, 2011).

Given the scope of this study and the limited possibilities to measure these factors, the selected socio-psychological factors that are included are the traveler's attitude towards **trying new technologies** and **openness to sharing and renting** in general, which are attitudes that are linked to the willingness to try shared mobility services in studies by Alonso Gonzalez, Liu, Cats, Oort, & Hoogendoorn (2018), and Zijlstra et al. (2019).

3.4 Conclusion

In this chapter, multiple perspectives of existing literature have been consulted in order to construct a theoretical basis for the rest of this research. By examining literature related to the rise of the so-called sharing economy, the first part of this chapter revealed the ambiguity that surrounds this concept. Many practices associated with the umbrella concept of the sharing economy have nothing to do with "true sharing". To describe sharing related activities such as use of shared mobility, is in this study therefore referred to as access based consumption.

The definition of shared mobility as "an innovative transportation strategy that enables users to gain short-term access to transportation modes on an "as-needed" basis" (Shaheen et al., 2015), as discussed in the second part of this chapter, can also be linked to the ambiguous use of sharing. Having short-term on-demand access to a mode has in many cases nothing to do with the social and non-reciprocal character of true sharing. It is rather that the shared modes are accessible to all travelers and therefore can be referred to as having shared access to.

The concept of shared mobility is, just like the term sharing economy, found to be an umbrella concept. In distinguishing different kinds of shared mobility business models, an important split can be made between sharing a vehicle or sharing a ride. The first category is deemed most relevant to include further in this study, mainly due to the popularity of walking and cycling in the current model split of access and egress mode in multimodal train trips. The included shared mobility services in the stated choice experiment are: shared bike, shared e-scooter (standing version), and the shared car.

As a first step in identifying what factors determine people's willingness to use shared mobility services as access or egress transport in multimodal train trips, literature regarding mode choice is consulted in the third part of this chapter. This results in the set of selected of factors presented in Table 3-1. Factors are selected based on their relevance to the topic of access- and egress transport and to the applied research method and underlying assumptions from viewpoint of the adopted behavioral theory.

Table 3-1 Overview of identified factors that could influence people's willingness to use shared mobility services as access or egress transport in multimodal train trips

Mode characteristics	Trip characteristics	Traveler characteristics
• Travel time • Travel costs • Level of service	Related to Home/activity based trip • Distance • Urban context • Transfer station Related to total trip • Purpose • Train trip duration Context factors • Time of day • Weather • Luggage	• Age • Gender • Income • Education • Driver's license • Vehicle ownership • Familiarity with shared modes • Digital literacy • Attitude towards trying new things • Attitude towards sharing in general

The results of this chapter are used as input for the stated choice experiments, that are discussed in Chapter 5. First however, in order to come to a workable set of variables, the most relevant factors from the identified set are selected in the next chapter via expert judgement.

4 Conceptual framework

In order to use the output of the literature review in the process of designing a stated preference experiment, this chapter provides a conceptual framework by defining the used concept of the multimodal door-to-door trip with train as main mode and by selecting – using expert judgement – a concise set of mode choice factors from the proposed factors resulting from the literature study.

4.1 Concept description

The multimodal door-to-door trip is composed out of three smaller trips: the home-base trip from home to railways station, a train trip between two railway stations[9], and the activity-based trip from railway station to the activity, the final destination. A schematic overview of the entire trip is depicted in Figure 4-1. For both the home-based (HB) and the activity-based (AB) trip, the traveler can choose a mode from the available choice set, which in this study varies based on the trip length of the trip. b

The total travel time of both the HB and the AB trip can be split further into three parts: transfer time A, the HB in-vehicle time, and transfer time B (see Figure 4-1). In case of the HB trip, the trip starts with a certain amount of transfer time before the in-vehicle time (actually moving with the chosen mode) can begin. Depending on the type of mode this transfer time A can consist of waiting for the bus, searching a shared mode nearby, or be zero in case of using a private vehicle. Transfer time B is the time needed between getting off/out of the HB mode and standing on the platform. Depending on the type of mode chosen, this can be linked to parking time or solely to walking to the platform.

For the case of the AB trip, the role of the travel time components is similar to the HB trip and can thus be split in Transfer time C, the AB in-vehicle time, and transfer time D. Transfer time C is linked to the time between arriving by train and "boarding" the chosen AB mode and can be about searching or waiting. Transfer D is similar to transfer time B and addresses the time need to disembark from the AB mode and walk to the final destination, if necessary this time can also include parking time.

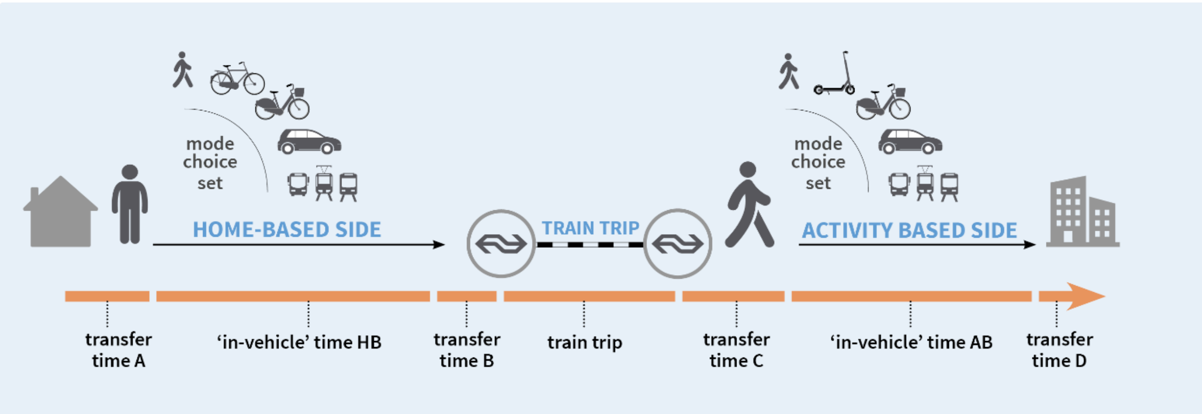

Figure 4-1 Schematic overview of the concept of the multimodal train trip.

4.2 Factors that could affect the willingness to use shared modes

The identified factors in the previous chapter can be inserted into the conceptual overview discussed above. The resulting overview is depicted in Figure 4-2. As can be noted, the conceptualized travel time components are listed at the mode characteristics category since these components are dependent on the type of mode, i.e. the in-

[9] Since factors related to transferring between trains is not taken into account here, the train trip is simplified to a single trip between two stations.

vehicle time relates to the mode's speed and the transfer times can be linked to walking to- and waiting at a station (BTM), parking (bike, car, e-scooter), or searching and walking to a vehicle (shared modes). Besides categorizing different travel time components, also a distinction is made between the impact of general trip characteristics that relate to the entire multimodal trip such as trip purpose and carrying luggage, and trip characteristics that are specifically linked to the AB or HB trip like trip distance and weather conditions.

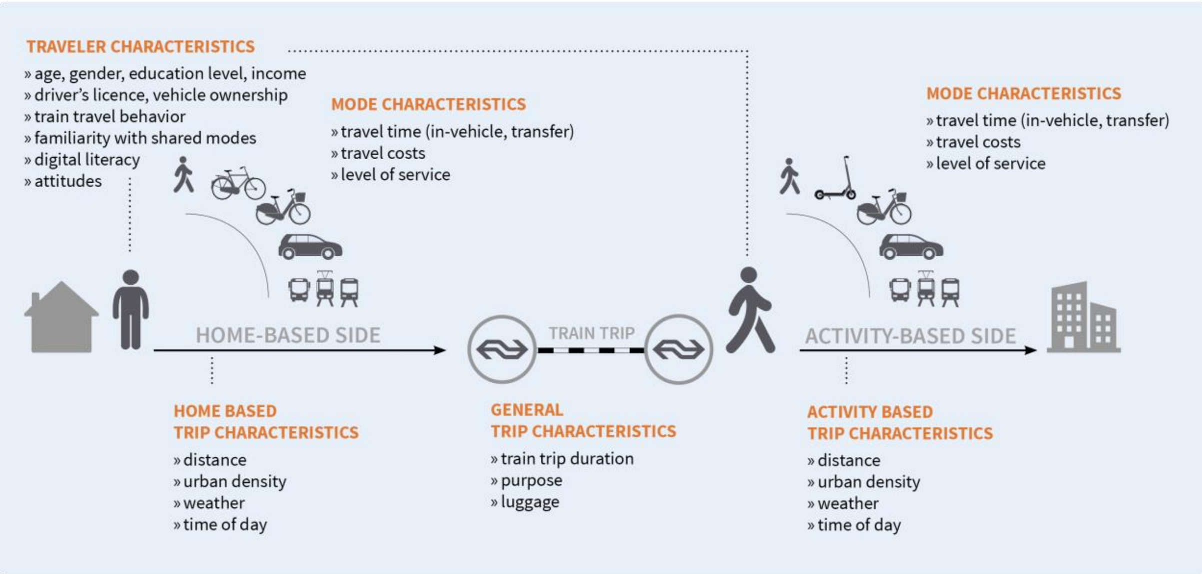

Figure 4-2 The identified mode choice factors in Chapter 3 and their place in the conceptual framework.

4.3 Factor selection

To come to a final set of factors that are to be used in the stated choice experiments, the most relevant factors were selected based on expert judgement using expert interviews[10] and the more practical requirement of measurability in the stated choice experiment itself. The resulting final conceptual framework is shown in Figure 4-3.

Since multiple experts stressed the importance of costs vs 'convenience' (level of service) in mode choice, the different transfer time components were included as separate factors. This is because time related to searching or waiting is considered to contribute to the level of convenience of the mode. Besides, separating different types of transfer times is useful because they can be perceived differently (Arentze & Molin, 2013). In addition to transfer time components, the level of service of shared modes is also operationalized by including different degrees in accessibility through different unlocking methods.

Availability of the shared modes also emerged as an important factor from the expert interview, in particular the amount of uncertainty on whether a mode is available, i.e. "will there be an OVfiets available when I arrive at the station?" However, because of expected measurability issues[11] in the stated choice experiments, it was decided not to include in the final selection.

Next to factors related to the modes, trip characteristics are mainly to be included as context variables in the stated choice experiments. Their categories are combined into trip scenarios and to limit the amount of trip scenario's, it is desirable to include only the most interesting trip characteristics as context variables. Therefore weather and carrying luggage were excluded as these are only occasionally impacting the mode choice (in case of rain or heavy luggage).

Regarding factors linked to the traveler, familiarity emerged from the expert interviews as an important variable to include in the model. As none of the proposed traveler characteristics were found irrelevant by the experts, all traveler related factors identified in the literature review are included in the final conceptual

[10] The list of interviewed experts can be found in Appendix A.

[11] Adding the possibility of being unavailable to the (shared) mode alternatives in the choice experiments is assumed to cause for too much additional complexity for the respondents.

framework, also because collecting data on these variables is done separately from the stated choice experiments and therefore does not cause for measurability issues.

The final conceptual framework resulting from the selection process is presented in Figure 4-3. It shows the three groups of included factors and how these relate to the home-based and activity based trip. Mode characteristic are dependent on the availably mode choice set per trip and are therefore presented separately for the HB and AB trip. This also goes for trip characteristics, except for the factors of trip purpose, train trip duration, and time of day[12]. Since respondents are selected from the NS customer database, data on home-addresses is available and is included to test for the impact of urban density on the home-based trip[13]. Traveler characteristics are measured separately from the stated choice experiments.

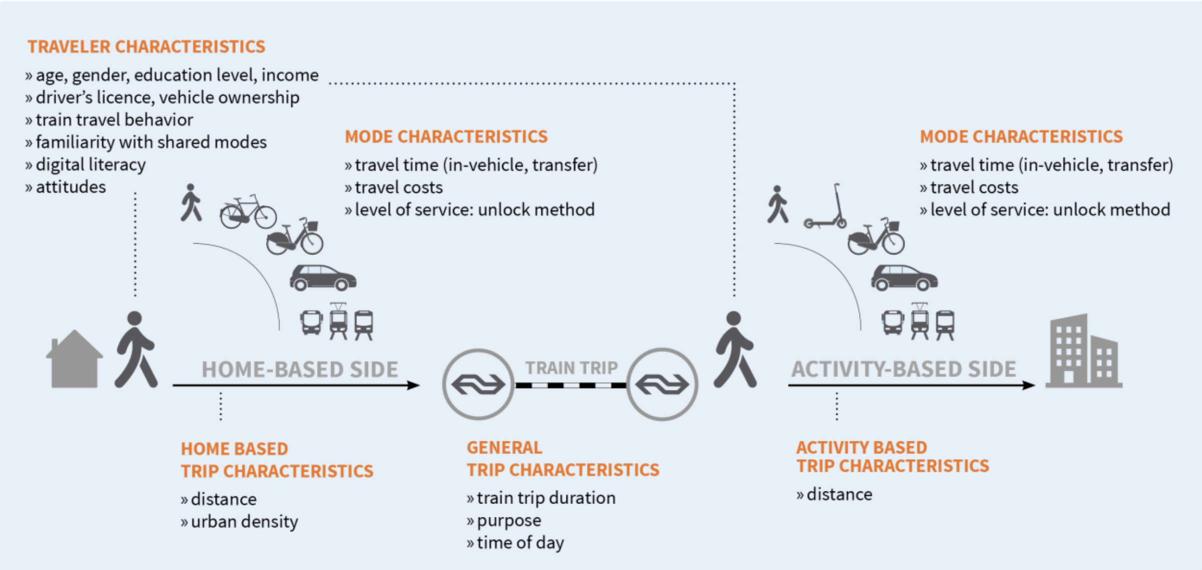

Figure 4-3 Final conceptual framework with selected factors for the stated choice experiments.

Having defined a clear conceptual framework and a set of to be included shared modes, the conceptualization phase of this research is finished and can be used to design the survey to collect choice data.

[12] In Chapter 3 time of day is mentioned to be a separate factor for HB and AB trip. In case of a long train trip, a trip can start during rush-hour (home-based trip) but does not necessarily finish during rush hour as well (activity-based trip). However, for simplicity reasons, time of day is only included here as one variable that is applicable to the entire trip.
[13] Because this data is already available, no additional systematic variation (causing extra complexity because of the need to test additional scenarios) is required.

5 Design of the stated choice experiment

This chapter discusses the design decisions that were made to create a design for the stated preference (SP) experiment. Such a process can generally be divided into three steps (ChoiceMetrics, 2018).
First, a model for which the SP experiment is designed needs to be defined (Section 5.1). For the case of choice modelling, this is about specifying utility functions for different alternatives. Second, an experimental design has to be constructed to ensure systematic variation of the hypothetical choice situation that the respondents are faced with (Section 5.2). As a third and final step, the questionnaire itself can be designed (Section 5.3). To test and improve the design of the questionnaire and experiment, a pilot survey was conducted, of which the results and improvement for the final survey are discussed in Section 5.4. The complete final survey can be found in Appendix 7.3.2D .

5.1 Model specification

Stated preference experiments are designed for testing a specific model (ChoiceMetrics, 2018). To specify the models of this research, this section discusses the design decisions regarding the included alternatives, attributes and contexts.

5.1.1 Alternatives

Given that this research focuses on the trade-offs travelers make when choosing between shared mobility services and other options, the alternatives are expected to offer a choice between shared mobility options and conventional mode options. In Chapter 3, three types of shared mobility services were selected to include. These are: *bike sharing*, *car sharing*, and *(standing) scooter sharing*. Together with the conventional access/egress modes walk, bike, bus/tram/metro (BTM), and car, this gives a total of seven different mode options that can be included as alternatives.

In deciding which combination(s) of alternatives are best at providing information on the trade-off between shared and non-shared mobility options, several aspects are important to pay attention to. In the first place, it is desirable to limit the total number of presented alternatives to a minimum due to practical limitations regarding task complexity and presenting and explaining the alternatives to the respondents (Arentze & Molin, 2013). On the other hand, too much restriction on the number of alternatives can make the survey "too simplistic and transparent" (Hess & Rose, 2009). Caussade, Ortúzar, Rizzi, & Hensher (2005) therefore recommend an optimum of four alternatives per choice set.

Secondly, not all modes are reasonable to combine as alternatives for all access/egress trip distances, i.e. for a trip distance of 500 meter, walking is much more likely to be chosen than car. This means that the set of chosen alternatives also depends on the trip distance(s) considered. Lastly, private modes are assumed to be unavailable at the activity based (egress) side of the total trip[14].

In total, four different alternative sets are designed, see **Table 5-1**. The next paragraphs explain the argumentation for constructing these four sets.

[14] Though in reality some commuters have a private bike parked at the activity based side of their trip, these are not included here as mode option because of the focus on incidental trips to unknown locations.

Table 5-1 The four alternative sets: split per distance class and type of trip.

	MODE OPTIONS	HOME BASED TRIP		ACTIVITY BASED TRIP	
		2 km	4 km	1 or 2 km	4 km
conventional options	walk	●		●	
	private bike	●	●		
	private car		●		
	BTM	●	●	●	●
shared options	shared e-scooter			●	
	shared bike	●	●	●	●
	shared car				●

Separate models for home-based and activity-based trip
In the first place, the to-be-estimated choice models are separated for the cases of the home-based- (access) and activity-based (egress) trips. The main reason to do so is task feasibility for the respondents. Choosing between entire door-to-door trip chains that vary in modes for both the home-based- and the activity-based trip (with a fixed train part), including several varying attributes, is considered to result into a too complex choice task, which would decrease the validity of the experiment. Therefore, the respondents were be presented with independent choice situations for home-based and activity-based trips. A disadvantage of this approach is that it does not allow for measuring possible interaction effects between the two mode choices within one trip chain.

Multiple trip distances included
Given the requirement to include multiple shared mobility options into the choice sets, the experiments consist of choice situations for different distances as not all modes can be combined into feasible alternative sets for each distance. Due to this link between trip distance and mode relevance, trip distance is not included as a regular context variable that is varied over all sets of alternatives. Instead, based on the mode preference data over distance, two alternative sets for different trip distances are created for both the home-based and the activity-based trip.

Home-based trip modes
The current modal split for the home-based trip is dominated by private bike (44%) (Table 5-2). The most interesting trade-off between private and shared mode usage is therefore the choice between use of private and shared bicycle. To make the choice set more realistic, other mode alternatives are added to the choice set. Since bike is the preferred mode for a range of distances (see Figure 5-1), two choice sets are constructed.

Table 5-2 Distribution of access and egress transport of train trips (NS, 2018).

Mode category	Walk	Bike	Car (driver)	Car (passenger)	BTM	Taxi
Home-based	22%	44%	7%	5%	21%	0%
Activity-based	49%	15%	2%	7%	27%	0%

The first one deals with a short distance of 2 kilometer[15] and includes, next to the private and shared bike option, the current second and third most popular access modes: walking and bus/tram/metro (BTM). As Figure 5-1 shows, walking and biking are particularly popular for trip distances up to 3 km. Because a realistic choice set was valued over maximizing choice information on sharing vs. non-sharing, the shared bike is the only shared mode included in this set of alternatives. In the ideal situation, the e-scooter would have been included as well. However, given the constraint of task complexity for the respondent, it was decided to limit the alternative set to four alternatives: private- and shared bike, walking, and BTM.

The second set of alternatives includes the other available private mode at this side of the door-to-door trip: the private car. Though the car is not one of the most popular mode options for the home-based trip, it is interesting to include from the perspective of the trade-off private vs. shared mode usage. Therefore, this second

[15] Initially, 1 km was also included as separate experiment, but was left out based on results from the pilot survey (see Section 5.4).

alternative set is linked to a larger distance (4 km) such that walking can be replaced by private car as a mode option.

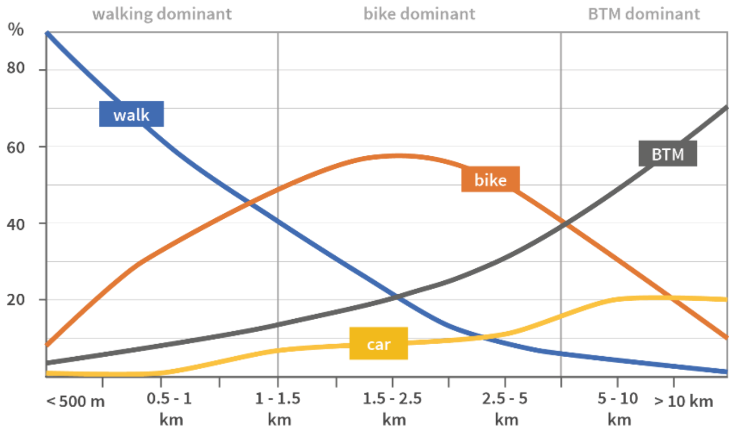

Figure 5-1 Distribution of modal share over access trip distance (Hauwert & van Hagen, 2011).

Activity-based trip modes

On the egress leg side of the total trip (station – destination), no private modes are assumed to be available except for walking. With a share of over 50%, walking is also the most popular egress mode, followed by BTM (Table 5.2). The popularity of walking can partly be explained by the high share of activity destinations that are located close to the station, for which walking is by far the most preferred mode (see Figure 5.2). Given this high share of destinations being close-by locations, it is relevant to design a set of alternatives that is realistic for these shorter distances. This results in a set with most popular (conventional) egress modes walking and BTM completed with the shared bike and shared e-scooter option for trip distances of 1 and 2 km. The shared e-scooter is particularly interesting here, as it can be considered as a mode in between bike and walking in terms of preference over distance. Next to the alternative set for shorter distances, another set is constructed to allow for the inclusion of the shared car as an alternative. This way, more variety of included shared modes can be accomplished. A distance of 4 km is selected for this case.

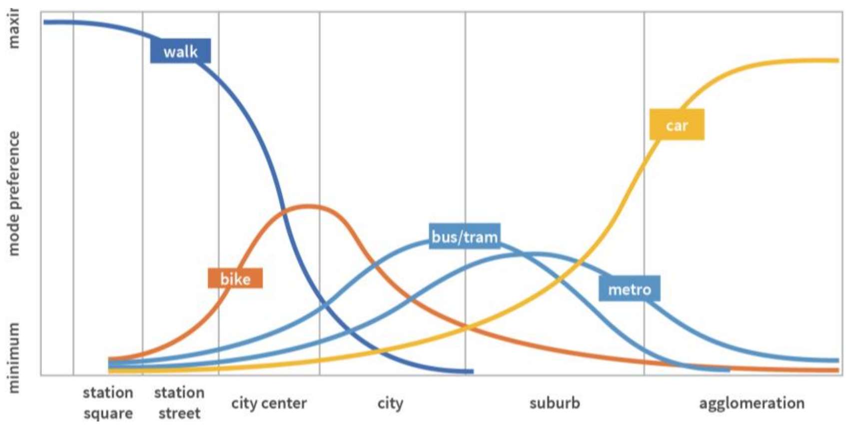

Figure 5-2 Distribution of mode preference for different egress trip distances (Bureau Spoorbouwmeester, 2012).

To sum up, four different choice sets are proposed to be able to measure a variety of trade-offs between conventional and shared mode options for access and egress trips (see Table 5-1). By including multiple distances and limiting the amount of alternatives to four per set, both choice task feasibility and realism of the choice sets are taken into account to ensure validity of the experiments. The next step is to specify the attributes that comprise the utility of each alternative. This is what the next section deals with.

5.1.2 Attributes

As presented in the Chapter 4, the factors to be included as attributes in the alternatives are travel time, travel cost and ease of use. For the 7 alternatives, these factors are operationalized into a total of 16 attributes, see **Table 5-3**.

Travel time

Since the choice experiments are conducted for fixed distances (1, 2, or 4 km), the actual on/in-vehicle time cannot be varied within each experiment. Therefore, additional travel time component are included which can be varied:

- Search time, which applies for the shared mode alternatives for both the home-based and the activity-based experiments. It represent the time it takes to walk towards the nearest shared bike/e-scooter/car available.
- Parking time is included for both private and shared modes in the home-based experiments. It represents the time it takes to find a parking spot and walk towards the station.
- Waiting time is the varying time attribute for the bus/tram/metro (BTM) alternative.

As these different travel time component are perceived differently (Arentze & Molin, 2013), the attributes are included here as alternative specific attributes, meaning that separate parameters are estimated for each of them.

Travel costs

Also for costs, alternative specific attributes are used. These are based on the most relevant type of costs involved for each mode when making a single trip. This means that for private modes, *parking costs* are included. Shared modes are linked to *usage costs* for using a shared vehicle for the single trip, and *ticket prices* are incorporated for the BTM alternative.

Ease of use

Opposite to travel time and costs, ease of use is a qualitative attribute, which are more complicated to operationalize (Hess & Rose, 2009). In order to be able to present clear distinctive levels of ease of use, the unlocking method is used to represent the ease of use. Different unlocking methods vary in convenience and can be used to define the attribute levels.

Table 5-3 Overview of the attributes assigned to each alternative

		Alternatives						
	Attributes	**Walk**	**Private bike**	**Private car**	**BTM**	**Shared bike**	**Shared e-scooter**	**Shared car**
	Move time*	(fixed)	(fixed)	(fixed)	(fixed)	(fixed)	(fixed)	(fixed)
Travel time	Parking time		x	x		x/ fixed **	(fixed)	(fixed)
	Search time					x	x	x
	Waiting time				x			
Level of service	Unlocking					x	x	x
Travel costs	Parking costs		x	x				
	Usage costs					x	x	x
	Ticket costs				x			

* Though move time are not varied, they are included in the presentation as attribute.

** For consistency between the shared bike concepts presented at the home-based and activity-based experiment, parking at the home-based trip and searching at the activity-based trip will both vary. At the activity-based trip, parking time is however assumed to be fixed, to keep the amount of presented varying attribute levels limited.

5.1.3 Contexts

Besides the constructed choice sets, the effect of context variables can also be tested for in stated preference experiments (Molin & Timmermans, 2010). In this case, context variables are used to construct a number of train travel situations for which the respondents make their mode choices. The included variables from the conceptual framework are: *duration of the train trip*, *travel purpose* and *time of day*. The latter two are varied in a combined way as customer segmentation research by NS shows that (train) trip purpose and whether people travel mostly during peak- or off-peak hours are strongly correlated (NS, 2019).

Context profiles are generated by varying over two levels for both train trip duration and the combination of trip purpose and time of day, see **Table 5-4**. The number of two levels was chosen to limit the amount of constructed context profiles. For train trip duration the two levels are: 30 minutes and 60 minutes, which were derived from the total distribution of train trips made by NS customers.

For trip purpose and time of day a distinction is made between traveling for business purposes during rush hour and traveling for leisure activities during off-peak hours. Since in general, the hypothetical trip is an incidental trip (to minimize travel behavior inertia), the business purpose is a hypothetical business meeting or job interview, and the leisure activity is a visit to museum, concert, or sports game. Combining the levels of the two variables results in a total of 4 context profiles. Assignment of respondents to these profiles is based on several profiling questions at the beginning of the questionnaire. That way, the realism of the choice sets can be increased which contributes to the goal of SP experiment of having respondents make informed choices (Hess & Rose, 2009).

To make the choice situation as clear as possible to imagine by the respondents, it was furthermore mentioned in the trip explanation that it is dry weather and that the respondent is only carrying a small handbag (which are most likely for the trip characteristics weather and luggage).

Table 5-4 Context variables and levels

Context variables	Levels
Duration of train trip	30 minutes, 60 minutes
Travel purpose + time of day	important (business) meeting + rush hour, leisure activity + off-peak hours (must vs. lust)

5.2 Experimental design

The experimental design describes which choice situations are presented to the respondents based on a systematic variation of the different chosen attribute levels. ChoiceMetrics (2018) provides a clear list of design decisions to make in constructing such design. This section addresses these decisions. The final experimental designs are presented in Appendix 7.3.2B .

5.2.1 Type of experimental design

The experiments in this study are *labeled experiments* since the designed alternatives represent specific modes. Besides, the type of experiment chosen is the *orthogonal design*. This type of experimental design minimizes the correlations between the attributes, which allows for the estimation of the main effects.

Efficient designs, which are often considered being superior to orthogonal designs (Hess, Smith, Falzarano, & Stubits, 2008) are not used here because of two reasons. In the first place because prevention of creating dominant alternatives[16], which is one of the big advantages of efficient designs over orthogonal ones (Bliemer & Rose, 2011), is considered of less importance for the case of this research, as mode preference regardless of time and costs attributes is expected to play an important role. In the second place, prior values would have to be estimated first (using a pilot study), as required input for the efficient design. The added benefits are not considered to outweigh the additional workload that comes with estimating these priors and constructing an additional completely updated survey.

The experimental designs are generated using software package *Ngene* in which *attribute level balance* can also be included as requisite. This balance is preferred as it contributes to parameter estimations with less bias (ChoiceMetrics, 2018; Hess & Rose, 2009).

[16] Dominant alternatives in the sense of attribute levels: a dominant alternative is both cheaper and faster than the other alternatives.

5.2.2 Attribute levels

Typically, 2-4 levels are used for each attribute (Hess & Rose, 2009). Therefore, three levels are included, which also allows for testing of non-linear effects. In designing the attribute level ranges, it is important to obtain balance between wide ranges which are preferred from a statistical point of view, and smaller ranges which are more realistic to the respondent (Bliemer & Rose, 2011; Hess & Rose, 2009). To obtain realistic values, the middle level (level 1) values are based on real travel costs (public transit tariffs, parking costs at NS stations, trip costs of existing shared bikes and e-scooters), and travel times (Google Maps route planner). The upper and lower level were subsequently varied around this realistic value, while taking into account value-of-travel-time ratios from literature within the alternatives. That way, maximum level value ranges could be included within a realistic trade-off space for respondents. Different from travel time and cost, the attribute unlocking method only has two attribute levels as including two levels of unlocking convenience is considered sufficient to test for the effect of this qualitative attribute.

The final attribute level values are shown in **Table 5-6** and Table 5-6. The pilot survey was used to optimize these values, see also Section 5.4.

Table 5-5 Final attribute level values of the HB experiments. Also the fixed attributes are displayed.

Attribute	Level value 2 km	Level value 4 km
Walking		
Walking time (fixed) [min]	26	-
Private bike		
Biking time [min]	8	16
Parking time [min]	1, 3, 6	1, 3, 6
Parking costs [€]	€ 0.00, € 1.20, € 2.00	€ 0.00, € 1.20, € 2.00
Shared bike		
Search time [min]	0,2,4	0,2,4
Biking time [min]	8	16
Parking time [min]	1,3,6	1,3,6
Usage costs [€]	€0.50, €1.00, €1.80	€0.50, €1.00, €1.80
Unlock method	smartphone, code	smartphone, code
Bus/tram/metro (BTM)		
Waiting time [min]	2, 5, 10	2, 5, 10
In-vehicle time [min]	12	24
Ticket cost [€]	€1.20, €1.60, €2.20	€1.40, €1.80, €2.30
Private car		
In-vehicle time [min]	-	12
Parking time [min]	-	1, 3, 6
Parking costs [€]	-	€1.00, €4.00, €7.00

Table 5-6 Final attribute level values of the AB experiments. Also the fixed attributes are displayed.

Attribute	Level value 1 km	Level value 2 km	Level value 4 km
Walking			
Walk_time [min]	13	26	-
Shared e-scooter			
Search time [min]	1, 3, 5	1, 3, 5	-
On-vehicle time (fixed) [min]	4	8	-
Parking time [min]	1	1	-
Usage costs	€ 1.00, € 1.60, € 2.10	€1.40, €2.00, €2.50	-
Unlock method	Smartphone, code	Smartphone, code	-
Shared bike			
Search time [min]	1, 3, 5	1, 3, 5	1, 3, 5
On-vehicle time [min]	4	8	16
Parking time [min]	1	1	1

Usage costs [€]	€ 1.00, € 1.60, € 2.10	€1.40, €2.00, €2.50	€1.50, €2.00, €2.60
Unlock method	Smartphone, code	Smartphone, code	Smartphone, code
Bus/tram/metro			
Waiting time [min]	2, 5, 10	2, 5, 10	2, 5, 10
In-vehicle time [min]	6	12	20
Ticket costs [€]	€0.90, €1.30, €1.80	€1.20, €1.60, €2.10	€1.40, €1.80, €2.30
Shared car			
Search time [min]	-	-	2, 4, 6
In-vehicle time [min]	-	-	12
Parking time [min]	-	-	1
Usage costs [€]	-	-	€2.00, €3.50, €5.50
Unlock method	-	-	Smartphone, code

5.2.3 Number of choice sets

Because of the large amount of parameters (due to many alternative specific parameters), the minimum number of choice set required for an orthogonal design is 36 rows. As a large sample of respondents is expected, these 36 rows are divided into 6 blocks of each 6 rows. That way respondents make two times six choices: Six in the home-based choice experiment, and six in the activity-based choice experiment. A small number of simple questions is asked in-between the two choice experiments to avoid respondent fatigue. The entire outline of the survey is discussed in the next section.

All complete experimental designs can be found in Appendix 7.3.2B .

5.3 Questionnaire design

To translate the experimental design into a workable and attractive survey for respondents, an online questionnaire was constructed using the online survey tool of research agency *MWM2.* The survey consists of several parts in order to collect data on personal characteristics, attitudes and choice observations. The structure, including routing elements, is outlined in Figure 5-3 and discussed below into more detail. The complete final survey can be found in Appendix 7.3.2D .

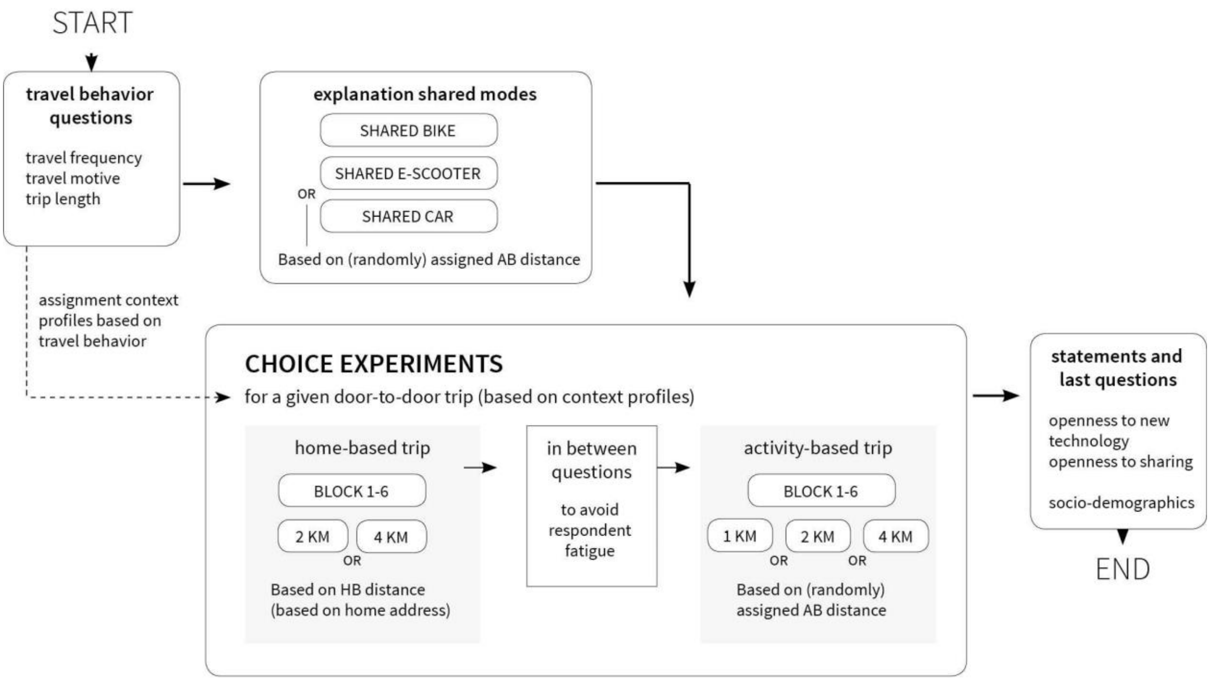

Figure 5-3 Survey outline and routing

Travel behavior questions

When conducting stated preference experiments, realism of the choice sets is of high importance (Hess & Rose, 2009). Several travel behavior questions are therefore asked at the beginning of the survey to characterize the respondents and to be able to present them with choice sets for an imaginary trip that resembles the respondent's travel behavior - and thus their perception of reality - as much as possible.

Explanation shared modes

Before starting the choice experiment, shared modes are briefly introduced to the respondents. The beforehand randomly assigned activity-based trip distance is used to display only relevant modes to the experiments: shared bike and shared scooter for the 1 and 2 km experiments, shared bike and shared car for the 4 km experiment. Two different unlocking methods are highlighted as they are incorporated as quality attributes in the choice experiments.

Choice experiment 1: home-based trip

At first respondents are introduced to their imaginary trip, which is based on one of the context profiles discussed in Section 5.1.3. Context profile assignment is based on answers to the travel behavior questions. Next, the setup of the choice experiments is explained. Hereafter, respondents make six choices of one of the HB-experiments (2 or 4 km). Assignment is based on the distance between the respondents home-address (postal zone code) and the nearest train station. Assignments to blocks is random. Both in the explanation- and in the choice set presentation, visual elements are used to make interpretation easier. This was done in a controlled way, to avoid presenting too much unnecessary information as advised by Cherchi & Hensher (2015).

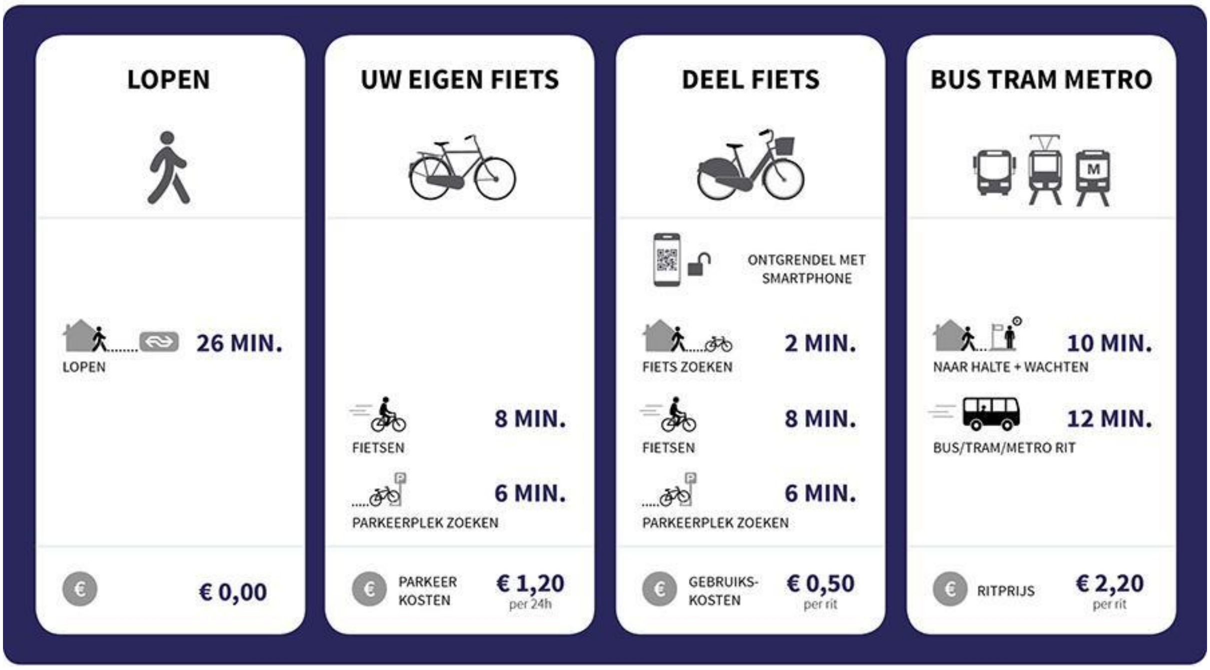

Figure 5-4 Example of a choice set presented at the home-based 2 km experiment.

In between questions

To avoid respondents fatigue and confusion between home-based trip and activity-based trip choice situations, a few questions are asked in between the two choice experiments. These are factual questions related to car ownership and education level which require less concentration to fill out and are assumed not to bias the choices in the second experiment.

Choice experiment 2: activity based trip

Next, respondents are reminded to the characteristics of their imaginary trip (context profile). After the explanation of the activity-based experiment respondents are presented with six choice situations of one of the AB-experiments. Here, assignment to both the trip distance and block are both random.

Statements and last socio-demographic questions
The last part contains questions to measure the respondents' attitudes towards new technology and sharing. Included statements were adapted from other studies on (shared) mode choice to improve their validity. This part of the survey also includes the last questions on personal characteristics, which were explicitly asked at the end of the survey to avoid them biasing the choice experiments (Hess & Rose, 2009).

Table 5-7 Included statements

	Statement	Source
1	I am willing to try new ways to travel.	(Alonso González et al., 2019)
2	My relatives and friends usually come to me for advice about new products and services.	(Alonso González et al., 2019)
3	I like the privacy in the car or bike.	(Alonso González et al., 2019)
4	I would rather prefer not to lend out my own possessions.	(Heydenrijk-Ottens et al., 2019)
5	I try new services, such as Netflix or Uber, before my friends and family.	(Alonso González et al., 2019)
6	I would like to have the convenience of a car without owning one myself.	(Alonso González et al., 2019)
7	I do not mind which transport mode I use, as long as it suits my trip needs.	(Alonso González et al., 2019)
8	(smartphone) Apps help me in daily life.	(Heydenrijk-Ottens et al., 2019)

5.4 Pilot survey

A pilot survey was conducted to check whether respondents understand the questionnaire and to test the setup of the experiment. The main outcomes and resulting adaptations to the final survey are presented here, the complete analysis can be found in Appendix 7.3.2C

The pilot survey was filled out by a small sample of 26 respondents (5.5%). This makes it difficult to estimate significant parameters, but gives an indication on the to be expected response rate for the final survey. Besides, a general score of 7.5 on a scale of 1-10 shows that respondents liked the (lay-out) of the survey. Also a median completion time of 11 minutes is satisfactory regarding the goal of designing a survey with a completion time of 10 minutes.

Based on these pilot results a number of improvements are made to come to a final survey design:

- The home-based 1-kilometer experiment is dropped because of the dominance of alternatives walking and own bike. That way also a better distribution between the 2 km and 4 km experiments can be accomplished.
- Attribute level ranges of travel times and costs are slightly increases to provide clearer differences between the alternatives and provide more information on the trade-offs for model estimations.
- The shared car alternative was hardly chosen in the pilot survey and was therefore made more attractive by lowering travel time and costs to get more information on the trade off with the other alternatives.
- More explicit explanations are added on how to continue during the choice experiment questions and on the variation of the unlocking attributes of the shared mode alternatives.

5.5 Conclusion

This chapter describes the design process of the stated preference experiment and the final survey that is used to collect choice observations and characteristics data of the respondents. Multiple sets of alternatives are proposed to observe choice tradeoff between conventional modes and shared modes for multiple distances in both home-based trip and activity-based trip scenarios. These five sets are constructed as follows:

- Home-based trip
  - 2 km: walk, own bike, shared bike, BTM
  - 4 km: own bike, own car, shared bike, BTM
- Activity based trip
  - 1 and 2 km: walk, shared e-scooter (step), shared bike, BTM
  - 4 km: shared bike, shared car, BTM

Attributes included for each alternative include travel time and travel costs. Additionally, the shared modes have an attribute describing ease of use attribute, which is operationalized as the unlocking method. Orthogonal designs of 36 choice sets are created for each of the 5 distances. Respondents are assigned to one distance for both the home-based (based on home-address) and the activity based trip (random) and are asked to make 6 choices for both trips. A pilot survey was conducted to test and improve the attribute levels and overall setup of the survey, which leads the final survey as presented in Appendix 7.3.2D .

6 Data analysis and model estimation

This chapter analyzes the data that was collected via the survey and choice experiments that were designed in the previous chapter. This analysis consists of two parts. First, descriptive statistics are used to characterize both the sample of respondents and their choices (Section 6.1). The second part of the chapter addresses the estimated discrete choice models. Section 6.2 outlines the estimation process and in Section 6.3 the final models are interpreted.

6.1 Descriptive statistics

Of all 2870 respondents that started the survey, 1841 filled out the complete survey (overall response rate: 9.5%). After data cleaning[17], the sample that is used for this research consists of 1835 respondents and a total of 22,020 choice observations. Overall, respondents rated the survey with a score of 7.1 of out 10 and the time it took them to complete the survey has a median value of 10.5 minutes. These are both considered indicators that validate the design of the survey.

To describe the sample and observations a threefold analysis is performed. First, the sample characteristics are compared with the total NS customer population. Next, distributions of the choice observations are examined, including a more detailed look into the group with fixed preferences. Lastly, the answers to the statements addressing the attitudinal factors are explored using factor analysis.

6.1.1 Sample characteristics

Table 6-1 presents the sample composition, which can be compared[18] to the NS customer population from NS Klimaat VI Personenonderzoek (NS, 2019). From this comparison several observations are noteworthy: Regarding the socio-demographic characteristics, the sample contains both higher shares of elderly and of higher educated people, who may be more interested in the topic or are more likely willing to spend time on filling out the survey. The resulting lower share of young travelers corresponds with a lower share of respondents traveling most often for school-related purposes.

Looking further into train travel behavior, commuters are found to be overrepresented in the sample, which is in line with the presented travel frequency distributions. In general, people that travel more often by train were more tempted to complete the survey compared to people that travel by train only a few times per year. This was also found when comparing the dropout respondents with the completing group and can be considered a reasonable finding as the topic of the survey is likely to be more appealing to travelers that travel more often by train.

Lastly, differences in the current modal split among respondents for both home-based and activity-based trips can be compared with the general modal split figures of NS. The fact that travelers living in more dense urban areas were selected for this study is reflected in lower shares of car and BTM, which are more likely to be chosen in less dense urban areas where travel distances to train stations increase compared to areas with a higher urban density. For the activity based trip, respondents (much) more often use BTM instead of walking in comparison with the overall model split for this type of trip.

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[17] Data cleaning consisted of removing respondents that had both no variation in choices and a completion time of less than 3 minutes, which is considered too low to make informed choices.

[18] In the original document, the detailed population characteristics of the NS Klimaat VI Personenonderzoek are presented in Table 6-1 as well. Given the confidentiality of that information, only a qualitative comparison is presented in this public version of the document.

All in all, the sample is found to be sufficient for this research. Although the distribution of characteristics like age, education, and travel frequency are not completely representative compared to the total NS customer population, the sample is not normalized because the character of this research is exploratory and not aiming at predicting exact future demands.

Table 6-1 Sample comparison with NS customer population.

Variable	Category	Sample
Gender	Male	42%
	Female	58%
Age	16-35	18%
	36-55	27%
	56-65	22%
	65+	34%
Education	WO	28%
	HBO	34%
	MBO	15%
	HAVO / VWO	11%
	VMBO / LBO	7%
	≤ primary school	1%
Travel purpose	Work	26%
	School	4%
	Business	7%
	Social	26%
	Leisure	32%
	Other	5%
Travel frequency	≥1 day/week	33%
	1-3 days/month	25%
	6-11 days/year	26%
	1-5 days/year	16%
Access mode (HB)	Walk	28%
	Bike (private / shared, folding)	40%
	BTM	20%
	Car (private / shared, driver / passenger)	10%
	Other	2%
Egress mode (AB)	Walk	42%
	Bike (private / shared, folding)	13%
	BTM	39%
	Car (private / shared, driver / passenger)	2%
	Other	4%

Respondents' familiarity with shared modes is displayed in **Figure 6-1**. Respondents appear to be most familiar with shared bikes. Almost 30% of the respondents has used a shared bike at least once compared to 7% for the case of shared car, and only 1% has used a shared e-scooter. These results are not surprising as the popularity of NS' own shared bike system OVfiets is rapidly growing compared to the hardly used combination of train + shared car and the fact that e-scooters cannot be used legally in public yet (Boot, 2018). The distributions of having used a shared mode correspond with the distribution of respondents that have never heard of shared modes. Half of the respondents do not know about the existence of shared e-scooter. A quarter has never heard of shared cars and only 15% has never heard of shared bikes. All in all, from the familiarity distributions it can be concluded that especially experience with shared modes is overall found to be low as 70% of the respondents has no experience with none of the studied shared modes. Besides, of the group that has experience, only 2.5% of the respondents uses a shared mode at least once a week (of which 80% shared bike). These are important findings to keep in mind when interpreting the choice model parameters, discussed in Section 6.3.

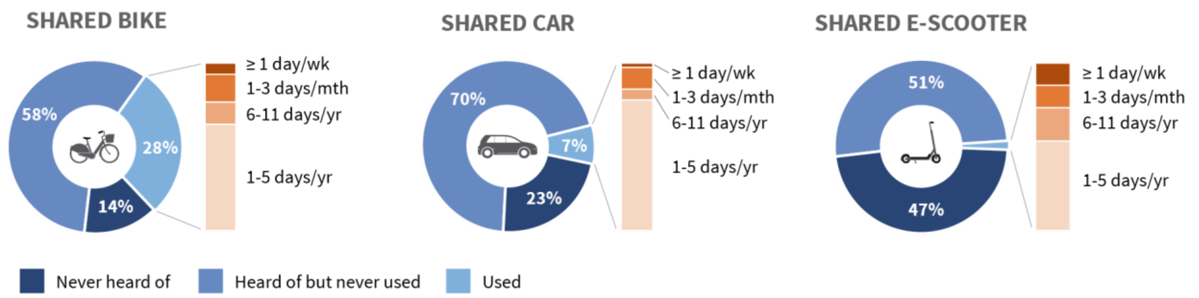

Figure 6-1 Respondents' familiarity with shared modes.

6.1.2 Choice distributions

Besides the personal characteristics of respondents, it is also useful to examine the distributions of their mode choices in the choice experiments. That way, some first general insights into the popularity of the different alternatives can be obtained. Note however, that these choices are heavily dependent on the presented attribute levels in the choice experiments and are therefore only used here to observe general trends in the choice data. Table 6-2 presents the general choice distributions for each of the five experiments. For the home-based trip scenario's, the private bike clearly dominates, which could be expected based on the current model split distributions over distance (as presented in Figure 5-1). The shared bike obtains a share that is ten times smaller. As distance increases BTM and private car both gain an equal split of the removed walking alternative, whereas the bike shares seem to be independent of distance. Interesting to note is also the similarity between the obtain modal splits in the experiments and those of the current situation (Figure 5-1) in terms shares for private bike, walking and BTM. These observed similarity as considered to validate of the setup of the choice experiments.

In the activity-based trip scenarios, it can be noted that the dominance of walking on a 1 km distance rapidly diminishes as trip distance increases to 2 km. BTM and also shared bike on the other hand gain share when distance increases. Also here similarity can be observed with the current modal splits of the activity based trip (see Figure 5-2). Shared modes car and e-scooter obtain only small shares, comparable to the shared bike alternative in the home-based trip scenario's. The relative popularity of the shared bike for the activity based trip could be related to its higher degree of familiarity and the increasing popularity of OVfiets.

Table 6-2 General choice distributions. These choices are heavily dependent on the presented attribute levels in the choice experiments and are therefore only used here to observe general trends in the choice data.

Home based trip			Activity based trip			
ALTERNATIVE	2 KM	4 KM	ALTERNATIVE	1 KM	2 KM	4 KM
Walk	22%		Walk	68%	32%	
Private bike	53%	55%	E-scooter	4%	5%	
Shared bike	6%	6%	Shared bike	8%	15%	22%
BTM	19%	29%	BTM	20%	48%	71%
Private car		10%	Shared car			7%

Apart from general choice distributions, the choice behavior of respondents can also be described in terms of switching between mode alternatives. By mapping the diversity of alternatives that a respondent picked, so called modal portfolios can be constructed (Alonso González et al., 2018), see Figure 6-2. What stands out of these portfolios is in the first place the similarity between all five portfolio distributions. Secondly, it can be noted that the majority of the respondents (on average 58%) had a fixed preference. So for either the six home-based choices or the six activity based choices (or for both), respondents chose the same alternative regardless of changing attribute levels. This is an important notion to keep in mind regarding the model estimation: intrinsic mode preferences are expected to play an important role. The details of the portfolio's follow the general choice distributions from Table 6-2 and can be found in Appendix 7.3.2E .

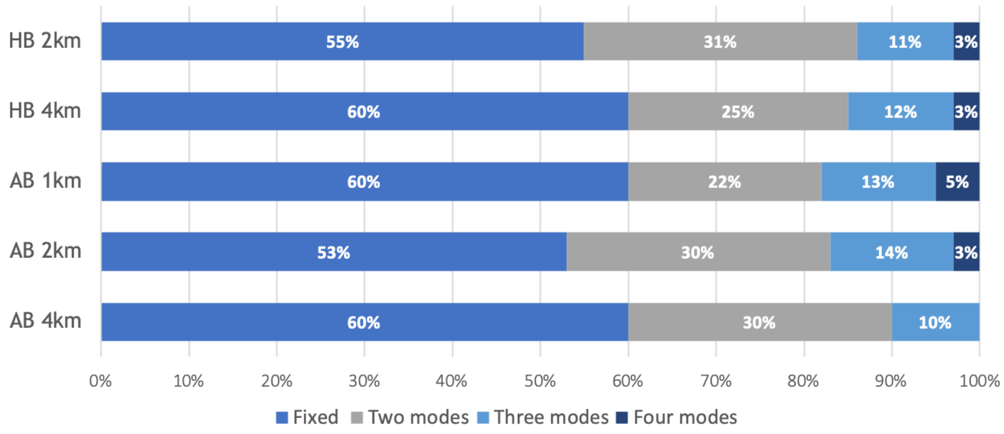

Figure 6-2 Modal portfolios describing how many different alternatives each respondent chose. Note that experiment AB 4 km consisted of only three alternatives in total.

6.1.3 Fixed preferences in the stated choice experiments

Of the large group that has a fixed preference portfolio in either the HB or AB experiment, 2/3 did not trade alternatives in both of their experiments (41% of all respondents). To gain a better understanding of this group of respondents, Chi Square Tests of Independence were performed to test for relationships between personal characteristics and fixed preference. As depicted in Table 6-3, four characteristics are found to have a significant effect ($p < 0.05$) on whether respondents have a fixed preference or not. These are: age, education level, travel frequency, and travel purpose.

Table 6-3 Results of Chi-Square Test of Independence between fixed preference and personal characteristics

Variable	Pearson Chi-Square	p-value
Socio-demographics		
Gender	3.28	0.070
Age	138.15	0.000
Education level	28.22	0.000
Income	3.21	0.201
Urban density	3.45	0.178
Travel behavior		
Travel purpose	26.26	0.000
Travel frequency	37.00	0.000

To further look into these relationships, the relative differences between the observed and expected values in the Chi Square contingency tables are plotted in Figure 6-3. The more positive the difference, the higher the observed fixed preferences count of that category compared to the expected count (which is expected when there is no relationship). From the plots it can be observed that the higher a respondent's age and the lower his education, the more likely it is that the respondent has a fixed preference. Regarding travel frequency and purpose, a more dichotomous relation is suggested by the figure: respondents that travel more often and for business, work or school purpose are less likely to have fixed preference[19]. This makes sense from the light of travel behavior inertia and especially goes for the home-based trip – which is always the same regardless of the destination – but also applies to the activity-based trip: if a traveler always takes an OVfiets from train station to work, he or she is likely to opt for OVfiets again when making a trip for a business meeting in a city he or she is not familiar with.

[19] This relationship was also checked for being dependent on age, but no effect was found.

All in all, the independence tests reveal that in particular young, highly educated people, who travel frequently by train for business or school purposes are most likely to switch between modes in the choice experiments and are thus most likely to opt for a shared mode[20].

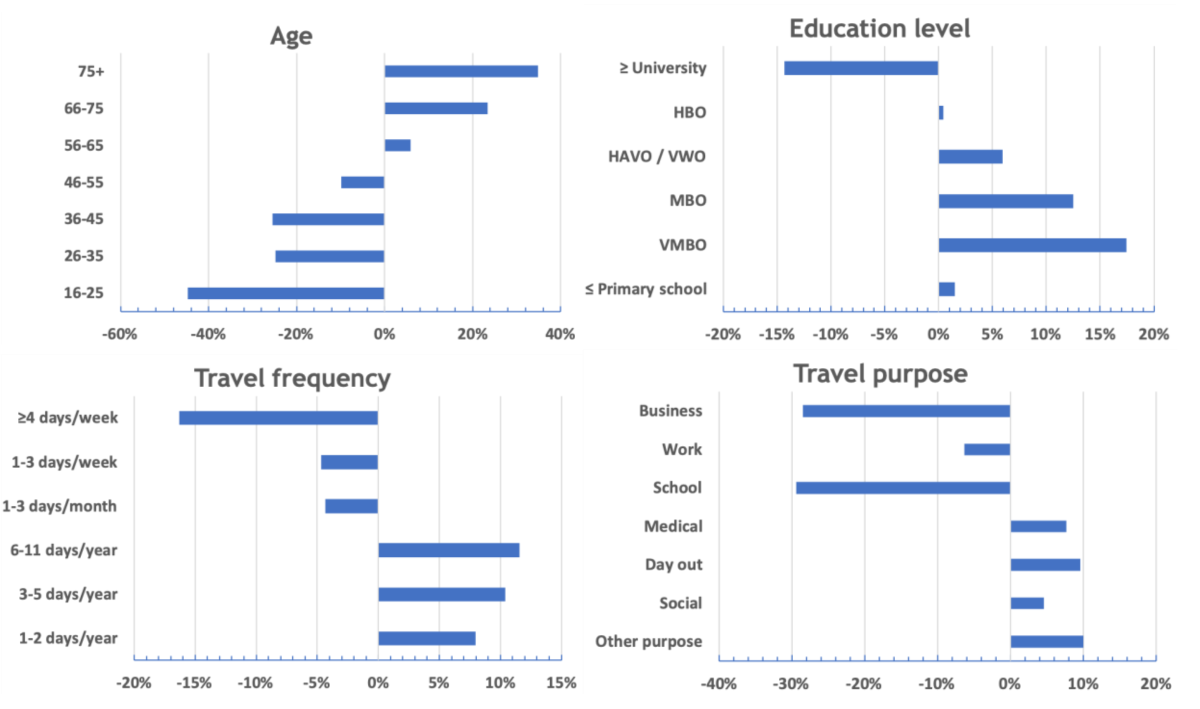

Figure 6-3 Relative differences between observed and expected counts display the relationships between personal characteristics and fixed preferences in the choice experiments. Positive scores imply higher likelihood of having fixed preference.

6.1.4 Attitudes towards sharing and new technologies

To determine the influence of attitudinal factors on the observed choices of respondents, a factor analysis is presented below. Attitudes were tested in the survey via 8 statements, see Table 6-4 below. As can be noted, mixed answers were given. The mean of statements directly linked to willingness to try new or different ways of traveling (statement 1 and 3) score a relatively high mean (3.6), while at the same time this also goes for statements linked to privacy (3) and being open to sharing (4) (indirect formulated).

Table 6-4 Descriptive statistics on the answers to the statements (1 = fully disagree, 5 = fully agree)

	Statement	Mean	Std. dev.
1	I am open to trying new ways of traveling.	3.63	0.914
2	My family and friends often ask me for advice about digital products and services.	2.81	1.16
3	I value my privacy when in my car or on my bike.	3.64	1.03
4	I would rather prefer not to lend out my own possessions.	3.60	1.10
5	I often try new services like Netflix or Uber as one of the first of my friends and family.	2.49	1.19
6	I would like to have the convenience of a car without possessing one.	2.71	1.19
7	I do not care which travel mode I use, as long as it fits my travel purpose.	3.48	1.10
8	(smartphone) Apps help me in daily life.	3.63	1.17

The first step in conducting a factor analysis is to test for the suitability of the actual factor analysis (Williams, Onsman, & Brown, 2010). This is done by computing the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity. The KMO indicates the strength of the underlying factors in a

[20] Shared modes are hardly chosen by the group with fixed preferences as can be noted in Appendix D : the share of shared modes varies between 1% (HB 1km) and 16% (AB 4km, with 2/3 modes being shared modes).

value between 0 and 1 while the Bartlett's test shows if there is significant correlation between the tested variables. Factor analysis can be applied when the KMO measure is > 0.50 and the Bartlett's test is significant (Williams et al., 2010). As **Table 6-5** shows, both requirements are met, meaning that the data is suitable for factor analysis.

Table 6-5 Factor analysis adequacy test of data

Test		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.730
Bartlett's Test of Sphericity	Approx. Chi-Square	1878.625
	Degrees of freedom	28
	Significance	.000

Next, factor extraction is applied to determine the smallest number of factors that represent the interrelation among the set of variables best (Field, 2009). Because of negative formulation related to the construct that is measured, the answers to statements 3 and 4 were reversed. Applying extraction using Principal Axis Factoring with Varimax rotation results in the factor loadings as presented in **Table 6-6**. Based on comparing the eigenvalues, two factors appear to fit the statement data best, although statement 6 and 7 obtain a rather low loading factor. Factor 1 can be linked to the attitude related to new technologies, factor 2 is about respondents' general attitude towards privacy and sharing.

Table 6-6 Rotated Factor Matrix with factor loadings per statements (n = 1835). Loadings < 0.30 are suppressed.

	Statement	Factor 1	Factor 2
1	I am open to trying new ways of traveling.	0.552	
2	My family and friends often ask me for advice about digital products and services.	0.570	
3	I value my privacy when in my car or on my bike.		0.525
4	I would rather prefer not to lend out my own possessions.		0.630
5	I often try new services like Netflix or Uber as one of the first of my friends and family.	0.706	
6	I would like to have the convenience of a car without possessing one.	0.405	
7	I do not car which travel mode I use, as long as it fits my travel purpose.	0.333	
8	(smartphone) Apps help me in daily life.	0.606	

To test the reliability of these two factors, the Cronbach's alpha value is computed. For the factor based on statements 3 and 4, this measure appears to be too low (0.50) for the factor to be reliable (threshold value is 0.70). Considering the other factor, two iterations were made to come to a final factor based on statements 1, 2, 5, and 8. This factor obtained a Cronbach alpha of 0.695 which is equal to Cronbach's alpha threshold value to be used as a factor.

A factor openness to new technology is therefore constructed by computing the mean sum score of the four involved statements. Computing the mean sum score allows for easy interpretation of the factor, but at the same time simplifies the contributions of the statement are assumed equal (Distefano et al., 2009) . The computed factor in incorporated with the other interaction variables in the discrete choice models, which are addressed in the next section of this chapter.

6.2 Model estimation

To assess the effect of the various included variables in the choice experiment, discrete choice modelling is applied. Several different model types are estimated of which the theoretical background is explained in Chapter 2. The modelling is performed by using *Python Pandas* and the most recent version of software package *Biogeme* (Bierlaire, 2018). To be able to validate the performance of the estimated models, the sample was split into two groups. A random 80% of the sample was used to estimate the models. Simulated choice predictions by the final models for both the 80% and the remaining 20% were then compared as an attempt to validate performances.

6.2.1 Modelling approach

In order to come to two final models, one for the home-based and one for the activity-based trip, five models are estimated for each trip type, see Figure 6-4. This section explains each of the five steps that work towards the final models. The final and most advanced models for both trip types are discussed in Section 6.3.

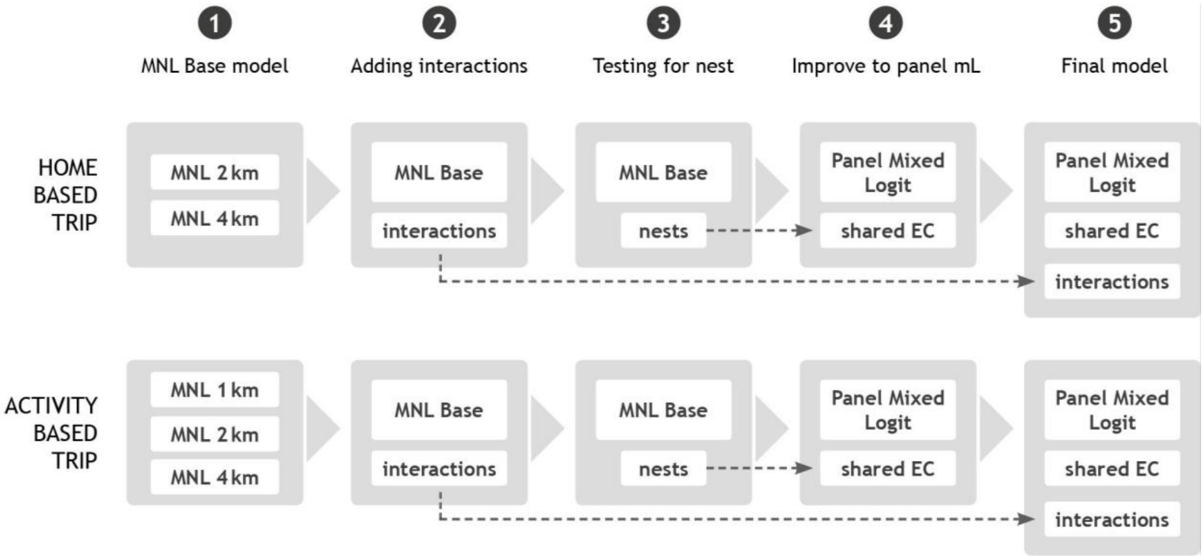

Figure 6-4 Schematic overview of modelling approach

1. Multinomial logit models (base models)

As a start, the multiple experiments for different distances were combined into one multinomial logit (MNL) model for the HB and one for the AB case. To account for the differences in distance between the experiments, multiple separate alternative specific constants (ASCs) are estimated for the alternatives that were present in multiple experiments. Because the shared bike ASC of the AB 1km and 2km experiment obtained the same value, they were combined into one ASC parameter.

Such check was also performed for the included attributes. As explained in Chapter 5, all attributes are incorporated as alternative specific attributes. When combining the models of different distances, it was checked whether parameters of the same kind obtained similar values and thus possibly could be represented by a generic parameter. This was not the case. Next to checking for generic parameters, it should be noted that only linear effects were tested in the MNL models. Being able to estimate multiple models (HB and AB trip and multiple distances) was valued over perfecting the utility functions by testing for the fit of possible quadratic components.

To show the composition of the MNL models, the utility functions for the MNL model of the AB trip are presented in Equations 6.1-5. ASCs present relative utility differences compared to the ASC of one alternative that is fixed to zero. The ASC for the BTM alternative is in this case fixed to zero and therefore not included in the corresponding utility function. Another aspect to be noted is that, matching the experiment design as discussed in Section 5.1.2, in-vehicle times are not included as attributes because of the fixed distances in each experiment. The differences in in-vehicle time (speed) therefore load on the ASCs.

$$U_{walk} = ASC_{walk\text{-}1km} + ASC_{walk\text{-}2km} + \varepsilon \quad (6.1)$$

$$U_{scooter} = ASC_{scoot\text{-}1km} + ASC_{scoot\text{-}2km} + \beta_{search\text{-}scoot} * search_{scoot} + \beta_{costs\text{-}scoot} * costs_{scoot} + \beta_{unlock\text{-}scoot} * unlock_{scoot} + \varepsilon \quad (6.2)$$

$$U_{sh.bike} = ASC_{sh.bike\text{-}1+2km} + ASC_{sh.bike\text{-}4km} + \beta_{search\text{-}sh.b} * search_{sh.bike} + \beta_{costs\text{-}sh.b} * costs_{sh.b} + \beta_{unlock\text{-}sh.b} * unlock_{sh.b} + \varepsilon \quad (6.3)$$

$$U_{BTM} = \beta_{wait\text{-}BTM} * wait_{BTM} + \beta_{costs\text{-}BTM} * costs_{BTM} + \varepsilon \quad (6.4)$$

$$U_{sh.car} = ASC_{sh.car\text{-}4km} + \beta_{search\text{-}sh.c} * search_{sh.car} + \beta_{costs\text{-}sh.c} * costs_{sh.car} + \beta_{unlock\text{-}sh.c} * unlock_{sh.car} + \varepsilon \quad (6.5)$$

Where:

U_{walk} = utility of alternative walk

$U_{scooter}$ = utility of alternative e-scooter
$U_{sh.bike}$ = utility of alternative shared bike
U_{BTM} = utility of alternative BTM
$U_{sh.car}$ = utility of alternative shared car

$ASC_{walk\text{-}\#km}$ = alternative specific constant for alternative walk for distance 1 or 2 km
$ASC_{scoot\text{-}\#km}$ = alternative specific constant for alternative e-scooter for distance 1 or 2 km
$ASC_{sh.bike\text{-}\#km}$ = alternative specific constant for alternative shared bike for distance 1, 2, or 4 km
$ASC_{sh.car\text{-}\#km}$ = alternative specific constant for alternative shared car for distance 4 km

$ß_{search\text{-}scoot}$ = alt. specific parameter for attribute search time for alternative e-scooter
$ß_{search\text{-}sh.b}$ = alt. specific parameter for attribute search time for alternative shared bike
$ß_{search\text{-}sh.c}$ = alt. specific parameter for attribute search time for alternative shared car
$ß_{wait\text{-}BTM}$ = alt. specific parameter for attribute waiting time for alternative BTM

$ß_{costs\text{-}scoot}$ = alt. specific parameter for attribute usage costs for alternative e-scooter
$ß_{costs\text{-}sh.b}$ = alt. specific parameter for attribute usage costs for alternative shared bike
$ß_{costs\text{-}BTM}$ = alt. specific parameter for attribute ticket costs for alternative BTM
$ß_{costs\text{-}sh.c}$ = alt. specific parameter for attribute usage costs for alternative shared car

$ß_{unlock\text{-}scoot}$ = alt. specific parameter for attribute unlocking method for alternative e-scooter
$ß_{unlock\text{-}sh.b}$ = alt. specific parameter for attribute unlocking method for alternative shared bike
$ß_{unlock\text{-}sh.c}$ = alt. specific parameter for attribute unlocking method for alternative shared car
ε = random error component

2. MNL model with interaction variables
As a first step to improve the base MNL models, personal characteristics and context variables are included into the models. The interaction effects of each of these dummy coded variables were first tested separately, where after all significant interactions were included into one model which was iterated until the solid significant interactions remained. For both the HB and AB model, significant effects of *age*, *familiarity with shared bike* and *openness towards new technology* were found. In addition, for HB model also *urban density* of the respondents home address, and respondents *travel motive* appeared to be relevant to include in the model. These interactions are interpreted in detail in the discussion of the final models in Section 6.3. The results of the iteration process of the testing for interactions can be found in Appendix F3.

3. Nested Logit models
Since some of the presented alternative in the choice experiments have shared characteristics (like private and shared bikes both being bikes), the base MNL models were enhanced by including nest components that can account for the shared elements between alternatives (Train, 2009). Two nests were found to be significant at a 95% confidence interval: *nest private bike - shared bike* in the HB model and *nest shared e-scooter - shared bike* in the AB model. As an additional check, the presence of these nests was also tested and found in the corresponding single-distance models. Just like the interactions, interpretation of the found nests is done at the interpretation of the final model in Section 6.3.

4. Panel Mixed Logit models with shared error components
To correct for correlations across the choice of one respondent, the multinomial logit models are replaced with panel mixed logit models. The nests found in the previous step are incorporated into these models as shared error components.

5. Panel Mixed Logit model with shared error components and interactions
As a last step, the panel mixed logits from step 4 are extended with the found interactions from step 2.

6.2.2 Model fit and validation
To check and compare the performance of the models, two approaches were applied. In the first place model fit measurements were inspected: the Likelihood Ratio Test statistic (LRS) and the adjusted rho-squared. LRS can be used to compare the goodness of fit between two estimated models, while the rho-squared value draws a comparison between the model of interest and the null model.

As can be seen in Table 6-7, models for both types of trip are performing better after each step (Log Likelihoods (LL) and rho-squared values both increase). Interesting to note is that by making the models more advanced, the HB model improves much more than the AB model. Especially the step from model 3 to model 4, greatly improves the HB model (rho-squared almost doubles), compared to as smaller improvement of the AB model for the same step. This could be caused by the fact that choices of the same respondent are heavier correlated (which the panel effect accounts for) for the HB trip data than for the AB trip data, which makes sense from the perspective that fixed choice patterns more often occur at the HB trip side which is the same for each multimodal train trip.

Table 6-7 Model fit indicators for the estimated models. The LRS is computed between the model of that row and the model in the row before (to indicate increase in performance per step).

Model	# parameters	Final LL	Rho²	Halton draws
0. Null	0	-12210	-	-
1. MNL HB24 base	16	-9681	0.207	-
2. NL HB24	17	-9640	0.228	-
3. MNL HB24 with interactions	25	-9339	0.235	-
4. Panel ML HB24 EC	17	-7012	0.426	1,000
5. Panel ML HB24 EC extended (with interactions)	24	-6818	0.442	10,000
0. Null	0	-11372	-	-
1. MNL AB124 base	18	-8283	0.272	-
2. NL AB124	19	-8278	0.245	-
3. MNL AB124 with interactions	27	-7955	0.298	-
4. Panel ML AB124 EC	19	-7055	0.378	1,000
5. Panel ML AB124 EC extended (with interactions)	24	-6933	0.388	10,000

The second measure that was taken to assess the performance of the models, is the validation comparison between simulated choice predictions for the 80% of choice data that were used to estimate the models and the remaining 20% choice data. This comparison is shown in Table 6-8. As can be noted the correct prediction rates between the two subsamples are slightly different, but considered a sufficient proof of validation of the model. Apart from this single cross validation, also obtained values of travel time savings (VoTTS) can be used as a more qualitative validation measure by comparing the computed values with values from literature. The VoTTS are computed in the next section.

Table 6-8 Simulated choice prediction rate of the models on different sub samples.

Model	% correct predictions 80% group	% correct predictions 20% group
Panel ML HB 24 EC	54.37 %	54.91%
Panel ML AB 124 EC	60.98 %	64.85 %

6.3 Model interpretation

The final parameter estimates can be interpreted to gain insight in the effects of the tested attributes on respondents mode choice. This discussion is presented separately for the home-based and the activity based trip.

6.3.1 Home-based trip model

Table 6-9 presents all 24 estimated parameter values of the home-based trip model. All parameters have the expected sign. Almost all of them are statistically significant (95% confidence level). Only the unlock parameter of shared bike and the parking time of private car are non-significant. They are nevertheless kept in the model because they have the expected sign and because it is assumed that their true values are not equal to zero, even though that cannot be proved via the t-test value. Keeping the parameters in the model aims at minimizing a specification error (type II) which would weaken the model more than the inclusion of an insignificant parameter (type I error, loss of efficiency) (Bierlaire, 2016). Furthermore, it can be noted that the shared error component between the private bike and shared bike alternative (sigma) is significant. This means that a nest is present between these two alternatives which captures what the private bike and shared bike alternative intuitively have in common, but is not captured in the deterministic part of the utility function (Train, 2009).

Table 6-9 Parameter estimations of the extended Panel Mixed Logit models for the home-based trips.
*statistically insignificant on a 95% confidence interval

Name	Description	Value	Robust SE	Rob. t-test	p-value
Walk					
ASC_WALK_2KM	Alt. specific constant of walk alternative	-0.443	0.151	-2.93	0.003
Private bike					
ASC_OWNBIKE_2KM	Alt. specific constant private bike - 2km experiment	1.24	0.275	4.51	0.000
ASC_OWNBIKE_4KM	Alt. specific constant private bike - 4km experiment	1.1	0.284	3.87	0.000
B_PARK_OWNBIKE	Parking time private bike	-0.0511	0.0139	-3.69	0.000
B_COST_OWNBIKE	Parking costs private bike	-0.693	0.0464	-14.9	0.000
Shared bike					
ASC_SHBIKE_2KM	Alt. specific constant shared bike - 2km experiment	-0.808	0.379	-2.13	0.033
ASC_SHBIKE_4KM	Alt. specific constant shared bike - 2km experiment	-0.972	0.384	-2.53	0.011
B_SEARCH_SHBIKE	Search time shared bike	-0.0692	0.0249	-2.78	0.005
B_PARK_SHBIKE	Park time shared bike	-0.0682	0.021	-3.25	0.001
B_COST_SHBIKE	Cost usage shared bike	-1.13	0.0996	-11.4	0.000
B_UNLOCK_SHBIKE	Unlocking method shared bike	-0.0798	0.083	-0.962	0.336*
BTM					
B_WAIT_BTM	Waiting time BTM	-0.0437	0.00995	-4.4	0.001
B_COST_BTM	Trip fare BTM	-0.353	0.0497	-7.11	0.000
Private car					
ASC_OWNCAR_4KM	Alt. specific constant private car (only 4km)	-2.14	0.286	-7.48	0.000
B_PARK_OWNCAR	Parking time private car	-0.0225	0.0207	-1.08	0.278*
B_COST_OWNCAR	Parking costs private car	-0.14	0.021	-6.66	0.000
Interactions					
B_MOTIVE-MUST_WALK	Effect of being a must-traveler on utility walking	-0.883	0.209	-4.22	0.000
B_FAM_SHBIKE2_OWNBIKE	Effect of having used sh.bike on utility own bike	3.11	0.398	7.81	0.000
B_AGE2_SHBIKE	Effect being a 65+ traveller on utility sh.bike	-1.11	0.195	-5.69	0.000
B_FAM_SHBIKE2_SHBIKE	Effect of having used sh.bike on utility sh.bike	3.01	0.404	7.46	0.000
B_NEW_TECH_SHBIKE	Effect of attitude towards new tech on utility sh.bike	0.288	0.102	2.81	0.005
B_URBAN_DENS1_OWNCAR	Effects of urban density of utility private car	0.785	0.303	2.59	0.010
B_URBAN_DENS2_OWNCAR	Effects of urban density of utility private car	1.53	0.319	4.79	0.000
Shared error components					
SIGMA_OWNBIKE_SHBIKE_STD	Shared error component between the bike alternatives	-5.65	0.266	-21.2	0.000

Time and cost attributes

Since parameter values provide information on the amount of utils gained or lost by a one unit increase of the attribute, the parameters of cost and time attributes are multiplied by their attribute levels to enable a better interpretation. The resulting utility contributions are shown in Figure 6-5.

Regarding the time components, sensitivity to increase in time is largest for both shared bike time components searching and parking. Sensitivity to increase in parking time for the private bike is slightly smaller, shortly followed by the BTM waiting time. Least affecting the amount of disutility is the parking time of the private car alternative, though it has to be noted that this parameter estimate is not statistically significant.

The cost sensitivity charts displays a similar order as the chart about time attributes. Also here, the highest sensitivity belongs to the shared bike alternative. However, the difference in costs sensitivity with the private bike alternative in much larger than is the case for time sensitivities. The value of the usage costs parameter linked to the shared bike alternative is almost twice as negative as the value of the parking costs parameter of the private bike (-1.13 vs. -0.69). This indicates a much larger sensitivity to costs related to using a shared bike compared to paying for parking one's own bike. Cost sensitivities for BTM fees and parking the private car both obtain much smaller values.

Lastly, when comparing cost and time sensitivities, it can be noted that for the applied attribute level ranges, the time attributes play an (often much) smaller role in the absolute utility contributions.

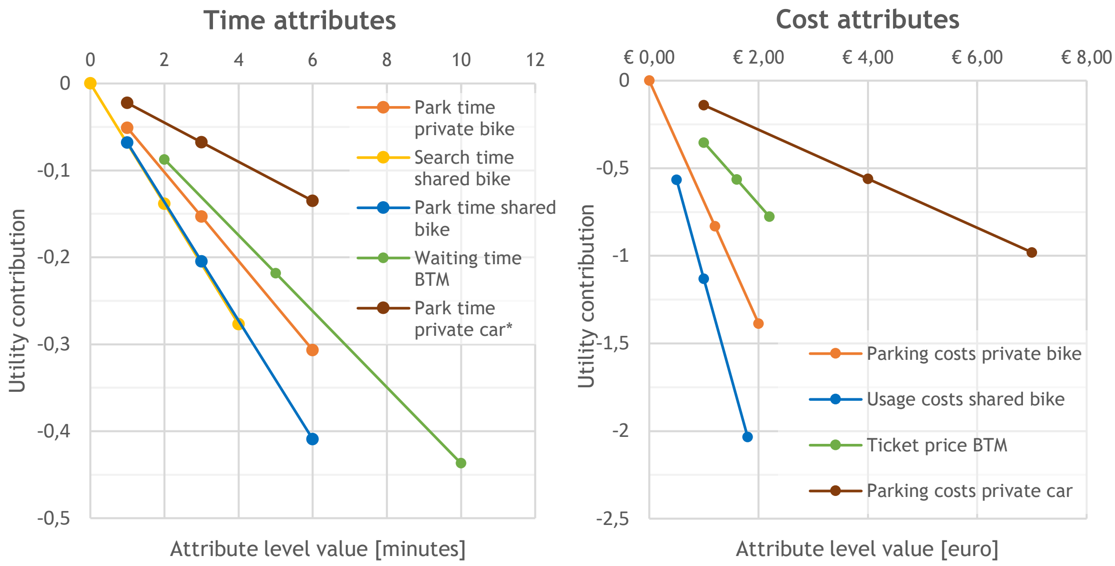

Figure 6-5 Changes in utility contributions of the different time and costs attributes. Note the difference in scale on the utility axes.

Alternative specific constants and the effect of personal characteristics and context variables
The parameters other than those related to time and cost attributes can be interpreted by directly examining their estimated values[21]. An overview is depicted in **Figure 6-6**. The model contains six alternative specific constants, which represent the respondent's preference for an alternative (for a specific distance) that is not captured by the included attributes in the model. Since the respondents were only presented with choice situations that had a fixed distance, the differences in 'in-vehicle' times of the different alternatives (speed characteristics) for that given distance are also represented by the ASC's. As explained in Section 6.2.2 these ASC values are relative utility contributions compared to the ASC of the BTM alternative which is kept at zero.

When comparing the ASC values of the different modes, it can in the first place be noted that when all modelled attributes are set at 0, the private bike alternative is preferred most (ASC values of +1.1 and +1.24). All other modes score a negative ASC, implying a lower preference than the BTM alternative. Most noteworthy is the relative large negative value of the private car ASC. Despite being the fastest mode (lowest fixed in-vehicle time), the total unobserved utility of this mode obtains the largest disutility of all alternatives. This could on the one hand be related to the fact that the private car option was shown to respondents regardless of whether they possess a driver's license or not, though this interaction variable did not emerge as a significant factor when testing the interactions.

On the other hand, the interaction variable urban density shows up to play a significant role in the preference for using the private car, which explains the relative large value of the private car ASC. For the 4 km experiment, the preference of using this alternative is inversely related to the urban density of the respondents' residential area: the lower the urban density the higher the preference for the private car alternative. Consequently, the relative large negative ASC of the private car only applies to respondents that live in highly urbanized areas, for which a large dislike of using one's private car to go to the (often larger) train station makes sense.

[21] This is not the case for the interaction variable NEW_TECH (openness to new technology) as it has values between 1 and 5 (mean-sum score as presented in Section 6.1.4. However, it is included in the discussion here (by multiplying with the min. and max. mean-sum score) because of its effect on the general preference of the alternative and its relevance compared to the ASC parameters.

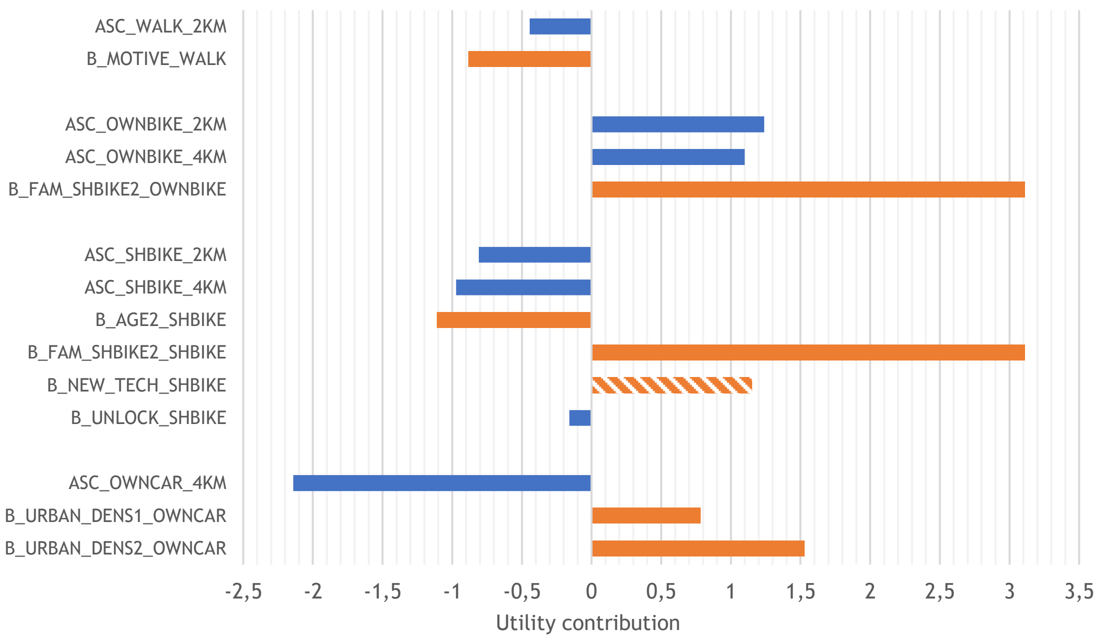

Figure 6-6 Utility contributions of ASCs (blue), the unlock attribute (blue), and interaction components (orange). The variable NEW_TECH (openness to new technology) is not a dummy variable and can also take values within the displayed range.

Besides the private car alternative, interaction variables also interact with other alternatives. With respect to travel behavior, the travel purpose significantly interacts with the preference for walking. Respondents that travel for business, school, or work purposes – and thus made an imaginary trip for business meeting or job interview purpose in the experiment – show to have a lower preference for walking than respondents that travel for other purposes (i.e. mainly leisure or social purposes). Besides travel purpose, (previous) travel behavior related to shared bikes appears to have a large impact on the preference towards bike alternatives (both shared and private) compared to the other alternatives: having used a shared bike before quadruples the preference for using a bike as access-transport. Furthermore, respondents with a more open attitude towards trying new technology are found to have a higher preference for using a shared bike compared to people that are less open to trying new technologies. On the other hand, respondents older than 65 have a much lower preference for shared bike.

Value of travel time savings

As an additional way to analyze the parameter estimations, the Value of Travel Time Savings (VoTTS) can be calculated for each of the included time attributes. VoTTs is a measure to present the monetary value of one unit of travel time reduction. In other words: how much are respondents willing to pay for one minute/hour in travel time reduction. Computing these values allows for comparison between alternatives within the model and between the two estimated models for home-based and activity-based trips. VoTTs values can be computed by dividing the time-parameter by the cost-parameter. **Table 6-10** presents the computed values. It can be noted that the highest costs sensitivities propagate into the lowest willingness to pay (wtp) values. Willingness to pay is lowest for shorter search and parking times of the shared bike alternatives. Wtp for reduced parking time for the private bike is only slightly higher.

Apart from comparison between the models, the obtained values can also be compared with values from literature. However, as most studies focus on the willingness to pay for less total travel time or in-vehicle time, only few comparable wtp values were found. Van Mil et al., (2018) find value of €0.08 of wtp for less parking time of private bike, which is comparable with the €0.07 found in this study. At the same time Molin & Maat (2015) obtained a wtp range of € 5.28 - € 17.28/hour, which is higher than the € 4.44 found in this research. With respect to the waiting time component of BTM trips, 6 states that wtp for less waiting time is generally two times bigger than the wtp for BTM in-vehicle time, which ranges between €6.00 and €19.00 in the Netherlands (Kouwenhoven et al., 2014). The identified BTM wtp value of €7.44/hour is within this range.

In general, the obtained wtp value thus do not exactly match the few found values in literature. This could be because of the model specification (Dell'Olio, Ibeas, & Moura, 2009), which in the case of this research strongly relies on the ASCs that also account for the fixed in-vehicle time differences. In addition, it should be noted that these are rough comparisons of studies with different goals. All in all, the obtained values are not extremely different from the values found in literature, and the comparison is considered to validate the results from the model.

Table 6-10 Computed values of the willingness to pay (wtp) for a decrease in travel time component.

Value of travel time savings	ß time	ß costs	€ / min	€ / hour
Private bike: wtp for less parking time*	-0,0513	-0,693	€0,07	€ 4,44
Private car: wtp for less parking time*	-0.0225	-0.14	€0,16	€ 9,64
Shared bike: wtp for less search time	-0,0683	-1,13	€0,06	€ 3,67
Shared bike: wtp for less parking time*	-0,0691	-1,13	€0,06	€ 3,63
BTM: wtp for less waiting time	-0,0439	-0,354	€0,12	€ 7,44

* Note that parking time is presented here as the sum of time spent looking for a parking space and the time it takes to walk to the (train station) platform.

Conclusion HB model

The parameter interpretation of the HB model is summarized in Figure 6-7. With respect to the willingness to use shared modes for the home-based trip, several conclusions can be drawn from the estimated model. Regarding the importance of the different tested factors that could impact the decision making process of choosing a shared bike (the only included shared mode in the home-based experiments), the following findings can be listed:

- Cost of using shared bike is a much more important factor in deciding to use a shared bike than the time it takes to search or park the bike.
- Difference in unlocking method (related to ease of use) was not found to play a role in the decision making process (of the respondents).
- Having used a shared bike before greatly increases the intrinsic preference for using a shared bike for the home-based trip. Although to a lesser extent, this also goes for one's openness to trying new technology.
- Respondents older than 65 years show to have a significantly larger dislike to shared bikes than respondents younger than 65.

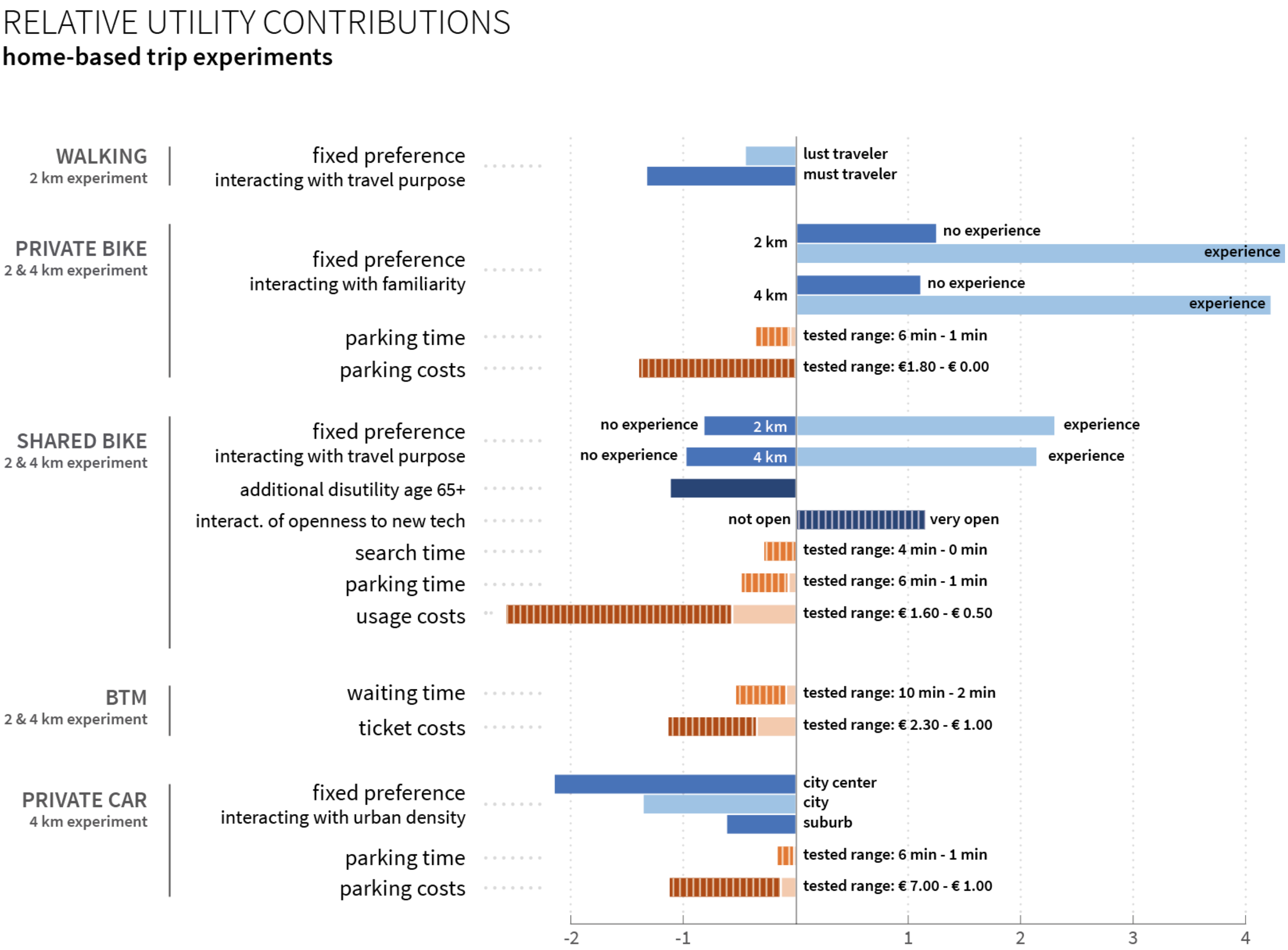

Figure 6-7 An overview of the parameter interpretation of the HB model parameters.

With respect to the preference for shared bike relative to the other included conventional modalities, these are the main outcomes:

- Intrinsic preference are the most important factors in the model.
- Regarding these intrinsic preferences, the shared bike is the least preferred alternative for lust travelers and the second-least preferred option for must travelers in the 1 and 2 kilometer experiments. For the case of the 4 km scenario, shared bike is the second-least preferred option for trip in areas with higher urban density and least preferred in less dense urban areas.
- In general, private bike and BTM obtain higher intrinsic preferences for all studied distances.
- However, travelers that have used a shared bike before show to have a significantly higher preference for both private and bike alternative. In those cases, private bike is still the most preferred option. Differences in intrinsic preference could be compensated for by differences in parking time and costs, but this only applies to scenarios with maximum attribute level differences as sensitivities for time and costs are lower for the private bike alternative than for the shared one.

6.3.2 Activity-based trip model

The model of the activity based trip contains 24 parameters. All parameters have the expected sign, except for the unlocking attributes of all three included shared modes (see Table 6-11). These parameters are also highly insignificant and their values are close to zero. This indicates that the unlocking method of the shared modes did not play a role in the decision making process when choosing between the modes. Since the t-test values of these parameters are very low, they are not incorporated in the further analysis. Also here, the estimated sigma parameter is significant, This means that a nest is present between the shared e-scooter and shared bike alternative which captures what the private bike and shared bike alternative intuitively have in common, but is not captured in the deterministic part of the utility function.

Table 6-11 Parameter estimations of the extended Panel Mixed Logit model for the activity-based trip

Name	Description	Value	Robust SE	Rob. t-test	p-value
Walk					
ASC_WALK_1KM	Alt. specific constant of walk alternative - 1km	0.452	0.136	3.33	0.001
ASC_WALK_2KM	Alt. specific constant of walk alternative - 2km	-1.29	0.145	-8.85	0.000
Shared e-scooter					
ASC_STEP_1KM	Alt. specific constant of e-scooter alternative - 1km	-4.62	0.631	-7.33	0.000
ASC_STEP_2KM	Alt. specific constant of e-scooter alternative - 2km	-5.11	0.618	-8.26	0.000
B_SEARCH_STEP	Search time shared bike	-0.203	0.042	-4.82	0.000
B_COST_STEP	Cost usage shared bike	-1.18	0.136	-8.68	0.000
B_UNLOCK_STEP	Unlocking method shared bike	0.0235	0.127	0.185	0.853
Shared bike					
ASC_SHBIKE_1+2KM	Alt. specific constant of shared bike alternative - 1/2km	-2.46	0.224	-11	0.000
ASC_SHBIKE_4KM	Alt. specific constant of shared bike alternative - 4km	-1.59	0.268	-5.95	0.000
B_SEARCH_SHBIKE	Search time shared bike	-0.0626	0.0259	-2.42	0.016
B_COST_SHBIKE	Cost usage shared bike	-1.2	0.0822	-14.6	0.000
B_UNLOCK_SHBIKE	Unlocking method shared bike	0.00515	0.0812	0.0635	0.949
BTM					
B_WAIT	Waiting time BTM	-0.0333	0.00828	-4.02	0.000
B_COST_BTM	Trip fare BTM		0.0525	-10	0.000
Shared car					
ASC_SHCAR	Alt. specific constant of shared car alt.	-4.56	0.66	-6.9	0.000
B_SEARCH_SHCAR	Search time shared bike	-0.0952	0.0332	-2.87	0.004
B_COST_SHCAR	Cost usage shared bike	-0.588	0.07	-8.4	0.000
B_UNLOCK_SHCAR	Unlocking method shared bike	0.0531	0.117	0.453	0.651
Interactions					
B_MOTIVE_WALK	Effect of being a must traveller on pref. walking	-0.591	0.154	-3.84	0.000
B_NEW_TECH_STEP	Effect of attitude towards new technology on pref. sh.bike	0.684	0.163	4.2	0.000
B_FAM_SHBIKE2_SHBIKE	Effect of having used shared bike before on pref. sh. bike	1.07	0.221	4.82	0.000
B_MOTIVE_WAIT_BTM	Effect of being a must traveler on sens. to waiting time BTM	-0.052	0.0151	-3.45	0.001
B_NEW_TECH_SHCAR	Effect of attitude towards new technology on pref. sh.car	0.852	0.184	4.64	0.000
Shared error comp.					
SIGMA_STEP_SHBIKE	Shared error component between e-scooter and sh.bike	3.32	0.153	21.7	0.000

Time and cost attributes

When looking at the time and cost parameters in the model, what stands out in the time sensitivity comparison is the relatively large sensitivity to search time for the shared e-scooter alternative (see **Figure 6-8**). Especially compared to the shared bike alternative, which was presented in the same choice sets, the difference is sensitivity to search time is noteworthy. Important to keep in mind however, is that the shared bike was included in all three AB distances and that this difference in sensitivity to search time between shared e-scooter and shared bike could thus be affected by the sensitivity to search time of the shared bike in the 4km experiment (in which the e-scooter alternative was not presented). Besides the difference between e-scooter and shared bike, another observation is that sensitivity to search time for a shared modality is higher than sensitivity to waiting time in a BTM trip for lust travelers but not for must travelers.

Considering costs, sensitivity to price is almost exactly the same for e-scooter and shared bike. Also shared car and BTM obtain the same score, although for the presented attribute level ranges, the absolute difference in disutility (for the same trip) is large. Disutility ranges that were present in the experiments can also be compared between time and costs sensitivity. This shows that in general price causes more disutility than the varied time component. Only for a few combinations this is not the case (for example: e-scooter 6 min search time, cost €0.70).

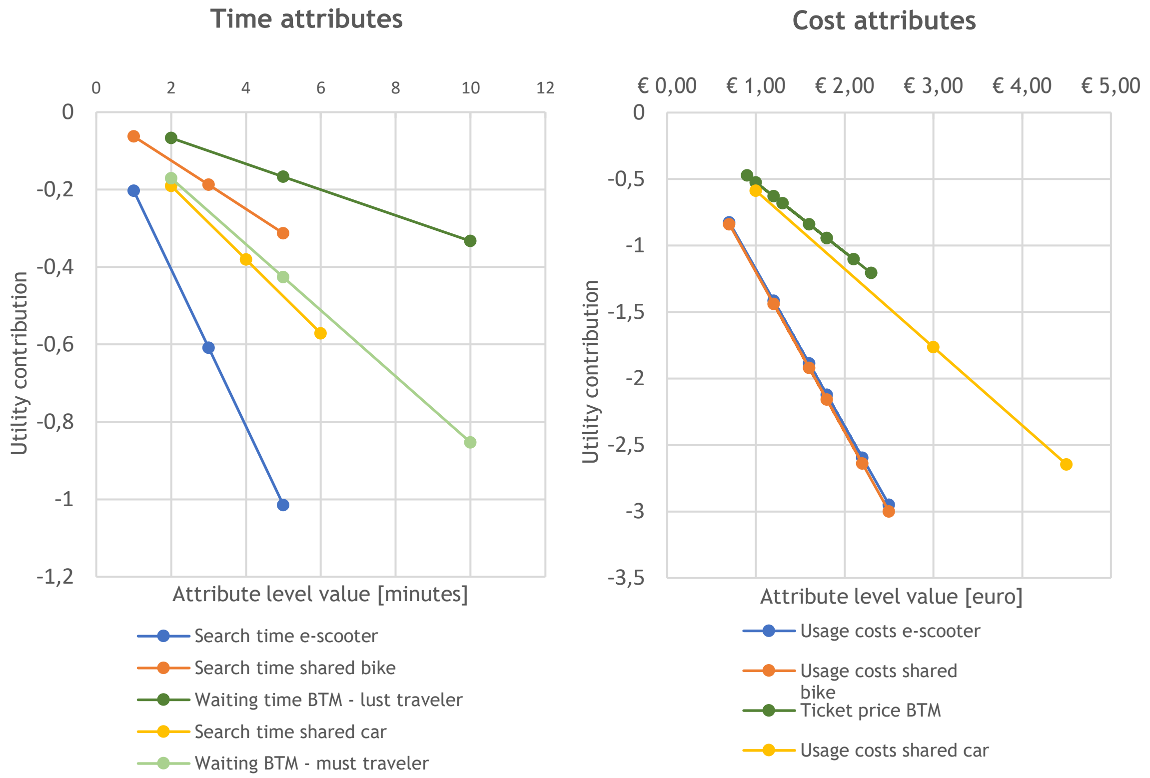

Figure 6-8 Changes in utility contributions of the different time and costs attributes. Note the difference in scale on the utility axes.

Alternative specific constants and the effect of personal characteristics and context variables

The parameters other than those related to time and cost attributes can be interpreted by directly examining their estimated values[22]. An overview is depicted in Figure 6-9. In the first place, the ASC values of the different modes can be compared[23]. Two parameter that attract attention are the ASCs of the shared e-scooter and shared car alternatives. Both score large negative values which indicates that based on intrinsic preferences, these modes are preferred least by the respondents. This also makes sense from the perspective of the general score distribution presented earlier in Section 6.1.2.

Considering the other ASCs, a distance effect can be noted between the different ASC's of the walking alternatives. In case of the 1km alternative, walking is preferred above all else (in terms of ASCs). But when distance increases, this preference quickly decreases. Such clear effect is not observed for the shared e-scooter and shared bike alternatives.

The preference for walking is furthermore found to be affected by travel purpose. Respondents that were making the imaginary trip for the purpose of a business meeting or job interview (must-traveler) were less tempted to opt for the walking alternative compared to travelers that were offered the leisure trip situation (lust-traveler).

When comparing the ASCs of the shared modes, it can be concluded that shared bike is most preferred shared mode. Large differences exist between the ASC of the shared bike for 1;2 km and the e-scooter ASCs as well as between the ASC shared bike 4km and the shared car ASC. This can be linked to the earlier observed distribution of familiarity with the shared modes. Familiarity with shared bike in terms of having used one at least once before is present in the model and increases the intrinsic preference of the shared bike alternative

[22] Just like at the HB model interpretation, this is not the case for the interaction variable NEW_TECH (openness to new technology) as it has values between 1 and 5 (mean-sum score as presented in Section 6.1.4). However, it is included in the discussion here because of its effect on the general preference of the alternative and its relevance compared to the ASC parameters.

[23] Again, these are relative values compared to the ASC of the BTM alternative which is fixed at zero.

significantly. In the 2km case, this preference becomes equal to that of walking. Familiarity with e-scooter and shared car are not (statistical) significantly present in the final model, which can be linked to the overall small number of respondents that either ever used an e-scooter or shared car in the past (1.3% e-scooter, 7% shared car) or picked one of these alternatives in the choice experiments (5% e-scooter in 1 and 2km experiments; 7% shared car in 4 km experiment). However, the interaction variable openness to new technology – which was found to be related to shared mode familiarity in Section 6.1.4 – does show up in the model to increase the preference of both e-scooter and shared car. Especially in the case of the e-scooter, this attitude plays a considerable role, which also makes sense in the light of the high share of respondents having never heard of e-scooters before.

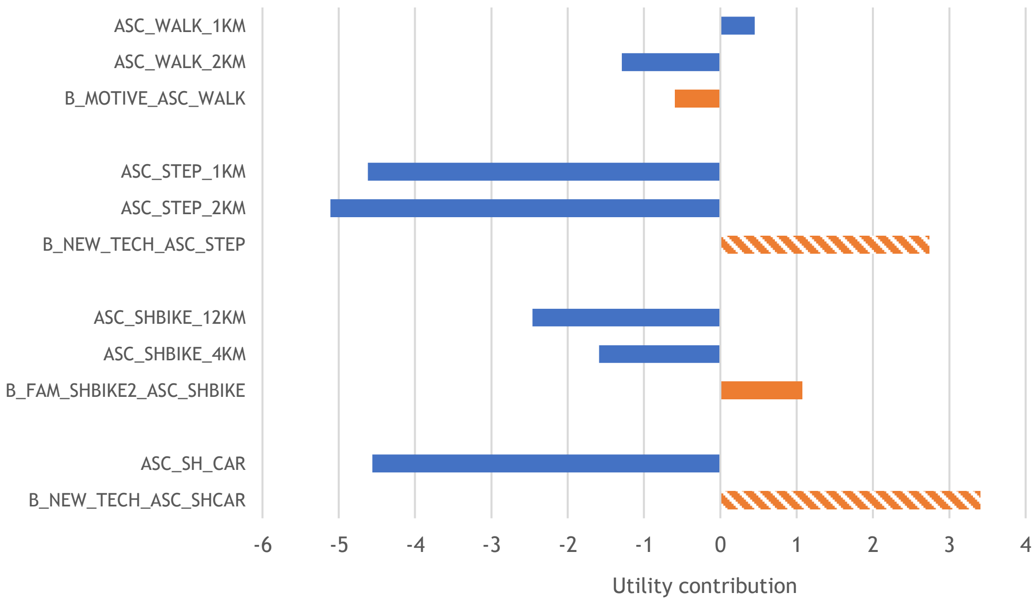

Figure 6-9 Utility contributions of ASCs (blue) and interaction components (orange). The variable NEW_TECH (openness to new technology) is not a dummy variable and can also take values within the displayed range.

Value of travel time savings

Also for the activity-based model values of travel time savings can be computed, see **Table 6-12**. Noteworthy are the large difference between the shared bike alternative and both the e-scooter and shared car. The willingness to pay for reduced search time for the shared bike is at least three times smaller than that for the e-scooter and the shared car. For the case of the e-scooter, this stresses the sensitivity for search time, while for the shared car alternative this relative high wtp value is also caused by the lower sensitivity for usage costs.

Comparing the obtained values with those of the home-based model, wtp for reduced search time of a shared bike is slightly lower in the AB case (€ 3.64 vs. € 3.12/h), which also applies to the wtp related to BTM waiting time (€ 7.44/h of HB vs (averaged) € 6.13/h of the AB model). This shows that more disutility is associated with these travel time components in case of the home-based trip than in the activity-based trip. As the obtained wtp values in the AB model are on the whole in line with the values found at the HB model, no additional comparison with literature is made here.

Table 6-12 Computed values of the willingness to pay (wtp) for decrease in travel time component.

Value of travel time savings	ß time	ß cost	€ / min	€ / hour
Shared e-scooter: wtp less search time	-0,202	-1,18	€0,17	€ 10,27
Shared bike: wtp for less search time	-0,0624	-1,2	€0,05	€ 3,12
Shared car: wtp for less search time	-0,0948	-0,588	€0,16	€ 9,67
BTM lust: wtp for less waiting time	-0,0356	-0,575	€0,06	€ 3,71
BTM must: wtp for less waiting time	-0,0818	-0,575	€0,14	€ 8,54

Conclusion AB model

The parameter interpretation of the HB model is summarized in Figure 6-10. To conclude, the interpreted results of the activity based model can be translated into a number of findings related to the willingness to use shared modes. Regarding the importance of the different tested factors the following findings can be listed:

- Usage cost plays a more dominant role in the utility function than the included search time components for all studied shared modes.
- Differences in unlocking method (related to ease of use) were not found to play a role in the decision making process of all studied shared modes.
- When comparing the shared modes, large differences intrinsic preference are observed. Shared bike is much more preferred. This can be linked to the earlier found large difference in familiarity with the different modes. Knowledge and experience with the shared bike concept are much more common than that of shared car and shared e-scooter, which are related to the e-scooter not yet being legalized for public use (in the Netherlands) and the general dislike of using a shared car as egress transport (in the presented scenarios of a trip in highly urban areas). Experience with shared bikes also shows up in the model as a significant interaction and increases the preference gap between the shared modes even further.
- Openness to trying new technology shows to significantly increase the intrinsic preference of using the shared e-scooter alternative as well as the shared car alternative.
- For the case of the short distance alternatives (1 and 2 km), search time shows up to be of much more importance for usage of the e-scooter than for using the shared bike.
- In the 4 km scenario, disutility contributions of usage costs and search time are approximately the same. Here, the intrinsic preference appears to be the only factor causing the (large) difference.

With respect to the preference for the shared modes compared with the other included conventional modes, these are the main outcomes:

- Conventional modes are generally preferred over shared modes. Familiarity with shared modes however appears to play a key role in the position of shared modes related to conventional modes. Intrinsic dislike of the shared bike shows to diminish to a large extent when travelers have previous experience with shared bikes. For the case of e-scooter this unfamiliarity can largely be ascribed to the not yet legalized status.
- For the studied type of activity-based trip with specified alternatives, the shared car seems to be an irrelevant alternative to consider for most travelers. Nevertheless, findings related to the role of familiarity and the willingness can also apply to relevant trip scenarios (with lower urban densities involved).

When comparing the home-based trip with the activity-trip, similarity can in the first place be noted with respect to the importance of familiarity with shared modes. In both cases having tried before or being willing to try plays an important role in the shared modes' chances of being picked by the respondents. Also the impact of cost and time attributes was in both trip-models found to be higher for the costs attributes. Apart from these similarities, comparison between the willingness to pay for less transfer time (waiting, parking, or search time) revealed that in general slightly more disutility is associated with these transfer times at the home-based side than at the activity-based side.

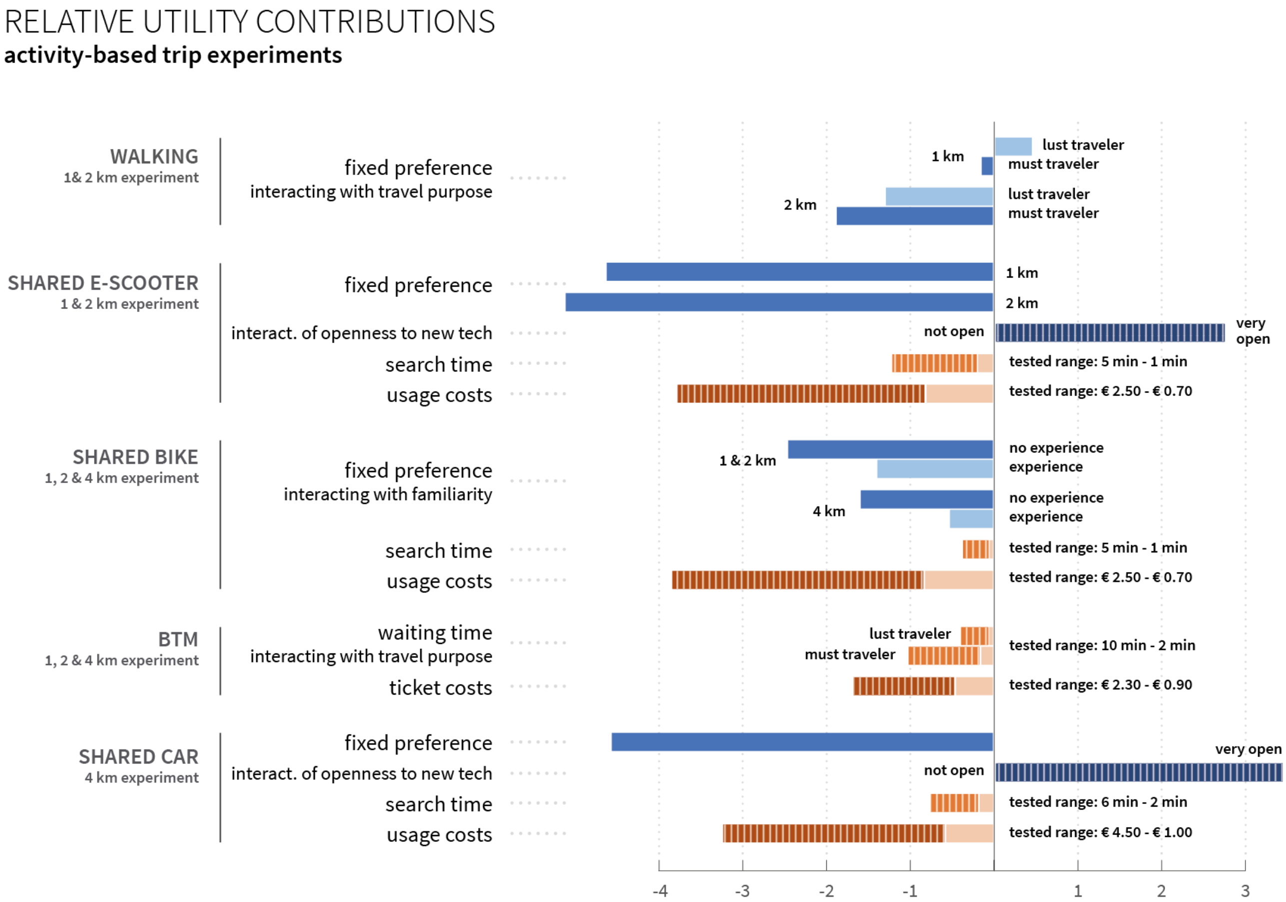

Figure 6-10 An overview of the parameter interpretation of the AB model parameters.

6.4 Conclusion

Obtained results based on model estimations as well as descriptive statistics are discussed in this chapter. The sample comparison shows, compared to the total NS customer population, that elderly and high educated customers are somewhat overrepresented in the sample. Model portfolios reveal a substantial share of the respondents to be travelers with a fixed preference. Regardless of changes in attributes, they keep preferring the same mode. This indicates important roles for the alternative specific constants in the estimated models, which was confirmed by the parameter estimations. Additionally, the degree of familiarity with shared modes was found to be generally low, in particular with respect to having used and e-scooter or shared car. To check for possible subtraction of factors from the statements that aimed at measuring attitudes, an explorative factor analysis was applied and as a result, the factor openness to new technology was incorporated into the model as an interaction variable.

Several choice modelling steps were performed in order to estimate two final models: one HB model and one AB model. Single cross validation shows that the model predictions between the training set (80% of the sample) and the test set (remaining 20%) were only slightly different. Together with the reasonable obtained willingness-to-pay values and the observations of similarity between the modal split in the choice data and the existing modal splits in train trips, the estimated models are assumed sufficiently validated.

The results of the estimated models for the AB and HB trip reveal a key role for familiarity with shared modes. The less familiar a shared mode, the larger the general intrinsic dislike. Besides costs were found to play a much more important role than the include transfer time components of searching and parking. Comparison between the two models revealed that more disutility is associated with the studied travel time components in case of the home-based trip than in the activity-based trip.

Using the findings presented in this chapter, the study can be concluded in the next chapter by combining the results of the different phases to answer the main research question.

7 Conclusions, discussion, and recommendations

Using the results of the previous chapters, this chapter concludes this research. It answers the research question posed in the introduction chapter and discusses how the findings of this research relate to the research gap (Section 7.1). Next, the results are discussed with respect to findings by other studies and the impact of the research design and scoping on the results is reflected upon (Section 0). Lastly, a number of recommendations is made regarding further research directions and regarding NS's strategy towards shared mobility in the door-to-door trip (Section 7.3).

7.1 Conclusions

This research started off by noting how the general trend of shifting toward sharing, or better put, access based consumption offers promising prospects for the case of mobility. At the same time, the true magnitude of impact that these shared mobility services will have on the organization of mobility still remains uncertain (Cherry & Pidgeon, 2018; Durand et al., 2018; Standing et al., 2018). For a company like NS it is therefore highly relevant to investigate how such services will relate to their business and, considering the urban scale of most of these types of shared mobility, in particular how these services can contribute to better first and last mile transportation within the multimodal train trip. Given the underexplored decision making process of individuals regarding the use of shared mobility services, the research question of this study was therefore:

What factors determine people's willingness to use shared mobility services as access or egress transport in multimodal train trips, and to what extent?

Just like the formulation of this question, the findings and conclusions of this study are composed of two parts. First, the most relevant types shared mobility as well as the most relevant choice factors in the case of access and egress transport to and from railway stations are selected to incorporate into stated choice experiments. The effects of these factors, tested via choice modelling, are then discussed and interpreted to conclude on the willingness to use shared mobility services within the multimodal train trip.

The most relevant shared mobility services and mode choice factors

Shared mobility can be conceptualized as an innovative transportation strategy that enables travelers to gain temporary access to transportation modes on an "as-needed" basis (Shaheen et al., 2015). Many different types of shared mobility services exist and in categorizing them, an important split can be made in what the travelers gains access to, a vehicle or a ride. Given the popularity of cycling and walking in the current modal split of access and egress trips and the potential of the shared (standing) e-scooter and shared bike, shared vehicles are found to be the most relevant type of shared mobility to investigate in terms of mode choice factors. Included in the choice experiments were therefore e-scooters, bikes and cars that can be accessed on an as-needed basis.

Considering mode choice factors, a general categorization can be made by distinguishing factors related to the modes/services available, factors related to the trip, and factors related to the traveler. Based on expert judgement and criteria related to the stated choice method and the applicability to the case of multimodal train trips, the most relevant factors were selected. These are depicted in Figure 7-1.

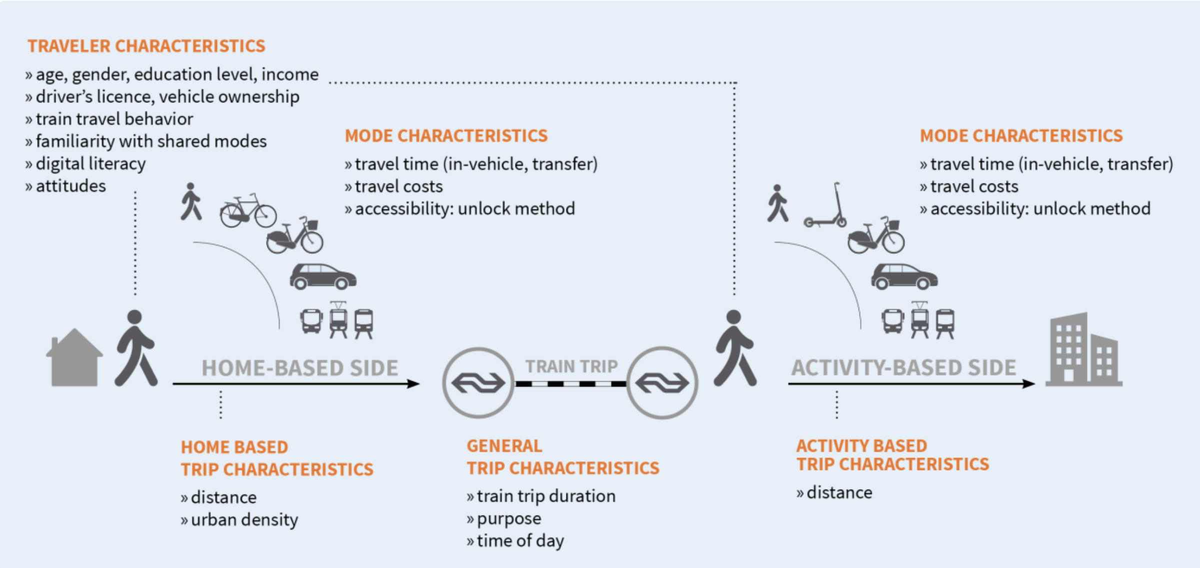

Figure 7-1 Investigated mode choice factors in this study.

Evaluating the impact of the selected factors

In order to conclude on the importance of the selected mode choice factors, the results from the stated choice experiments are analyzed using descriptive statistics and discrete choice modelling. What stands out from the descriptive statistics is, in the first place, the variety of different modes that respondents switched between in the choice experiments. A large share of respondents (58%) had a fixed preference for one mode in either the home-based or the activity-based trip experiment. This suggests that fixed mode preferences played an important role in the hypothetical choice situations. In total, 41% of the respondents did not switch mode in both experiments. Analysis of this group revealed that especially elderly, lower educated and less frequent train travelers are more likely not to switch to another (shared) mode when transfer time and travel costs are varied.

The second noteworthy result from the descriptive statistics is the degree of familiarity with shared modes among the respondents, which is depicted in Figure 7-2. Experience with shared modes is generally low. Besides, large differences exist between the different modes. Respondents are most familiar with shared bikes: 28% of the respondents has used a shared bike and only 14% has never heard of the concept while only 2% has experience with e-scooters which are new to almost half of the sample (47%). Though these differences are not surprising given the current availability of the different shared modes in the Netherlands, the familiarity distributions provide relevant background information when evaluating the results from the estimated choice models.

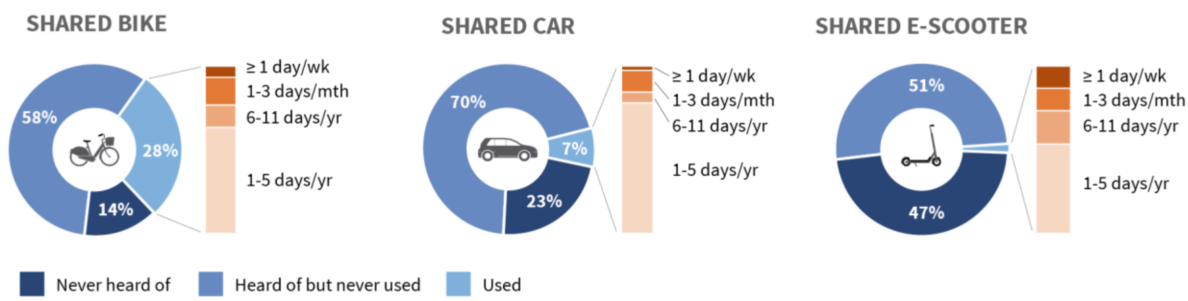

Figure 7-2 Respondents' familiarity with shared modes.

Due to the fundamental differences between these trips regarding (private) mode availability, route familiarity, and travel behavior inertia, the assessment of the effect of the selected factors was conducted via separate stated choice experiments for the home-based and the activity based trip.

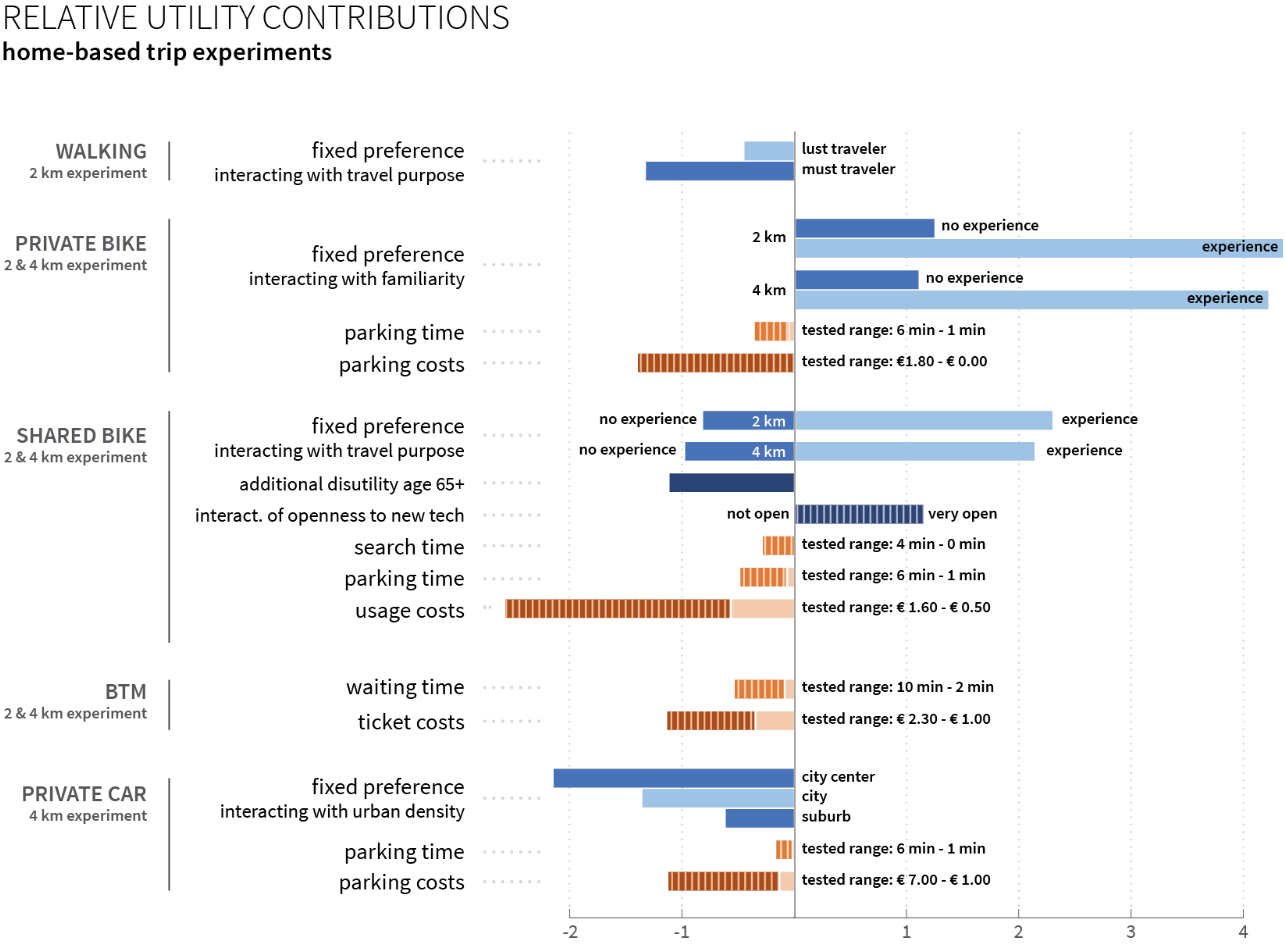

Figure 7-3 An overview of the parameter interpretation of the AB model parameters.

Results for the **home-based side** (Figure 7-3) reveal that *traveler characteristics* have the largest impact on the willingness to use a shared bike[24] as access mode. Especially whether travelers have previous experience with shared bikes strongly affects the mode choice process. Having used a shared bike before massively increases the preference for both the private and the shared bike alternative. In that case, the private bike is still intrinsically preferred over the shared bike, but differences in mode related factors of parking/usage costs and, to a lesser extent, also parking time can cause a substantial amount of disutility to let the shared bike become the preferred option. Overall however, the private bike was strongly preferred over the shared bike (53% of all choices vs. 6%) which can be linked to fact that the majority of the respondents (72%) has no previous experience with using a shared bike.

Besides, compared to the included conventional modes, this relative unpopularity of the shared bike can also be matched with the shared bike in general scoring lowest on intrinsic mode preference. These preferences play a substantial role, as was expected based on the discussed large share of respondents with a fixed preference and the fact that the in-vehicle times were not varied in the experiments and therefore load onto the fixed preference scores as well. The effect of *trip characteristics* travel purpose and urban density are found to change this preference order: The private car is least preferred for trips to railway stations in highly dense urban areas and travelers heading towards an important meeting (must-traveler) would quicker turn to using a shared bike compared to walking.

With respect *to mode characteristics*, costs and in particular (transfer) time attributes are found to be less important than the intrinsic mode preference interacting with traveler characteristics. In the case of the shared- and private bike alternatives, costs play a slightly less important role than the mode preferences, while the

[24] Shared bike is the only included shared mode in the home-based trip experiments.

impact of search- and parking time is approximately five times smaller. Sensitivity to both costs and transfer time is both highest for the shared bike alternative, which could be linked to the familiarity issue: costs and time elements are weighed heavier for never tried alternatives. Lastly, the included qualitative element of accessibility – the unlocking method of the shared bike– appeared not to be a significantly considered factor in the choice process.

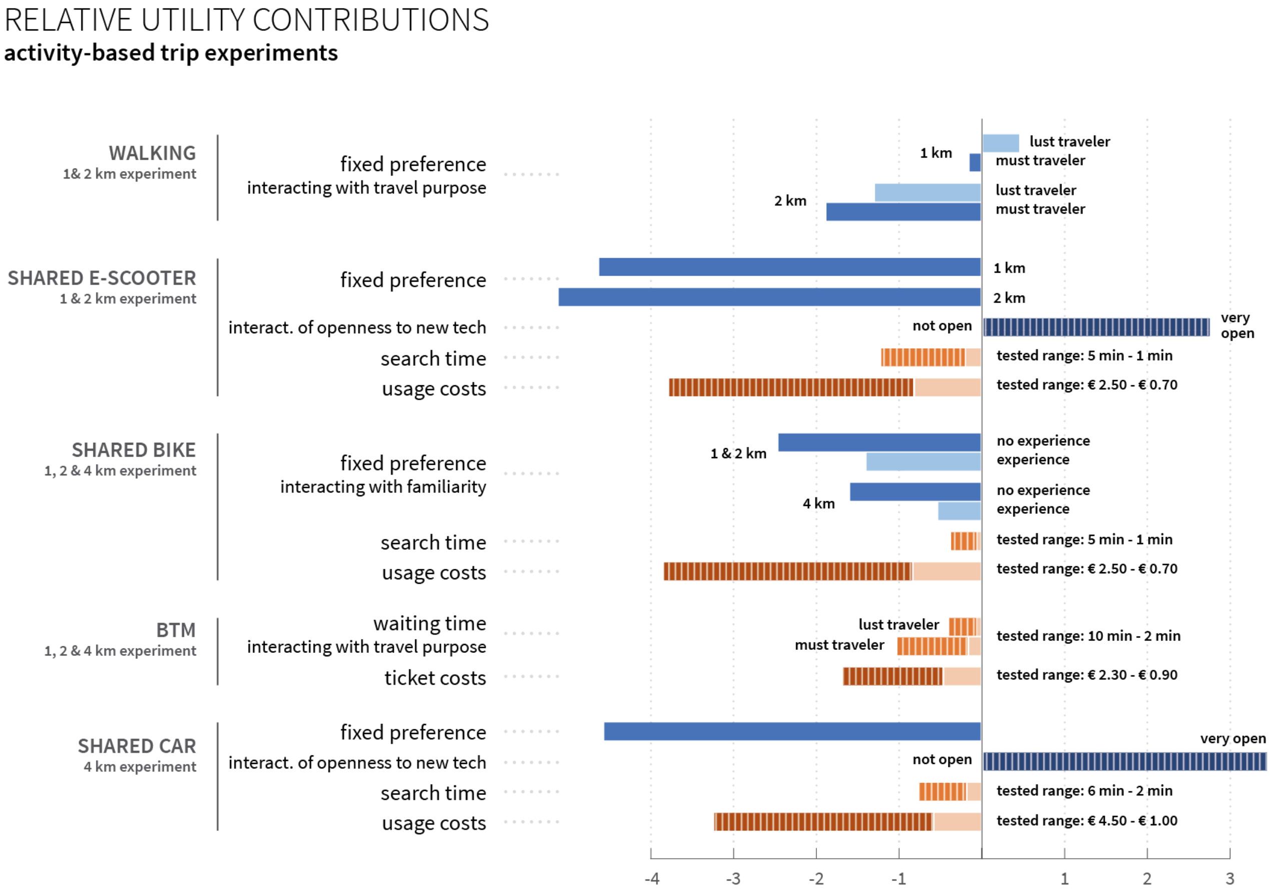

Figure 7-4 An overview of the parameter interpretation of the AB model parameters.

In the **activity-based trip** scenario (Figure 7-4), multiple shared modes were included: the e-scooter, bike and car. Similar to the home-based side, familiarity with the shared mode concepts emerged also here as a prominent factor in the mode choice process. Being unknown and therefore unpopular applies in particular to the shared e-scooter and shared car alternative. These alternatives score remarkable low on intrinsic mode preference, which can be linked to the general observed low familiarity with these modes in the sample. The shared bike is a much more common egress mode to the respondents (due to the availability of OVfiets) which correspondents with a much less dominating intrinsic preference and a larger impact of costs and time attributes compared to the shared e-scooter and car.

Traveler characteristics related to one's openness to trying new technologies and (again) having experience with shared modes emerges as interaction variables that are significantly related with the intrinsic mode preference of the shared modes. The more respondents can be characterized as early adopters, the smaller the difference between the intrinsic mode preferences of shared and conventional modes. Apart from these static preferences, the *trip characteristic* travel purpose is found to affect the sensitivity to travel time in such way that must travelers are more likely to consider a shared bike than lust travelers due to higher sensitivities to walking time and BTM waiting time. However, sensitivity to costs for shared bike usage is much stronger associated with disutility than is the case for costs of a BTM ticket.

Thus, regarding the impact of the tested factors on the willingness to use shared modes, it can be concluded that when the familiarity with the shared mode is too low (e-scooter and car), the role of time and cost attributes is in general too small to play a significant role. In case of a more familiar shared mode (shared bike), travel time- and especially costs attributes can make a differences. However, sensitivity to the tested cost attributes among the alternatives was found to be highest for the shared bike (and e-scooter), which means that for equal increase in travel costs, higher disutilities are associated with the shared modes compared to the conventional ones. Lastly, the tested impact of ease of usage (unlocking methods) of the shared modes was – similar to the home-based results – not found to play a role in the mode choice process of the respondents.

When comparing the home-based trip with the activity-trip, similarity can in the first place be noted with respect to the importance of familiarity with shared modes. In both cases having tried before or being willing to try plays an important role in the shared modes' chances of being picked by the respondents. Also the impact of cost and time attributes was in both trip-models found to be higher for the costs attributes. Apart from these similarities, comparison between the willingness to pay for less transfer time (waiting, parking, or search time) revealed that in general slightly more disutility is associated with these transfer times at the home-based side than at the activity-based side.

Shared mobility in the multimodal train trip

Considering these findings and the questions asked at the beginning of this study, the following conclusions can be drawn with respect to the willingness to use and the potential role of shared mobility services in access and egress trips.

In general, the chances of shared modes are found to be strongly influenced by travelers' experience and familiarity with these modes. This can be linked to the adoption time of these new modes. The less travelers are accustomed to having a particular shared mode in their choice set, the larger the dominance of an intrinsic dislike. Half of the respondents had never heard of e-scooter before and less than 0.01% had used one, which translates into a dominant intrinsic preference factor and also relatively large sensitivities to costs and search time. The shared bike exemplifies a mode that is already a more familiar option, especially for the activity-based trip, which results in a different hierarchy of mode related factors. The intrinsic mode preference become less dominant and other mode characteristics such as search time and usage costs gain more importance.

In this adoption stadium of the shared bike, usage costs become the most decisive factor. Sensitivity to costs of using a shared modes are compared to other modes still high, but this could decrease as the familiarity-burden decreases and the benefits of shared modes in terms of speed increase in valuation. In such future stage, the ease of usage – like the tested unlocking methods – could also become a more relevant factor in the mode choice process, but for now such effect is completely overshadowed by the intrinsic dislike factor.

Naturally, the above made point is generalized and its applicability also depends on the type of traveler and the type of trip. The more that a traveler can be identified as an early adopters of innovations, the smaller the dominance of the found intrinsic mode dislike in his mode choice process. In line with the findings from the presented modal portfolio's, in particular travel purpose and age show to affect the willingness to use shared modes. The type of traveler that is younger and travels often by train (commuting) is more likely to switch to or try a shared mode in his door-to-door trip.

Regarding the *potential role of the different studied shared modes* this research shows clear opportunities for the shared bike, while chances of the shared e-scooter and car are less straightforward to conclude on, which can mainly be attributed to the high degree of unfamiliarity with the modes among the respondents. Via OVfiets, the shared bike is an already proved concept at the activity-based side of the multimodal train trip and results of this study show that when travelers have experience with shared bikes, this mode has potential to compete with the private bike at the home-based side trip. However, that only goes in case of substantial differences in (parking) costs and parking time and would require to move away from the current situation of free bicycle parking at every railway station.

Due to the large impact of the unfamiliarity with shared e-scooter and shared car as egress modes, it is difficult to interpret the estimated effects of the other included attributes on the chances of these modes. Until (private) e-scooters are allowed on the Dutch roads, the familiarity effect will not decrease and type of trip tested may have been too general to highlight the benefits of the train + shared car combination. Nevertheless, the shared e-scooter and shared car were seriously considered by an early adopter group (5% of all choices e-scooter in 1 and 2 km experiments, 7% shared car in 4 km experiment), which shows that despite the familiarity-burdens there is already a group seriously considering these modes in their choice set.

All in all, this study has contributed to filling the research gap of the underexplored decision-making process regarding the willingness to use shared modes. The results show that in further studying the potential of these new mobility services, it is important to take the adoption-rate of the included services into account. The case of the shared e-scooter shows that unfamiliarity can overshadow the effect of potentially interesting details such as willingness to pay. This advocates for more research based on trials. The case of shared bikes on the other hand showed that in case of a more commonly familiar mode, the role of more detailed attributes such as price and possibly also type of parking systems can be investigated to obtain more concrete and quantitative results on the potential of these shared mobility services.

7.2 Discussion

Apart from discussing the findings of this study to answer the research question, also a comparison with findings in other studies (Section 7.2.1) and the impact of the research design (Section 7.2.2) and scope (Section 7.2.3) can be discussed, after which several limitation of this study are listed (Section 7.2.4).

7.2.1 Comparison with literature

In order to gain better understanding on how to interpret the results of this study, it is useful to reflect on the outcomes of this study by comparing them with findings in related studies. However, as the amount of literature addressing the combined topic of mode choice and shared mobility as first and last mile in the multimodal train trip is scarce, a direct comparison between the detailed findings and existing literature is hard to make. Nevertheless, the results of this study can be compared both on a more general level with mode choice factors linked to shared mobility usage found in literature, as well as with literature addressing the adoption of shared mobility services and Mobility-as-a-Service (MaaS).

Stated preference studies on the role of shared bikes as access and egress transport by Van der Nat (2018) and Van Heijningen (2016) both find usage costs as a key factor in choosing a shared bike. This is in line with the findings of this study, though the interaction effect of having previous experience is in this study found to have a bigger impact in the home-based trip scenario. Other studies addressing choice factors of shared bike usage, however, find different factors to be more decisive. A study by Bachand-Marleau, Lee, and El-Geneidy (2012) on the likeliness of using a shared bike system in Montreal finds distance to the nearest available shared bike (and thus search time) to be the most decisive factor in the mode choice process. This difference could be related to the fact that the search time for a shared bike in this study was never larger than 5 minutes. Another contrasting finding is by Zhao and Li (2017) who find in a study on the integration between shared bikes and metro in Beijing, China that trip distance is the most important factor in choosing the bike alternative or not. The fact that distance did not emerge in this study as an important factor could be related to the tested trip distances, which are close to the average biking distance (3.4 km) to railway stations in the Netherlands (Jonkeren et al., 2018). In addition, also (biking) culture difference are likely to explain the difference in importance of trip distance.

Apart from mode choice factors related to travel costs, travel time or trip characteristics, the findings in this study suggesting the important role of experience with (new) shared modes is confirmed by the extensive literature review on the expected impacts of MaaS by Durand et al. (2018). Also corresponding findings regarding the characteristics of the early adopters of shared modes are found to be in line with findings from a study on the potential of demand responsive transit by Alonso-González et al. (2017) and a recent study on characterizing the early adopter of MaaS by Zijlstra et al. (2019). Both studies show that higher educated young travelers are likeliest to adopt shared mobility services, which was also found in the modal portfolios of this study.

To sum up, the results of this research seem predominantly to match with findings in related literature. Differences are in particular found to occur in case of studies conducted outside of the Dutch context or in case of completely different setups. Therefore the role of this study's scoping and research approach are discussed in the next two subsections.

7.2.2 Research design

As was depicted in Figure 3-6, selecting the variables that represent choice determining factors to include into the model is strongly affected by the assumed behavioral theory. Since discrete choice modelling was applied in this study, selecting variables focused on rational elements such as travel time and travel costs, which would fit in the model based on utility maximization. Given the found importance of the fixed mode preferences and traveler characteristics like familiarity with shared modes, it can be argued that the chosen model setup may have been focusing too much on detailed travel time and cost components and that instead more attention should have been paid to the interaction variables. The inclusion of many alternative specific costs and transfer times could have introduced too much complexity to the model causing many insightful interaction effects of traveler characteristics to remain statistically insignificant. A less complex model with respect to travel time and costs could have resulted into more obtained information on the relation between trade-offs and traveler characteristics.

Apart from the applied modelling paradigm, also the role of the stated preference survey and the collected data can be commented on. When conducting stated choice experiments, one should be aware of the hypothetical bias that comes with this type of data collection (Hess & Rose, 2009). Respondents may have misunderstood some of the explained concepts in the survey. Though few respondents filled out OVfiets at "other" instead of picking the shared bike option in one of the last questions on current egress transportation, the majority of the respondents indicated that they found the survey clear (45 %) or very clear (10%) compared to only 16% considering the survey unclear or very unclear. Therefore, the hypothetical bias is assumed not to play a significant role in affecting the findings of this survey, though it remains a general drawback of the research method which is discussed further into Section 7.2.4.

As mentioned previously when discussing the modal portfolio's, the sample contains a large share of non-traders (both models 58% on average). This means that a large group did not perceive the presented attributes or the differences in attributes levels as relevant enough to switch away from their preferred mode. On the one hand this could be linked to the slight overrepresentation in the sample of travelers that are also found in other studies (see previous section) to be less likely to try new modes (elderly). This is likely to have affected the found dominance of the fixed mode preferences as less information was available on the trade-offs between attribute values. However, it should also be noted that within the total customer population of NS, the less-likely-to-trade group is also a much larger group than the group found likeliest to switch to new modes (young, highly educated, frequently travelling). Therefore, apart from sample bias, also the discussed possibly overemphasized importance of travel time and costs in the model setup or the attribute level ranges can have caused for this relative large amount of respondents having a fixed preference.

7.2.3 Scoping of this study

Since this study was conducted for NS, the scope of this study was the door-to-door trip when traveling by train in the Netherlands. With respect to the effect of this scope on the general applicability of this study's findings two comments can be made.

In the first place, the unique biking culture in the Netherlands can have effect on the willingness to use shared modes and in particular the shared bike. On the one hand, the familiarity with biking and the high quality and quantity of available biking infrastructure are in favor of the potential of shared bikes. These factors are in fact contributing to the popularity of the (private) bike as egress mode (Van Mil et al., 2018). The potential of shared bikes is already proved by the growing popularity of OVfiets on the activity based trip. On the other hand, the high share of private bike ownership could give a distorted view on found factors related to the willingness to use- and the potential of shared bikes as feeder mode for train traveling (home-based side of the trip). Especially since free parking of private bikes at railway stations is currently the norm in the Netherlands.

Secondly, also the findings related to the potential of the shared e-scooter could be influenced by the Dutch context of this study. The suggested link between the low preference for the shared e-scooter in the stated choice data and the degree of unfamiliarity with this mode could be affected by the Dutch context in the sense that respondents were more likely to opt for the shared bike instead of the shared e-scooter because of their general familiarity with (private) bikes. That also raises the question to what extent the increasing popularity of e-scooter in cities outside the Netherlands can be translated into potential for Dutch cities. This should be addressed in future research, as will be discussed in Section 7.3.1.

All in all, it can be stated that the Dutch bike infrastructure and the strong familiarity with biking and having a private bike available is likely to affect the willingness to use shared modes both in positive and negative ways. This also decreases the extent to which the in particular more detailed findings are generally applicable (at an international level).

7.2.4 Limitations of this study

This study is not without limitations. Apart from the discussed impact of the research design and the scoping of the study, also more concrete design decisions can be listed that limit this study. In the first place, the decision to include multiple sets of mode alternatives to enable inclusion of multiple trip distances provides this research with an explorative but also a less in-dept character. The commonly separated factors intrinsic mode preference and in-vehicle time were combined into one parameter which limited the amount of information that could be obtained from the models and excluded the possibility to calculate the willingness to pay for in-vehicle time, which is a useful measure that enable comparison between modes of different models[25].

Secondly, the identified openness towards new technology attitude was in this study directly included in the model as an interaction variable. This however is an outdated technique and only provides an indicative manner to study the effect of the attitude. A much more elegant way would be to construct an integrated choice and latent variable (ICLV) model as discussed in Chapter 2. That way the impact of the attitude would be included in the model via its impact on socio-demographic variables (which are directly included in the model). This would also increase the feasibility to replicate this study.

Third, a more general comment can be made regarding the use of stated preference (SP) experiments as research method. As mentioned, a drawback of this method is the hypothetical bias, meaning that uncertainty exists with respect to whether respondents would make the same choices in reality in case the hypothetical choice options would really exist. In general models estimated based on SP data tend to overestimate the choice probabilities for the new, not yet existing option (McFadden, 2017).

Besides the hypothetical bias, a last comment can be made regarding the role of familiarity in SP experiments and the so called SP paradox. Respondents can make informed choices best when they are familiar with the offered alternatives and attributes, while at the same time the possibility to test new hypothetical alternatives (to which the respondents is unfamiliar) is one of the key reasons to conduct such SP experiment (Ben-Akiva, McFadden, & Train, 2018). This notion should be kept in mind when interpreting the outcomes of the model estimations, and in case of this study in particular when interpreting the found importance of familiarity with shared modes. Additional research applying different methods are necessary to further investigate the willingness to use shared modes. Several suggestions are listed in the next section.

7.3 Recommendations

Based on the outcomes of this study, multiple recommendations can be made regarding both future research and application this studies results in practice.

7.3.1 Further research

A drawback of studying the willingness to use of multiple shared modes in one study is that potentially relevant detailed attributes or trip scenario's cannot be tested. Therefore a first recommendation is to study the willingness to use a shared car, bike or e-scooter separately, which would allow for including relevant attributes and trip characteristics such as availability, parking systems (free-floating vs station-based) or in case of the shared car, trips is less urban dense area's having a longer distance than the distances tested in this study. That way, the potential of these modes can be further explored while at the same time such research can be used to verify the results of this study.

A second recommendations is about applying different research methods. As discussed, use of stated preference data allows for testing new types of mode alternatives, but at the same time also comes with drawbacks related to its hypothetical bias. Given the rising number of OVfiets usage and emerging shared bike

[25] Willingness to pay (wtp) values were calculated for the different transfer time component, but since these types of travel times were different (i.e. parking time, waiting time, search time), comparison was only possible between a few modes. Furthermore, general wtp values for in-vehicle time are also available on a much larger scale in exiting literature, which would have allowed for better interpretation of this study's findings.

systems in multiple cities in the Netherlands, research based on revealed preference data becomes an increasingly realistic and interesting option to further explore the role of the shared bike in the multimodal train trip. Related to the found importance of traveler characteristics in the adoption process, collaboration with NS on OVfiets data would be a relevant direction because OVfiets is linked to OV chipcard data, which could provide connections with relevant traveler characteristics like train travel behavior or socio-demographic data.

A third and last comment regarding future research is a more conceptual-related recommendation on the perception of sharing within the context of studying shared mobility. As shown in the literature review, controversy surrounds the usage of the term sharing economy, in particular because many related practices are more about access-based consumption. This also goes for shared mobility. The core of the concept is the quickly accessible service of being able to ride a vehicle. Therefore, it is important to focus in the first place on why people would use these services, rather than to focus on why travelers would give up ownership, because that is only a possible effect of opting to use shared mobility services. For example in the case of shared bike usage in the home-based trip scenario, travelers that would opt for the shared bike to go the railway station, do not immediately give up their own bike. They just prefer the shared bike for the specific trip, possibly because of parking costs and time, over using their own bike. The recommendation thus is to be careful with including ownership related factors when studying the role of shared mobility as access and egress transport, especially since private vehicles are often not available at the activity-based side of the total trip.

7.3.2 Recommendations to practice

From the perspective of offering a better door-to-door trip, and testing what can be the potential of shared mobility services within this trip, the findings of this study can be used to list several recommendations to NS and other transport operators and authorities.

Since one of the main outcomes of this study is the importance of familiarity, the first and main general recommendation is to provide travelers with opportunities to try a shared bike, e-scooter, or shared car. Research by Strömberg, Rexfelt, Karlsson, & Sochor (2016) shows that the “triability” of new shared mobility services can play an important role in the adoption process and that trails could therefore be a useful strategic tool. Authorities can play a role here from the perspective of rules and regulations while operators could cooperate with existing shared mobility businesses or start pilots with shared modes themselves.

More specifically, recommendations to NS are made to offer such trials of the less adopted modes shared e-scooter and car via the new NS Lab app, which is likely to be used mostly by early adopters.
With respect to shared bike a broader public can be approached. 58% of the respondents has heard of shared bike, but never used one. Given the importance of traveler characteristics, more research into current OVfiets users could help identifying and inviting the group of travelers that is most likely to use OVfiets but misses the experiences to actually switch.

A second recommendation to NS is about the potential of the shared bike at the home-based side of the door-to-door trip. As suggested in this study, costs and parking time benefits of shared bikes over private bikes can trigger people into using shared bikes to travel to the railway station. Given the capacity issues due to the popularity of the private bike as access mode (Jonkeren et al., 2018), this potential of shared bike usage at the home-based is highly relevant to investigate into further detail. More detailed results of this study on perception differences between travel times and costs could be helpful starting points in this process.

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Appendices

The following appendices are included:

A. Expert interviews

B. Experimental designs

C. Pilot survey

D. Final survey

E. Descriptive statistics

F. Model results

G. Scientific paper

A Expert interviews

The following list gives an overview of the expert interviews that were conducted during this study. Experts provide a ‘unique source’ of in-depth information on current developments in their field (Dorussen, Lenz, & Blavoukos, 2005; Rubin & Rubin, 2005). The conducted interviews were used to convert the more general list of factor identified in literature into a feasible set of to be included factors in the stated choice experiments. The following experts were interviewed:

Anne Durand, researcher at Kennisinstituut voor Mobiliteitsbeleid (KiM)
Discussed topics: factors related to the potential of Mobility as a Services, the importance of reliability, what type of people are most likely to adopt MaaS services first

Paul Haarman and **Danielle Dijkman**, NS Proposition and Pricing
Discussed topics: the importance of perception and familiarity, innovation adoption curve, the dominance of costs, link with the value of the asset

Ronald Haverman, Mobike Netherlands
Discussed topics: factors that play a role in choosing a shared bike including ranking importance, differences between Mobike and OV-fiets, the potential of shared bike systems

Wouter de Koning, head of Mobility Services NS Stations
Discussed topics: most important factors related to OV fiets usage and sharing in general, challenges regarding bicycle parking at railway stations, differences between OVfiets and free-floating systems, the role of unlocking methods

Interviews were conducted in a semi-structured way to ensure that the amount of data offered by the experts is not limited by the setup of the interview (Fielding & Thomas, 2008). An interview guide was used to ensure similarity in setup between the interviews. This guide consisted of three parts:

1. Question to the interviewee on how shared mobility relates to his/her profession.
2. Brainstorm question on which factors are most important regarding whether a travelers chooses a shared mode for access or egress transport.
3. Discuss the importance of the factors identified in the literature review.

B Experimental designs

This appendix contains all generated experimental designs with software application Ngene.

B.1 Home based experiments 1 and 2 kilometer

Ngene syntax

```
Design
? Home-based trip: 1 and 2 km
;alts = walk, own_bike, sh_bike, BTM
;rows = 36
;orth = sim
;block = 6
;model:
U(walk)     = b1 /
U(own_bike) = b2 + b3 * time_park_bike[0,1,2] + b4  * cost_park_bike[0,1,2] /
U(sh_bike)  = b5 + b6 * time_search[0,1,2]     + b3 * time_park_bike[0,1,2]      + b7  * cost_use[0,1,2]        + b8 * access[0,1] /
U(BTM)      =       b9 * time_wait[0,1,2]       + b10 * cost_ticket[0,1,2]
$
```

Table 0-1 Ngene generated experimental design

Final index	Choice situation	Block	own_bike.time_park_bike	own_bike.cost_park_bike	sh_bike.time_search	sh_bike.time_park_bike	sh_bike.cost_use	sh_bike.access	btm.time_wait	btm.cost_ticket
25	1	5	1	1	0	0	0	0	1	0
1	2	1	2	2	1	1	1	0	2	1
13	3	3	0	0	2	2	2	0	0	2
14	4	3	2	1	2	1	1	1	1	0
26	5	5	0	2	0	2	2	1	2	1
2	6	1	1	0	1	0	0	1	0	2
19	7	4	0	0	2	2	0	0	2	0
31	8	6	1	1	0	0	1	0	0	1
7	9	2	2	2	1	1	2	0	1	2
8	10	2	1	0	1	0	2	1	2	0
20	11	4	2	1	2	1	0	1	0	1
32	12	6	0	2	0	2	1	1	1	2
3	13	1	2	0	0	2	1	0	0	0
15	14	3	0	1	1	0	2	0	1	1
27	15	5	1	2	2	1	0	0	2	2
33	16	6	1	2	2	1	2	1	0	0
9	17	2	2	0	0	2	0	1	1	1
21	18	4	0	1	1	0	1	1	2	2
22	19	4	1	2	1	2	1	1	1	0
34	20	6	2	0	2	0	2	1	2	1
10	21	2	0	1	0	1	0	1	0	2
28	22	5	2	1	1	2	2	1	0	0
4	23	1	0	2	2	0	0	1	1	1
16	24	3	1	0	0	1	1	1	2	2
11	25	2	0	2	2	0	1	0	0	0
23	26	4	1	0	0	1	2	0	1	1
35	27	6	2	1	1	2	0	0	2	2
36	28	6	0	0	1	1	0	0	1	0
12	29	2	1	1	2	2	1	0	2	1
24	30	4	2	2	0	0	2	0	0	2
5	31	1	0	1	0	1	2	1	2	0
17	32	3	1	2	1	2	0	1	0	1
29	33	5	2	0	2	0	1	1	1	2
18	34	3	2	2	0	0	0	0	2	0
30	35	5	0	0	1	1	1	0	0	1
6	36	1	1	1	2	2	2	0	1	2

B.2 Home based experiments 4 kilometer

Ngene syntax

```
Design
? Home-based trip: 4 km
;alts = own_car, own_bike, sh_bike, BTM
;rows = 36
;orth = sim
;block = 6
;model:
U(own_car)  = b1 + b2  * time_park_car[0,1,2]                          + b3  * cost_park_car[0,1,2] /
U(own_bike) = b4 + b5  * time_park_bike[0,1,2]                         + b6  * cost_park_bike[0,1,2] /
U(sh_bike)  = b7 + b8  * time_search[0,1,2] + b5  * time_park_bike[0,1,2] + b9  * cost_use[0,1,2]       + b10 * access[0,1] /
U(BTM)      =      b11 * time_wait[0,1,2]                              + b12 * cost_ticket[0,1,2]
$
```

Table 0-2 Ngene generated experimental design

Final index	Choice situation	Block	own_car.time_park_car	own_car.cost_park_car	own_bike.time_park_bike	own_bike.cost_park_bike	sh_bike.time_search	sh_bike.time_park_bike	sh_bike.cost_use	sh_bike.access	btm.time_wait	btm.cost_ticket
25	1	5	1	1	1	0	0	0	0	0	1	0
1	2	1	2	2	2	1	1	1	1	0	2	0
13	3	3	0	0	0	2	2	2	2	0	0	0
19	4	4	0	2	0	2	2	0	0	1	2	0
31	5	6	1	0	1	0	0	1	1	1	0	0
7	6	2	2	1	2	1	1	2	2	1	1	0
14	7	3	1	1	2	2	1	0	1	1	0	1
26	8	5	2	2	0	0	2	1	2	1	1	1
2	9	1	0	0	1	1	0	2	0	1	2	1
8	10	2	0	2	1	1	0	0	2	0	0	1
20	11	4	1	0	2	2	1	1	0	0	1	1
32	12	6	2	1	0	0	2	2	1	0	2	1
3	13	1	0	0	2	0	2	0	1	0	1	2
15	14	3	1	1	0	1	0	1	2	0	2	2
27	15	5	2	2	1	2	1	2	0	0	0	2
33	16	6	2	0	1	2	1	0	2	1	2	2
9	17	2	0	1	2	0	2	1	0	1	0	2
21	18	4	1	2	0	1	0	2	1	1	1	2
22	19	4	2	1	1	1	2	0	1	0	0	1
34	20	6	0	2	2	2	0	1	2	0	1	1
10	21	2	1	0	0	0	1	2	0	0	2	1
28	22	5	1	0	2	1	2	0	2	0	2	2
4	23	1	2	1	0	2	0	1	0	0	0	2
16	24	3	0	2	1	0	1	2	1	0	1	2
11	25	2	2	0	0	2	0	0	1	1	1	2
23	26	4	0	1	1	0	1	1	2	1	2	2
35	27	6	1	2	2	1	2	2	0	1	0	2
36	28	6	0	1	0	1	1	0	0	0	1	0
12	29	2	1	2	1	2	2	1	1	0	2	0
24	30	4	2	0	2	0	0	2	2	0	0	0
17	31	3	2	2	2	0	0	0	0	1	2	0
29	32	5	0	0	0	1	1	1	1	1	0	0
5	33	1	1	1	1	2	2	2	2	1	1	0
6	34	1	1	2	0	0	1	0	2	1	0	1
18	35	3	2	0	1	1	2	1	0	1	1	1
30	36	5	0	1	2	2	0	2	1	1	2	1

B.3 Activity based experiments 1 and 2 kilometer

Ngene syntax

```
Design
? Activity-based trip: 1 and 2 km
;alts = walk, e-scooter, sh_bike, BTM
;rows = 36
;orth = sim
;block = 6
;model:
U(walk)      = b1 /
U(e-scooter) = b2 + b3 * time_search[0,1,2] + b4  * cost_use[0,1,2]    + b11 * access[0,1] /
U(sh_bike)   = b5 + b6 * time_search[0,1,2] + b7  * cost_use[0,1,2]    + b8 * access[0,1] /
U(BTM)       =      b9 * time_wait[0,1,2]   + b10 * cost_ticket[0,1,2]
$
```

Table 0-3 Ngene generated experimental design

Choice situation	Block	e-scooter.time_search	e-scooter.cost_use	e-scooter.access	sh_bike.time_search	sh_bike.cost_use	sh_bike.access	btm.time_wait	btm.cost_ticket
1	5	0	1	0	0	1	0	0	0
2	1	1	2	0	1	2	0	1	1
3	3	2	0	0	2	0	0	2	2
4	3	1	2	1	2	1	1	0	1
5	5	2	0	1	0	2	1	1	2
6	1	0	1	1	1	0	1	2	0
7	4	2	0	0	2	0	1	0	0
8	6	0	1	0	0	1	1	1	1
9	2	1	2	0	1	2	1	2	2
10	2	0	1	1	1	0	1	0	2
11	4	1	2	1	2	1	1	1	0
12	6	2	0	1	0	2	1	2	1
13	1	2	2	0	0	0	0	0	1
14	3	0	0	0	1	1	0	1	2
15	5	1	1	0	2	2	0	2	0
16	6	1	1	1	2	2	0	0	2
17	2	2	2	1	0	0	0	1	0
18	4	0	0	1	1	1	0	2	1
19	4	2	1	1	1	2	0	0	1
20	6	0	2	1	2	0	0	1	2
21	2	1	0	1	0	1	0	2	0
22	5	2	2	1	1	1	1	0	2
23	1	0	0	1	2	2	1	1	0
24	3	1	1	1	0	0	1	2	1
25	2	0	0	0	2	2	0	0	1
26	4	1	1	0	0	0	0	1	2
27	6	2	2	0	1	1	0	2	0
28	6	1	0	0	1	0	1	0	0
29	2	2	1	0	2	1	1	1	1
30	4	0	2	0	0	2	1	2	2
31	1	1	0	1	0	1	0	0	2
32	3	2	1	1	1	2	0	1	0
33	5	0	2	1	2	0	0	2	1
34	3	0	2	0	0	2	1	0	0
35	5	1	0	0	1	0	1	1	1
36	1	2	1	0	2	1	1	2	2

B.4 Activity based experiments 4 kilometer

Ngene syntax

```
Design
? Activity-based trip: 4 km
;alts = sh_car, sh_bike, BTM
;rows = 36
;orth = sim
;block = 6
;model:
U(sh_car)   = b1 + b2  * time_search_car[0,1,2]  + b3  * cost_use_car[0,1,2]  + b4 * access_car[0,1] /
U(sh_bike)  = b5 + b6  * time_search_bike[0,1,2] + b7  * cost_use_bike[0,1,2] + b8 * access_bike[0,1] /
U(BTM)      =      b9 * time_wait[0,1,2]         + b10 * cost_ticket[0,1,2]
$
```

Table AAA Ngene generated experimental design

Final index	Choice situation	sh_car.time_search_car	sh_car.cost_use_car	sh_car.access_car	sh_bike.time_search_bike	sh_bike.cost_use_bike	sh_bike.access_bike	btm.time_wait	btm.cost_ticket	Block
1	1	0	1	0	0	1	0	0	0	5
2	2	1	2	0	1	2	0	1	1	1
3	3	2	0	0	2	0	0	2	2	3
4	4	1	2	1	2	1	1	0	1	3
5	5	2	0	1	0	2	1	1	2	5
6	6	0	1	1	1	0	1	2	0	1
7	7	2	0	0	2	0	1	0	0	4
8	8	0	1	0	0	1	1	1	1	6
9	9	1	2	0	1	2	1	2	2	2
10	10	0	1	1	1	0	1	0	2	2
11	11	1	2	1	2	1	1	1	0	4
12	12	2	0	1	0	2	1	2	1	6
13	13	2	2	0	0	0	0	0	1	1
14	14	0	0	0	1	1	0	1	2	3
15	15	1	1	0	2	2	0	2	0	5
16	16	1	1	1	2	2	0	0	2	6
17	17	2	2	1	0	0	0	1	0	2
18	18	0	0	1	1	1	0	2	1	4
19	19	2	1	1	1	2	0	0	1	4
20	20	0	2	1	2	0	0	1	2	6
21	21	1	0	1	0	1	0	2	0	2
22	22	2	2	1	1	1	1	0	2	5
23	23	0	0	1	2	2	1	1	0	1
24	24	1	1	1	0	0	1	2	1	3
25	25	0	0	0	2	2	0	0	1	2
26	26	1	1	0	0	0	0	1	2	4
27	27	2	2	0	1	1	0	2	0	6
28	28	1	0	0	1	0	1	0	0	6
29	29	2	1	0	2	1	1	1	1	2
30	30	0	2	0	0	2	1	2	2	4
31	31	1	0	1	0	1	0	0	2	1
32	32	2	1	1	1	2	0	1	0	3
33	33	0	2	1	2	0	0	2	1	5
34	34	0	2	0	0	2	1	0	0	3
35	35	1	0	0	1	0	1	1	1	5
36	36	2	1	0	2	1	1	2	2	1

C Pilot survey

A pilot survey was conducted to check whether respondents understand the questionnaire and to test the setup of the experiment. This section presents and discusses the results of the pilot.

Descriptive statistics

In total, 25 out of 495 respondents filled out the pilot survey. The median time needed to complete the survey was 11 minutes. Table 0-4 presents a number of characteristics of the respondents. Noteworthy are the high share of respondents unknown to shared e-scooters and a slightly skewed gender distribution.

Table 0-4 Descriptive statistics of respondents pilot survey

Number of respondents	**26** out of **495** (5.3 %)
Completion time	Minimum **5 min**, median **11 min**, maximum **28 min**
Age	**32%** 15-35, **34%** 35-65, **34%** 65+
Gender	**36%** male, **64%** female
Train travel frequency	1-5 days/year: **19%**, 1-11 days/month: **58%**, ≥1 day/week: **23%**
Familiarity with shared bike	Used: **23%** Heard of, never used: **62%** Never heard of: **15%**
Familiarity with shared e-scooter	Used: **0%** Heard of, never used: **28%** Never heard of: **72%**
Familiarity with shared car	Used: **0%** Heard of, never used: **86%** Never heard of: **14%**

All respondents provided feedback on the survey. On a scale from 1-10, the survey was rated a 7.5, which indicates respondents liked the survey. The majority of the respondents (74%) found the choice situations clear or very clear. The main points from additional feedback consisted of 1) the unlocking aspect being not clearly enough communicated as a varying feature and 2) small issues encountered by some respondents in continuing to the next choice set within the choice experiments.

Model estimations

To test the setup of the experiments, simple multinomial logit (MNL) models were estimated using software package *Biogeme*. As only 26 respondents completed the entire survey, the choices made by 30 drop-out respondents were included as well. This results in a total of 437 choices. Due to the small sample size, interaction effects were not estimated.

Since the attribute unlocking method is a qualitative and categorical variable, its different categories were coded to enable incorporation into the choice models. This coding can be done using either effects coding or dummy coding (Hensher, Rose, & Greene, 2015). In case of dummy coding, utility differences are presented relatively to one of the levels, whereas in effects coding these are differences with the average utility of all attribute levels. Dummy coding is considered to be more convenient for the case of this research and the two levels of the unlocking attribute were coded as displayed in Table 0-5. Choice distributions and parameter estimations are presented in the tables below and are discussed separately for the home-based (HB) and activity-based (AB) models.

Table 0-5 Dummy coding of attribute unlocking method

Attribute level	UNLOCK
Unlock with smartphone	0
Unlock with code	1

Table 0-6 Choice frequency distribution in the home-based (HB) experiments

	HB 1		HB 2		HB 4		Total	
Walk	67	64%	9	17%			76	30%
Own bike	33	32%	23	43%	63	66%	119	47%
Shared bike	1	1%	10	19%	6	6%	17	7%
BTM	3	3%	12	22%	15	16%	30	12%
Own car					11	12%	11	4%
Total	104		54		95		253	

For the home-based experiments, it can be noted that only half as much respondents were assigned to the 2-kilometer experiment (Table 0-6). Since HB distance assignment is based on respondents home address (distance home to nearest station), this distribution over all experiments therefore should not be expected to be spread evenly. Still however, the share assigned to HB2 remains small, which could result to estimation problems for the final results.

Apart from the distribution of respondents, Table 0-6 shows that the HB1 experiment is dominated by choice for walking (64%) and own bike (33%). The shared mode option was chosen only once out of 104 times. From this fact it can be concluded that the relevance of including this distance for observing the trade-off shared vs. nonshared is minimal. Therefore, the 1-kilometer experiment will be left out in the final survey. By reassigning the respondents to either HB2 or HB4, also a more balanced distribution between the two experiments can be accomplished.

Table 0-7 Parameter estimations for the home-based experiments

	HB 1			HB 2			HB4			HB 1+2+4		
Name	Value	Rob. t-test	Rob. p-value	Value	Rob. t-test	Rob. p-value	Value	Rob. t-test	Rob. p-value	Value	Rob. t-test	Rob. p-value
ASC_WALK	1.27	0.545	0.586	-2.01	-1.35	0.178				1.58	1.98	0.0475
ASC_OWNBIKE	1.2	0.508	0.612	-0.764	-0.452	0.651	1.08	0.656	0.512	1.64	1.93	0.0533
B_PARK_OWNBIKE	-0.060	-0.559	0.576	0.046	0.325	0.745	0.0391	0.342	0.732	0.0010	0.0156	0.988
B_COST_OWNBIKE	-0.473	-1.65	0.098	-0.43	-1.05	0.293	-0.16	-0.533	0.594	-0.328	-1.86	0.0633
ASC_SHBIKE	-89.6	-1000	0	-1.32	-0.73	0.465	-0.956	-0.49	0.624	-0.424	-0.364	0.716
B_SEARCH_SHBIKE	6.26	9.05	0	-0.084	-0.33	0.741	-0.15	-0.748	0.454	-0.088	-0.645	0.519
B_PARK_SHBIKE	9.84	18.4	0	0.204	1.14	0.254	0.109	0.506	0.613	0.188	1.53	0.126
B_COST_SHBIKE	-1.14	-1.57	0.116	-1.05	-1.19	0.235	-0.293	-0.296	0.767	-0.57	-0.975	0.33
B_UNLOCK_SHBIKE	-48	-4.2e+22	0	-0.152	-0.191	0.848	0.0566	0.0673	0.946	-0.16	-0.313	0.754
B_COST_BTM	-1.01	-0.465	0.642	-1.06	-1.29	0.198	-0.259	-0.33	0.742	-0.042	-0.099	0.921
B_WAIT	-0.107	-0.451	0.652	-0.0023	-0.023	0.981	0.0151	0.27	0.787	0.0020	0.0417	0.967
ASC_CAR							-0.302	-0.184	0.854	0.0169	0.0164	0.987

B_PARK_OWNCAR							0.0251	0.152	0.879	0.0261	0.161	0.872
B_COST_OWNCAR							-0.122	-0.969	0.332	-0.126	-1	0.317

Regarding the HB parameter estimations presented in Table 0-7, several things stand out. In the first place, none of the parameters is **significant** on a standard 95% confidence interval (except for the parameters of the only once chosen shared bike option in experiment HB1). This can be explained by the small number of observations and is not a problem here.

In the second place, a number of estimated parameters does not have the **expected sign**. Parking time parameters for the private bike, shared bike, and private car alternatives obtain positive values whereas negative ones would be expected since utility is expected to decrease when the amount of time it takes to park increases. However, the relative utility contributions of these parameters for each alternative appear to be low and close to zero (for example 0.188 compared to -0.424 (ASC) and -0.57 (parking costs) for the shared bike alt. in the combined HB1+2+4 model). Therefore, these unexpected parameters signs can be linked to the small sample size as well and are expected to flip during the final model estimations using a much larger final sample.

All in all, the setup of the home-based experiment is adequate. The few extreme values and unexpected positive estimations can be linked to the small number of observations and a skewed choice distribution of the 1-km experiment. Towards the final survey, this 1-km experiment is dropped and the time-cost ranges are slightly increased (while considering literature VoT ranges) to present respondents with clearer differences and obtain more information from the trade-offs.

Table 0-8 Choice frequency distribution in the activity-based (AB) experiments

	AB 1		AB 2		AB 4		Total	
Walk	31	65%	18	24%			49	27%
Shared e-scooter	4	8%	3	4%			7	4%
Shared bike	5	10%	21	28%	11	18%	37	20%
BTM	8	17%	34	45%	49	82%	91	49%
Shared car					0	0%	0	0%
Total	48		76		60		184	

For the activity-based choice experiment, choice distributions look plausible, except for the shared car not being chosen at all. Therefore, the attractiveness of this alternative is increased in the final version of the survey by lowering both the fixed travel time and all parking costs attribute levels.
Regarding the parameter estimations, similarities exist between the activity-based and the home-based trip. Most parameters are not significant on a 95% confidence interval and also a small number of parameters with an unexpected sign are encountered. These observations can however, again be linked to the small sample size and number of observations used to estimate these MNL models. Using a much larger sample size of the final survey is expected to solve these issues.

Table 0-9 Parameter estimations for the activity-based experiments

	AB 1			AB 2			AB4			AB 1+2+4		
Name	Value	Rob. t-test	Rob. p-value	Value	Rob. t-test	Rob. p-value	Value	Rob. t-test	Rob. p-value	Value	Rob. t-test	Rob. p-value
ASC_WALK	0.523	0.321	0.748	-1.11	-0.971	0.331				0.418	0.667	0.505
ASC_STEP	6.57	1.82	0.068	27.5	9.2	0.00				4	2.16	0.0304
B_SEARCH_STEP	-1.61	-3.94	0.00	-0.0187	-0.0506	0.96				-0.476	-1.7	0.0889
B_COST_STEP	-4.43	-1.85	0.064	-20.5	-18.4	0.00				-2.78	-2.63	0.0086
B_UNLOCK_STEP	2.76	1.95	0.052	-1.03	-0.755	0.45				0.0588	0.0762	0.939

ASC_SHBIKE	6.11	1.86	0.0624	-0.124	-0.0775	0.938	4.19	0.251	0.802	0.654	0.633	0.527
B_SEARCH_SHBIKE	-1.23	-2.89	0.0039	0.0655	0.403	0.687	-0.028	-0.121	0.904	-0.0797	-0.656	0.512
B_COST_SHBIKE	-3.3	-1.59	0.112	-0.482	-0.825	0.409	-0.366	-0.457	0.648	-0.398	-0.998	0.318
B_UNLOCK_SHBIKE	-0.232	-0.237	0.813	-0.168	-0.323	0.747	-0.751	-0.978	0.328	-0.261	-0.673	0.501
B_WAIT	-0.111	-0.813	0.416	-0.0593	-0.814	0.416	-0.568	-0.39	0.696	-0.0896	-1.75	0.0801
B_COST_BTM	-0.182	-0.189	0.85	-0.0883	-0.138	0.89	4.24	0.326	0.744	0.565	1.41	0.157
ASC_SH_CAR							-5.1	-1.07e+12	0	-1.3	-0.592	0.554
B_SEARCH_SH_CAR							-13	-7.61e+23	0	-3.83	-11.3	0
B_COST_SH_CAR							-13.3	0	1	-3.8	-8.42	0
B_UNLOCK_SH_CAR							-2.73	-2.81e+24	0	-0.67	-0.737	0.461

Improvements for final survey

To sum up, the pilot survey was filled out by a small sample of 26 respondents (5.5%). This makes it difficult to estimate significant parameters, but gives an indication on the to be expected response rate for the final survey. Besides, a general score of 7.5 on a scale of 1-10 shows that respondents liked the (lay-out) of the survey. Also a median completion time of 11 minutes is satisfactory regarding the goal of designing a survey with a completion time of 10 minutes.

Based on these pilot results a number of improvements are made to come to a final survey design:

- The home-based 1-kilometer experiment is dropped because of the dominance of alternatives walking and own bike. That way also a better distribution between the 2 km and 4 km experiments can be accomplished.
- Attribute level ranges of travel times and costs are slightly increases to provide clearer differences between the alternatives and provide more information on the trade-offs for model estimations.
- The shared car alternative was made more attractive by lowering travel time and costs to get more information on the trade off with the other alternatives.
- More explicit explanations are added on how to continue during the choice experiment questions and on the variation of the unlocking attributes of the shared mode alternatives.

The final survey can be found in Appendix 7.3.2D

D Final survey lay-out

This Appendix displays (part of) the final survey that send to the respondents. As explained in Section 5.3, multiple “survey routes” were available to respondents based on their profile. Since this Appendix is in particular about showing the lay-out of the survey, only one route is presented in the screenshots below.

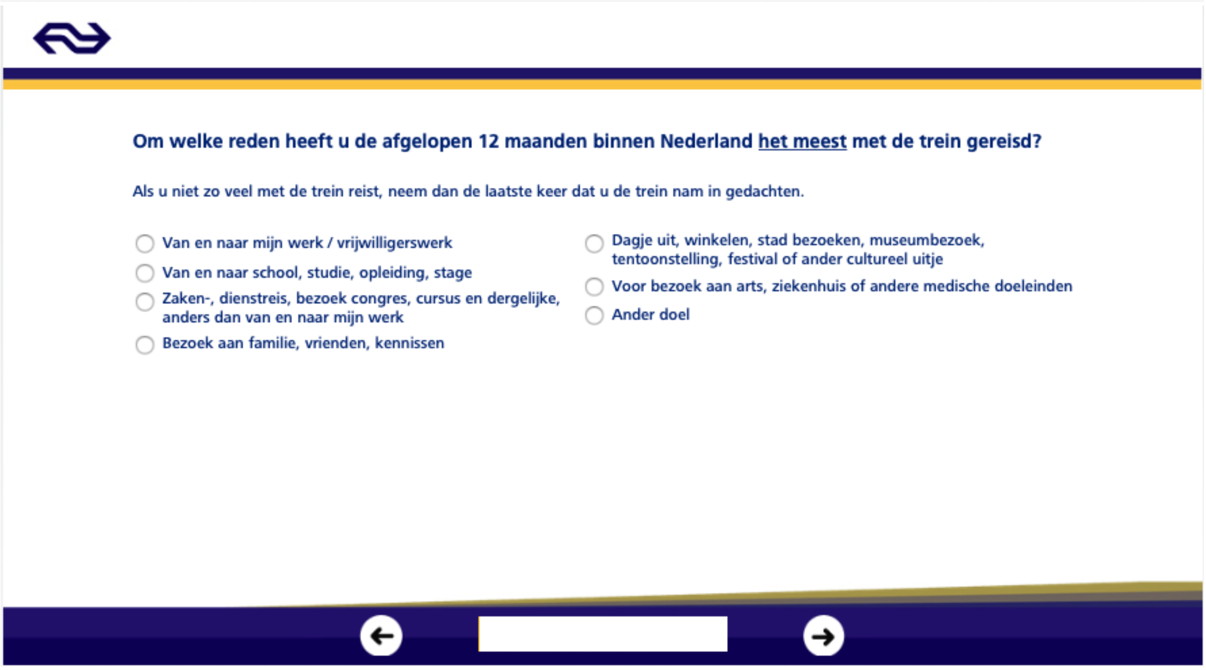

Welkom!

Fijn dat u mee wilt doen aan dit onderzoek over reisgedrag van en naar een treinstation!

Om te bepalen wat voor type treinreiziger u bent, volgen eerst een paar vragen over uw treinreizen.

Hoe vaak heeft u de afgelopen 12 maanden binnen Nederland met de trein gereisd?

- 4 dagen per week of meer
- 1 tot 3 dagen per week
- 1 tot 3 dagen per maand
- 6 tot 11 dagen in de afgelopen 12 maanden
- 3 tot 5 dagen in de afgelopen 12 maanden
- 1 of 2 dagen in de afgelopen 12 maanden


Om welke reden heeft u de afgelopen 12 maanden binnen Nederland het meest met de trein gereisd?

Als u niet zo veel met de trein reist, neem dan de laatste keer dat u de trein nam in gedachten.

- Van en naar mijn werk / vrijwilligerswerk
- Van en naar school, studie, opleiding, stage
- Zaken-, dienstreis, bezoek congres, cursus en dergelijke, anders dan van en naar mijn werk
- Bezoek aan familie, vrienden, kennissen
- Dagje uit, winkelen, stad bezoeken, museumbezoek, tentoonstelling, festival of ander cultureel uitje
- Voor bezoek aan arts, ziekenhuis of andere medische doeleinden
- Ander doel

Reist u meestal op een vast traject met de trein of is uw bestemming sterk wisselend?

- Meestal op een vast traject
- Ik reis met wisselende bestemmingen

Hoelang duurde de totale treinrit tijdens uw laatste treinreis?

Het gaat hier om de totale reistijd met de trein, dus inclusief eventuele overstappen tussen treinen.

- minder dan 20 minuten
- 20 tot 40 minuten
- meer dan 40 minuten

Verderop in deze vragenlijst wordt u gevraagd om een keuze te maken tussen verschillende vervoersmiddelen.

Daarbij kunt u onder andere kiezen uit gedeelde vervoersmiddelen.

Over deze vervoersmiddelen volgt hieronder een korte uitleg.

De deelfiets

Een deelfiets is een huurfiets die u voor een beperkt tarief ook voor enkel ritje kunt huren en vaak niet per sé op dezelfde plek hoeft in te leveren. Sommige deelfietsen hebben een slim slot dat u met een app of code kunt ontgrendelen waarna u er op kunt fietsen.

Voorbeelden van deelfietsen in Nederland

Donkey Republic
(o.a in Amsterdam, Rotterdam, Haarlem)

OV fiets
(landelijk)

Mobike
(Delft, Rotterdam)

Keobike
(o.a. in Amersfoort, Arnhem, Apeldoorn, Harderwijk)

Hoe bekend bent u met het concept deelfiets?

- ◯ Ik heb wel eens een deelfiets gebruikt
- ◯ Ik heb van deelfietsen gehoord maar nooit een gebruikt
- ◯ Ik heb nog nooit van deelfietsen gehoord

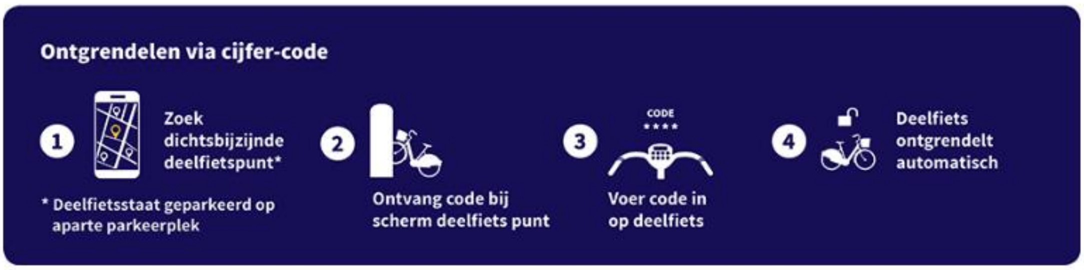
Hoe vaak maakt u gebruik van een deelfiets?

- ◯ 4 dagen of meer per maand
- ◯ 1 tot 3 dagen per maand
- ◯ 6 tot 11 dagen in de afgelopen 12 maanden
- ◯ 1 tot 5 dagen in de afgelopen 12 maanden
- ◯ Één of meerdere keren meer dan 12 maanden geleden

Ontgrendelen van een deelfiets

U kunt straks **kiezen** uit **twee soorten deelfietsen**. De deelfietsen verschillen in hoe u ze kunt **ontgrendelen**.
Hieronder is uitgelegd hoe dat werkt.

Lees deze informatie goed door!



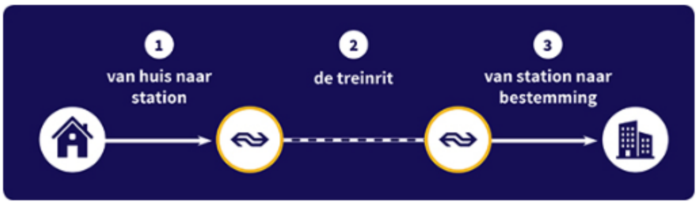
Not included: explanations of shared car and shared e-scooter. They are similar to the explanation of the shared bike.

Het volgende deel van de vragenlijst gaat over een denkbeeldige treinreis.

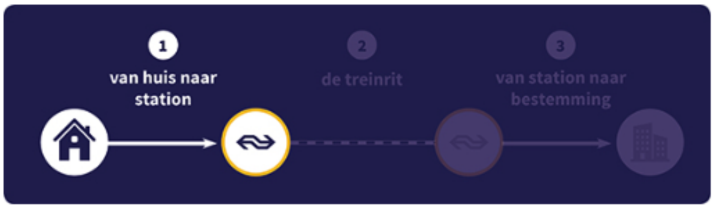
Stel u gaat een treinreis maken om ***een museum/sportwedstrijd/concert te bezoeken***

- De eindbestemming ligt op een locatie ***waar u nog niet eerder bent geweest***.
- U vertrekt ***buiten de spits***
- De treinreis duurt ongeveer ***30 minuten***
- Het is droog weer en u neemt alleen een handtas of rugzak mee.

Uw reis kan worden opgedeeld in drie delen:



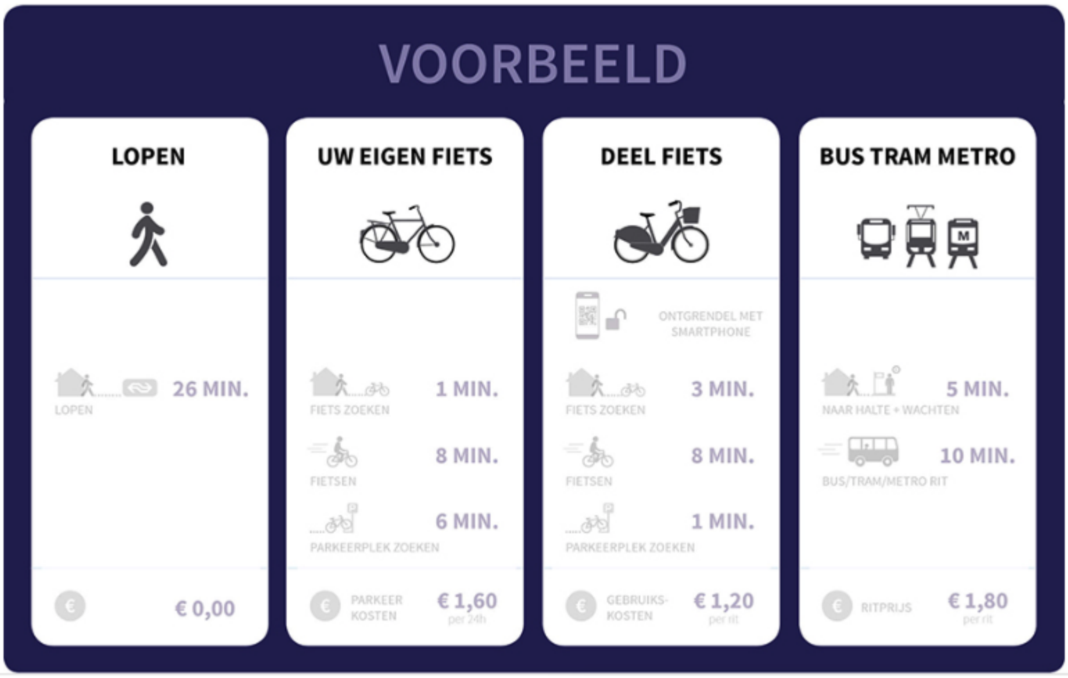
In dit gedeelte van de vragenlijst ligt de focus op het **eerste stuk** van uw reis:



Stelt u zich voor dat de afstand van uw huis naar het station **kilometer** is.

Op de volgende pagina wordt u gevraagd om voor **dit gedeelte van uw reis** een vervoersmiddel te kiezen.

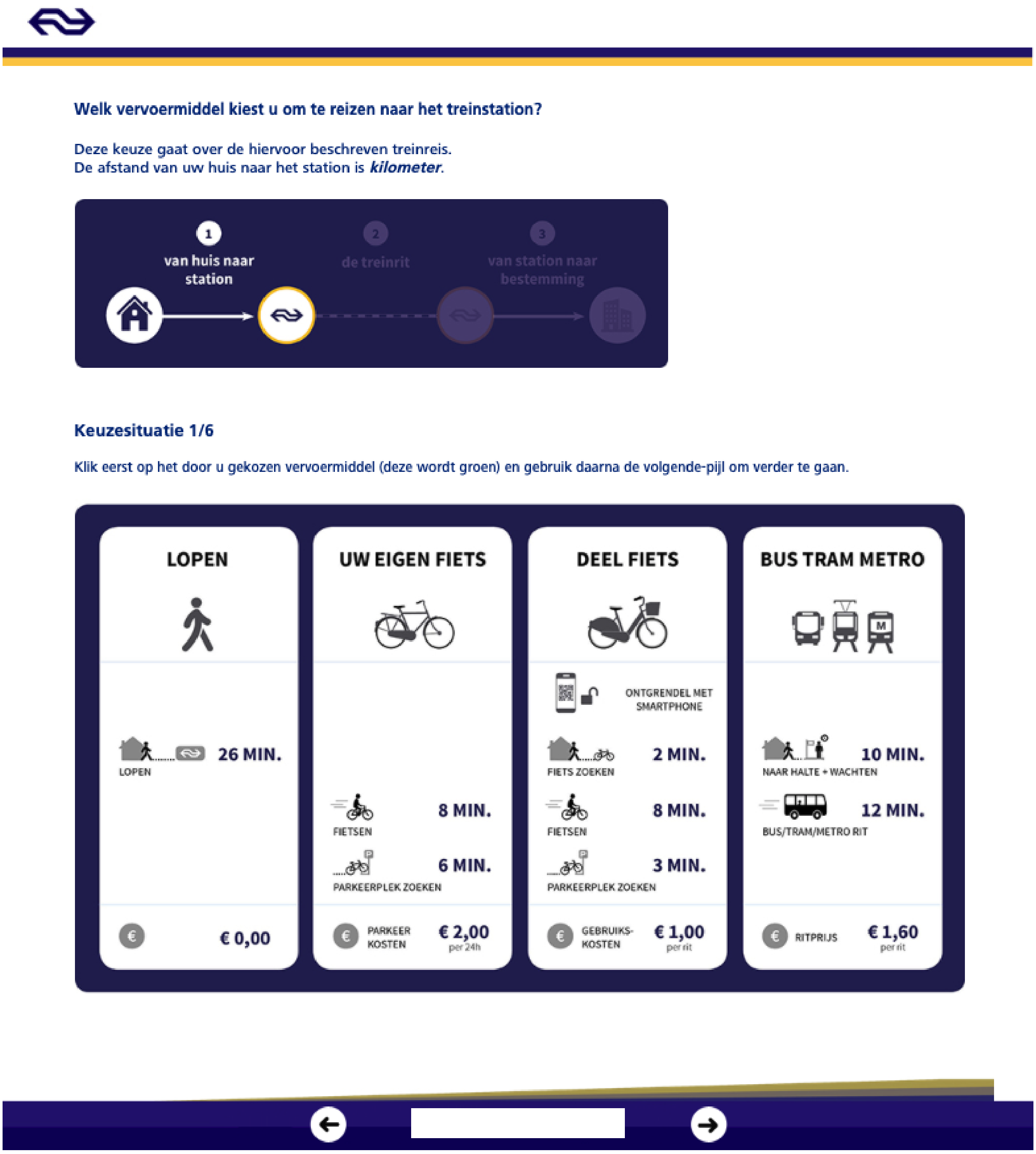
U kunt kiezen uit vier opties: lopen, uw eigen fiets, een deel fiets, of bus/tram/metro.



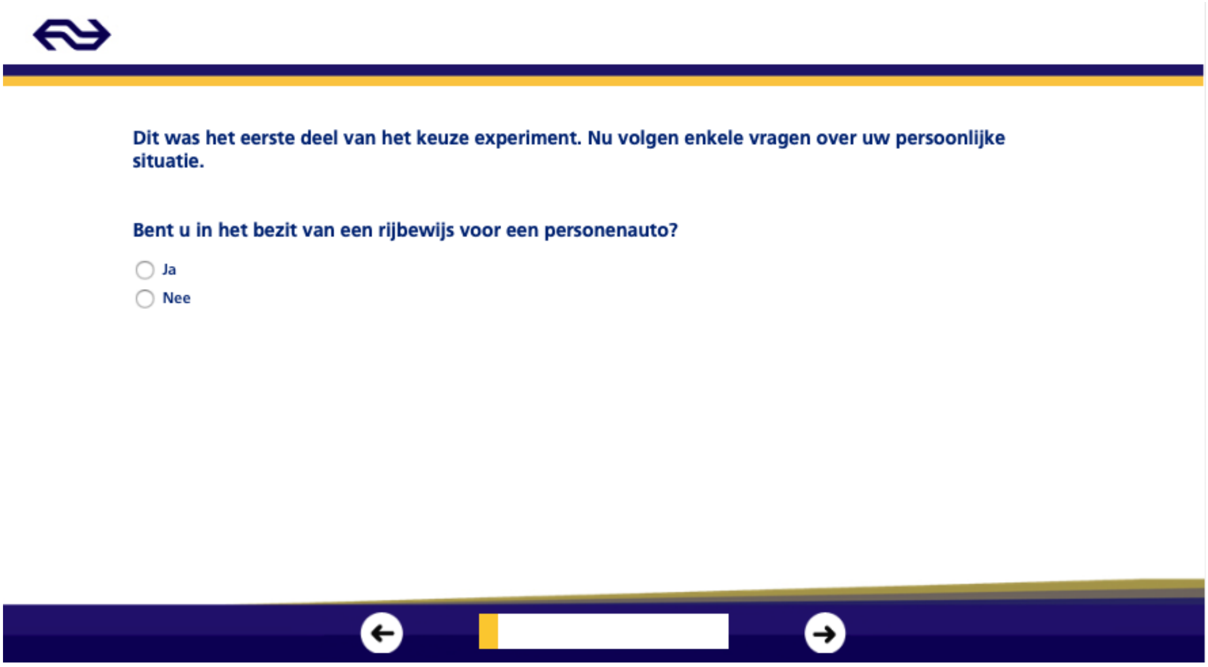
Voor iedere optie staan de **reistijd, kosten en manier van ontgrendelen** aangegeven. Deze **variëren per keer** dat u een keuze maakt.

Het voorbeeld hieronder laat de reistijd, kosten en manier van ontgrendelen zien voor de deelfiets optie.

Klik op volgende-pijl om het keuze experiment te starten



Followed by 5 other choice situations with different attribute levels.



Dit was het eerste deel van het keuze experiment. Nu volgen enkele vragen over uw persoonlijke situatie.

Bent u in het bezit van een rijbewijs voor een personenauto?

- Ja
- Nee

Heeft u binnen uw huishouden beschikking over een auto?

- Ja, wanneer ik wil
- Ja, alleen ik moet dit wel afstemmen met huishouden
- Nee, maar ik kan soms lenen van vrienden of familie
- Nee, nooit

Wat is uw hoogst afgeronde opleidingsniveau?

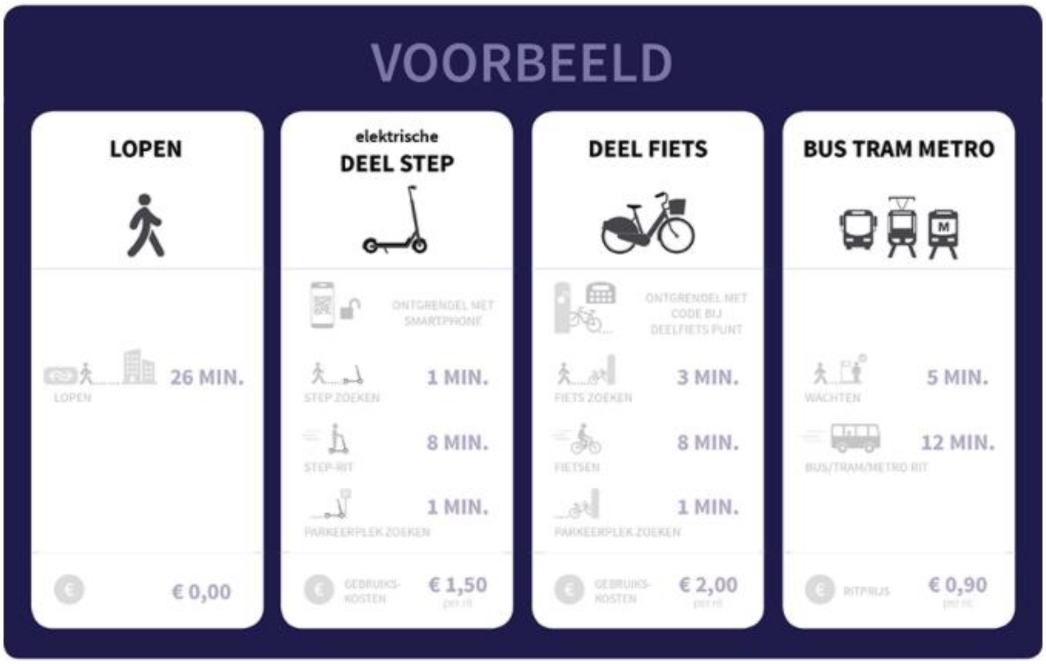
- Geen of Lagere school
- VMBO / MAVO / LBO
- MBO
- HAVO / VWO
- HBO
- Universiteit of hoger
- Wil niet zeggen

In dit gedeelte van de vragenlijst ligt de focus op het **laatste stuk** van uw reis:

Stelt u zich voor dat de afstand van het station naar uw eindbestemming **kilometer** is.

Op de volgende pagina wordt u gevraagd om voor **dit gedeelte van uw reis** een vervoersmiddel te kiezen.

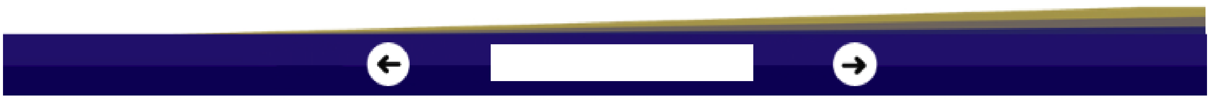
U kunt kiezen uit vier opties: lopen, een deel step, een deel fiets, of bus/tram/metro.



Voor iedere optie staan de **reistijd, kosten en manier van ontgrendelen** aangegeven. Deze **variëren per keer** dat u een keuze maakt.

Het voorbeeld hieronder laat de reistijd, kosten en manier van ontgrendelen zien voor de deelstep optie.

Klik op volgende-pijl om het keuze experiment te starten

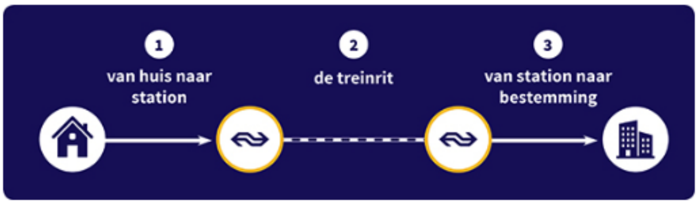


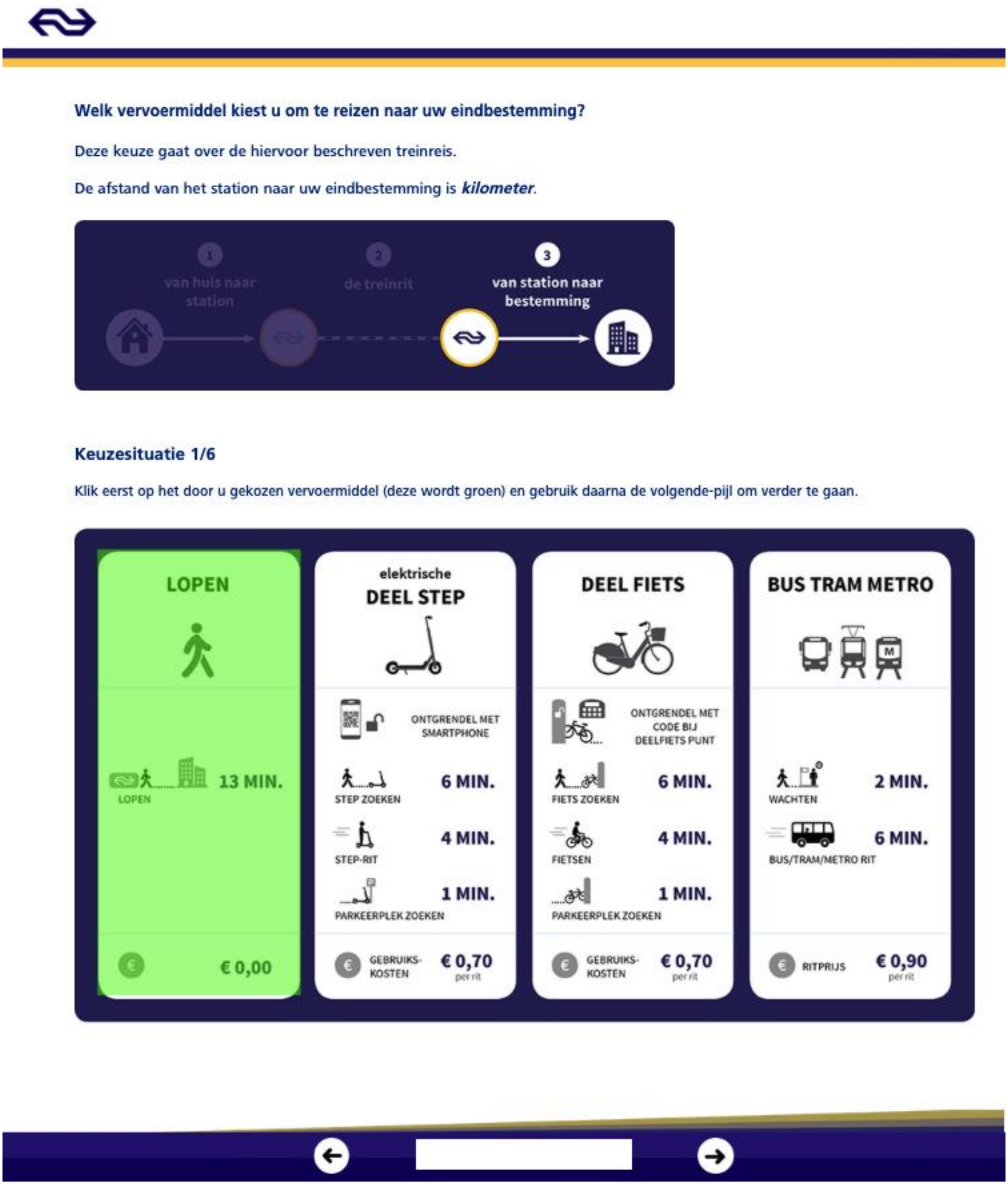
Herinnering:

U gaat een treinreis maken voor een ***een museum/sportwedstrijd/concert te bezoeken***

- De eindbestemming ligt op een locatie ***waar u nog niet eerder bent geweest***.
- U vertrekt ***buiten de spits***
- De treinreis duurt ongeveer ***30 minuten***
- Het is droog weer en u neemt alleen een handtas of rugzak mee.

De volgende vragen gaan over het laatste gedeelte van uw reis.





Followed by 5 other choice situations.

Tot zover het keuze experiment. Nu volgen nog enkele stellingen.

In hoeverre bent u het eens met de volgende stellingen?

	Helemaal mee oneens	Mee oneens	Niet eens/niet oneens	Mee eens	Helemaal mee eens
Ik leen mijn eigen spullen liever niet uit.	○	○	○	○	○
Ik sta ervoor open om nieuwe manieren van reizen te proberen.	○	○	○	○	○
Ik hecht waarde aan mijn privacy in de auto of op de fiets.	○	○	○	○	○
Mijn familie en vrienden vragen mij vaak om advies over digitale producten en diensten.	○	○	○	○	○

In hoeverre bent u het eens met de volgende stellingen?

	Helemaal mee oneens	Mee oneens	Niet eens/niet oneens	Mee eens	Helemaal mee eens
(smartphone) Apps helpen mij in het dagelijks leven	○	○	○	○	○
Ik probeer nieuwe diensten, zoals Netflix of Uber, eerder uit dan mijn vrienden en familie.	○	○	○	○	○
Ik zou graag het gemak van een auto willen hebben, zonder dat ik zelf een auto bezit.	○	○	○	○	○
Het maakt mij niet uit met welk vervoersmiddel ik reis, zolang het maar geschikt is voor de reis die ik wil maken.	○	○	○	○	○

Bent u in het bezit van een smartphone?

- ◯ Ja
- ◯ Nee

Hoe vaak gebruikt u uw smartphone om verschillende reismogelijkheden af te wegen?

- ◯ Bij (bijna) iedere reis
- ◯ Bij ongeveer de helft van mijn reizen
- ◯ Bij ongeveer een kwart van mijn reizen
- ◯ (bijna) Nooit

Welk vervoermiddel gebruikt u meestal om vanaf huis naar het treinstation te reizen?

U kunt meerdere antwoorden geven.

- ☐ Lopend
- ☐ Eigen fiets, vouwfiets
- ☐ Deelfiets
- ☐ Eigen of deel- scooter
- ☐ Bus, tram, metro
- ☐ Eigen auto (bestuurder)
- ☐ Eigen auto (passagier)
- ☐ Deelauto
- ☐ Taxi
- ☐ Anders, namelijk

Welk vervoermiddel gebruikt u meestal om vanaf uw aankomststation naar uw eindbestemming te reizen?

U kunt meerdere antwoorden geven.

- ☐ Lopend
- ☐ Eigen fiets, vouwfiets
- ☐ Deelfiets
- ☐ Eigen of deel- scooter
- ☐ Bus, tram, metro
- ☐ Eigen auto (bestuurder)
- ☐ Eigen auto (passagier)
- ☐ Deelauto
- ☐ Taxi
- ☐ Anders, namelijk

Wat is het bruto jaarinkomen van uw gehele huishouden?

- ○ Minder dan modaal (< € 35.000)
- ○ 1 tot 2 keer modaal (€ 35.000 – € 70.000)
- ○ Meer dan 2 keer modaal (> € 70.000)
- ○ Weet niet/ wil ik niet zeggen

Bijna klaar! Als afsluiting kunt u hieronder uw mening geven over deze vragenlijst.

Wat is uw algemeen oordeel over deze vragenlijst?

1 = zeer slecht, 10 = uitmuntend

1 2 3 4 5 6 7 8 9 10

Hoe duidelijk vond u de keuze situaties met de verschillende vervoersopties?

- ○ Heel onduidelijk
- ○ Onduidelijk
- ◉ Neutraal
- ○ Duidelijk
- ○ Heel duidelijk

Heeft u verder nog opmerkingen over deze vragenlijst?

Dit is het einde van deze enquête. Uw antwoorden zijn verzonden.

Bedankt voor uw deelname! 😃

Wilt u kans maken op **één van de vijf tegoedbonnen** voor de ***Spoordeelwinkel*** ter waarde van € 100,- ? Vul dan hieronder uw e-mailadres in.

De winnaars worden per email op de hoogte gesteld.

Uw e-mailadres:

E Descriptive statistics

E.1 Model portfolio's

Table 0-10 Complete modal portfolios of the HB experiments

DISTANCE 2 KM (n = 940)	%	rel. %
Fixed preference	**55 %**	
Own bike	31 %	(58%)
Walk	13 %	(23%)
BTM	10 %	(19%)
Shared bike	0,3 %	(1%)
Choosing between 2 modes	**31%**	
Walk / own bike	10%	(31%)
Own bike / shared bike	9%	(30%)
Own bike / BTM	7%	(23%)
Walk / BTM	4%	(14%)
Shared bike / BTM	0,4%	(1%)
Walk / shared bike	0,2%	(1%)
Choosing between 3 modes	**11%**	
Own bike / shared bike / BTM	5%	(51%)
Walk / own bike / BTM	3%	(28%)
Walk / own bike / shared bike	2%	(18%)
Walk / shared bike / BTM	0%	(3%)
Choosing between all 4 modes	**3%**	

DISTANCE 4 KM (n = 895)	%	rel. %
Fixed preference	**60%**	
Own bike	35%	(59%)
BTM	19%	(32%)
Own car	5%	(9%)
Shared bike	0,4%	(1%)
Choosing between 2 modes	**25%**	
Own bike / BTM	9%	(38%)
Own bike / shared bike	8%	(30%)
own bike / own car	4%	(16%)
BTM / own car	3%	(10%)
Shared bike / BTM	1%	(4%)
Shared bike /own car	0,4%	(2%)
Choosing between 3 modes	**12%**	
Own bike / shared bike / BTM	6%	(48%)
Own car /own bike / BTM	3%	(27%)
Own car / own bike / shared bike	3%	(23%)
Own car / shared bike / BTM	0%	(2%)
Choosing between all 4 modes	**3%**	

Table 0-11 - Complete modal portfolios of the AB experiments

	1 KM (n = 599)		2 KM (n = 621)	
	%	rel. %	%	rel. %
Fixed preference	**60 %**		**53 %**	
Walk	49 %	(%)	21 %	(%)
BTM	9 %	(%)	27 %	(%)
Shared bike	2 %	(%)	4 %	(%)
Scooter	1 %	(%)	1 %	(%)
Choosing between 2 modes	**22%**		**30%**	
Walk / BTM	15%	(%)	15%	(%)
Walk / shared bike	3%	(%)	2%	(%)
Walk / step	2%	(%)	0%	(%)
Shared bike / BTM	1%	(%)	10 %	(%)
Step / BTM	0,5%	(%)	1 %	(%)
Step / shared bike	0,5%	(%)	2%	(%)
Choosing between 3 modes	**13%**		**14%**	
Walk / shared bike / BTM	6%	(%)	5 %	(%)
Walk / step / shared bike	4%	(%)	1 %	(%)
Step / shared bike / BTM	1%	(%)	7%	(%)
Walk / step / BTM	1%	(%)	1%	(%)
Choosing between all 4 modes	**5 %**		**3 %**	

	4 KM (n = 615)	
DISTANCE 4 KM (n = 895)	%	rel. %
Fixed preference	**60%**	
BTM	51%	(%)
Shared bike	8%	(%)
Shared car	0.7%	(%)
Choosing between 2 modes	**29%**	
Shared bike / BTM	22%	(%)
BTM / shared car	5%	(%)
Shared bike / shared car	2%	(%)
Choosing between all 3 modes	**10%**	

E.2 Contingency tables

This appendix contains the Chi Square contingency tables that are calculated as part of the performed Chi Square Tests of Independent as discussed in Section 6.1.3.

Table 0-12 Contingency table Chi Square test of independence with variable age.

PREFERENCE	COUNT	AGE CATEGORY							
		16-25	26-35	36-45	46-55	56-65	66-75	75+	All
Non-fixed	Observed	101	156	145	185	222	213	55	1077
	Expected	70	125	116	168	236	278	84	1077
Fixed	Observed	18	57	52	102	180	261	89	759
	Expected	49	88	81	119	166	196	60	759
All		119	213	197	287	402	474	144	1836
	% of total	6%	12%	11%	16%	22%	26%	8%	

Table 0-13 Contingency table Chi Square test of independence with variable education level.

PREFERENCE	COUNT	EDUCATION LEVEL						
		≤ Primary school	VMBO	MBO	HAVO / VWO	HBO	≥ University	All
Non-fixed	Count	11	65	145	115	364	346	221
	Expected	11	79	166	122	366	303	256
Fixed	Count	8	69	137	93	258	169	214
	Expected	8	55	116	86	256	212	179
All		19	134	282	208	622	515	435
	% of total	4%	31%	65%	48%	143%	118%	

Table 0-14 Contingency table Chi Square test of independence with variable travel purpose.

PREFERENCE	COUNT	TRAVEL PURPOSE							
		Other purpose	Social	Day out	Medical	School	Work	Business	All
Non-fixed	Count	38	263	315	13	60	297	92	1078
	Expected	42	276	349	14	46	279	72	1078
Fixed	Count	34	207	279	11	19	179	30	759
	Expected	30	194	245	10	33	197	50	759
All		72	470	594	24	79	476	122	1837
	% of total	4%	26%	32%	1%	4%	26%	7%	

Table 0-15 Contingency table Chi Square test of independence with variable travel frequency.

PREFERENCE	COUNT	TRAVEL PURPOSE						
		1-2 d/yr	3-5 d/yr	6-11 d/yr	1-3 ds/mth	1-3 d/wk	≥4 d/wk	All
Non-fixed	Count	54	102	246	278	196	202	1078
	Expected	59	114	278	266	187	174	1078
Fixed	Count	46	92	228	176	123	94	759
	Expected	41	80	196	188	132	122	759
All		100	194	474	454	319	296	1837
	% of total	5%	11%	26%	25%	17%	16%	

F Model results

F.1 Dummy coding

To be able to include all measured variables from the survey, categorical variables were recoded into indicator variables. This allows the nominal and ordinal variables to be included into the numerical choice models. All socio-demographic variables, context variables, and the attribute unlocking method were dummy coded into indicator variables with 2 or 3 levels. An example is shown in Table AAA.

Table 0-16 - Example of dummy coding: variable travel frequency

	Indicator variables	
Categories	**FREQUENCY1**	**FREQUENCY2**
1-2 days/year	0	0
3-5 days/year	0	0
6-11 days/year	1	0
1-3 days/month	1	0
1-3 days/week	0	1
≥4 days/week	0	1

Table 0-17 – dummy coding of all included interaction variables

NAME	HB	AB	CODING
AGE	Yes	Yes	16-35 = 0, 36-65=1, 65+=2
GENDER	Yes	Yes	M=0, V=1
INCOME	Yes	Yes	< modaal = 0, modaal = 1, > modaal = 2
EDUCATION LVL	Yes	Yes	≤MBO = 0, HBO = 1, WO = 2
TRAIN TRAVEL FREQUENCY	Yes	Yes	1 of 2 dagen in de afgelopen 12 maanden = 0 3 tot 5 dagen in de afgelopen 12 maanden = 0 1 tot 3 dagen per maand = 1 6 tot 11 dagen in de afgelopen 12 maanden = 1 1 tot 3 dagen per week = 2 4 dagen per week of meer = 2
TRAIN TRAVEL MOTIVE	Yes	Yes	sociaal-recreatief = 0, werk/school/zakelijk = 1
DURATION TRAIN TRIP	Yes	Yes	meer dan 40 minuten = 1 (60 min in exp.) minder dan 40 minuten = 0 (30 min in exp.)
USAGE SHARED BIKE	Yes	Yes	Never heard of = 0 Head of, never used = 1 Used = 2
USAGE SHARED CAR	No	Yes	Never heard of = 0 Head of, never used = 1 Used = 2
USAGE SHARED E-SCOOTER	No	Yes	Never heard of = 0 Head of, never used = 1 Used = 2
DRIVERS LICENSE	No	No	No = 0, Yes = 1
CAR AVAILABILITY	No	No	No = 0, Yes = 1
SMARTPHONE POSSESSION	Yes	Yes	No = 0, Yes = 1
DIGITAL LITERACY	No	No	No significant factor
OPENNESS TO NEW TECHNOLOGY	Yes	Yes	Mean sum score
OPENNESS TO SHARING	No	No	No significant factor
URBAN DENSITY OF RESIDENCE	Yes	No	0=1, 1=2, 2=3 (higher is lower density)

F.2 MNL base models

F.2 Home-based Base MNL model

Biogeme syntax - HB MNL base

```
# # Simple MNL estimation: home-based 2+4 km experiment

import biogeme
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import numpy as np

# Hide all the warnings
import warnings
warnings.filterwarnings('ignore')

# Importing the data
choice_data2 = pd.read_csv('HB2choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data4 = pd.read_csv('HB4choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")

# Convert choices to numeric
def convert_HB2(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Lopen']] = 1
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen fiets']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

def convert_HB4(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen auto']] = 5
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen fiets']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

convert_HB2(choice_data2)
convert_HB4(choice_data4)

# Add dummy variables for distance
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions
def add_av2(df):
    df['AV_WALK'] = 1
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 0

def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 1

add_av2(choice_data2)
add_av4(choice_data4)

# Merge the data
choice_data = pd.concat([choice_data2, choice_data4], axis=0, sort=False)
choice_data = choice_data.replace(np.nan, 0)

# Convert data to biogeme format
database = db.Database("DATA", choice_data)
from headers import *


# ## Model specification

# Parameters to be estimated <br>
# Arguments: name, starting value, lower bound., upper bound., fixed(1) or not(0)

ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-1000,1000,0)

ASC_OWNBIKE_2KM = Beta('ASC_OWNBIKE_2KM',0,-1000,1000,0)
ASC_OWNBIKE_4KM = Beta('ASC_OWNBIKE_4KM',0,-1000,1000,0)
B_PARK_OWNBIKE = Beta('B_PARK_OWNBIKE',0,-1000,1000,0)
B_COST_OWNBIKE = Beta('B_COST_OWNBIKE',0,-1000,1000,0)

ASC_SHBIKE_2KM = Beta('ASC_SHBIKE_2KM',0,-1000,1000,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-1000,1000,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-1000,1000,0)
B_PARK_SHBIKE = Beta('B_PARK_SHBIKE',0,-1000,1000,0)
B_COST_SHBIKE = Beta('B_COST_SHBIKE',0,-1000,1000,0)
B_UNLOCK_SHBIKE = Beta('B_UNLOCK_SHBIKE',0,-1000,1000,0)

B_WAIT = Beta('B_WAIT',0,-1000,1000,0)
B_COST_BTM = Beta('B_COST_BTM',0,-1000,1000,0)

ASC_CAR_4KM = Beta('ASC_CAR_4KM',0,-1000,1000,0)
B_PARK_OWNCAR= Beta('B_PARK_OWNCAR',0,-1000,1000,0)
B_COST_OWNCAR = Beta('B_COST_OWNCAR',0,-1000,1000,0)


# Utility functions

# Walking alt.
V1 = ASC_WALK_2KM * DIST2_DUMMY

# Own bike alt.
V2 = ASC_OWNBIKE_2KM * DIST2_DUMMY + ASC_OWNBIKE_4KM * DIST4_DUMMY +
B_PARK_OWNBIKE * OWN_BIKE_TIME_PARK + B_COST_OWNBIKE * OWN_BIKE_COSTS

# Shared bike alternative.
V3 = ASC_SHBIKE_2KM * DIST2_DUMMY + ASC_SHBIKE_4KM * DIST4_DUMMY +
B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH + B_PARK_SHBIKE * SH_BIKE_TIME_PARK +
B_COST_SHBIKE * SH_BIKE_COSTS + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS

# Own car alt.
V5 = ASC_CAR_4KM * DIST4_DUMMY + B_PARK_OWNCAR * OWN_CAR_TIME_PARK +
B_COST_OWNCAR * OWN_CAR_COSTS


# Associate utility functions with the numbering of alternatives

V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}


# Associate the availability conditions with the alternatives

#AV1 = 1
#AV2 = 1
#AV3 = 1
#AV4 = 1

av = {1: AV_WALK, 2: AV_OWNBIKE, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_OWNCAR}


# Define the contribution to the log likelihood function

logprob = bioLogLogit(V,av,CHOICE)


# ## Model estimation

biogeme = bio.BIOGEME(database,logprob)
biogeme.modelName = "Estimations_MNL_HB24_BASE"

results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations

pandasGeneralStat = results.getGeneralStatistics()
pandasGeneralStat
```

Estimation report - HB MNL Base

Number of estimated parameters:	16
Sample size:	8808
Excluded observations:	0
Init log likelihood:	-12210.48
Final log likelihood:	-9680.547
Likelihood ratio test for the init. model:	5059.868
Rho-square for the init. model:	0.207
Rho-square-bar for the init. model:	0.206
Akaike Information Criterion:	19393.09
Bayesian Information Criterion:	19506.43
Final gradient norm:	1.6373E-01
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	128
Iterations:	117
Data processing time:	0:00:00.000004
Optimization time:	0:00:02.787076
Nbr of threads:	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_CAR_4KM	-1.07	0.161	-6.68	2.47e-11	0.161	-6.65	2.91e-11
ASC_OWNBIKE_2KM	0.919	0.113	8.1	4.44e-16	0.115	8.01	1.11e-15
ASC_OWNBIKE_4KM	0.51	0.12	4.26	2.03e-05	0.12	4.24	2.22e-05
ASC_SHBIKE_2KM	-0.205	0.172	-1.19	0.233	0.173	-1.19	0.235
ASC_SHBIKE_4KM	-0.658	0.176	-3.73	0.000189	0.174	-3.79	0.000153
ASC_WALK_2KM	-0.402	0.107	-3.77	0.000166	0.108	-3.73	0.000194
B_COST_BTM	-0.221	0.0543	-4.07	4.64e-05	0.0543	-4.08	4.6e-05
B_COST_OWNBIKE	-0.285	0.0265	-10.8	0	0.0265	-10.7	0
B_COST_OWNCAR	-0.118	0.0213	-5.57	2.55e-08	0.0217	-5.46	4.82e-08
B_COST_SHBIKE	-1.04	0.0967	-10.8	0	0.0988	-10.5	0
B_PARK_OWNBIKE	-0.0205	0.0105	-1.95	0.0509	0.0105	-1.95	0.051
B_PARK_OWNCAR	-0.0234	0.0249	-0.939	0.348	0.0251	-0.93	0.352
B_PARK_SHBIKE	-0.0704	0.0221	-3.19	0.00144	0.0218	-3.22	0.00127
B_SEARCH_SHBIKE	-0.0562	0.0271	-2.07	0.038	0.0276	-2.03	0.0419
B_UNLOCK_SHBIKE	-0.0858	0.089	-0.964	0.335	0.0884	-0.971	0.331
B_WAIT	-0.0279	0.00777	-3.6	0.000323	0.00779	-3.59	0.000337

F.3 Activity-based Base MNL model

Biogeme syntax - AB MNL base

```
# # Simple MNL estimation: activity-based 1+2+4 km experiment

# Import packages

import biogeme
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import numpy as np

# Hide all the warnings
import warnings
warnings.filterwarnings('ignore')


# ## Preparing the data
# Import the data

choice_data1 = pd.read_csv('AB1choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data2 = pd.read_csv('AB2choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data4 = pd.read_csv('AB4choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")

# Convert choices to numeric

def convert_AB12(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Lopen']] = 1
    df.CHOICE[df.index[df['Choice'] == 'Step']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

def convert_AB4(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Deelauto']] = 5
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

convert_AB12(choice_data1)
convert_AB12(choice_data2)
convert_AB4(choice_data4)


# Add dummy variables for distance
choice_data1['DIST1_DUMMY'] = 1
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions

def add_av12(df):
    df['AV_WALK'] = 1
    df['AV_STEP'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_SHCAR'] = 0

def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_STEP'] = 0
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_SHCAR'] = 1

add_av12(choice_data1)
add_av12(choice_data2)
add_av4(choice_data4)

# Merge the data

choice_data = pd.concat([choice_data1, choice_data2, choice_data4], axis=0,
sort=False)

choice_data = choice_data.replace(np.nan, 0)
choice_data

# Convert to (special) dataframe for Biogeme

database = db.Database("DATA", choice_data)
from headers import *


# ## Model specification

# Parameters to be estimated <br>
# Arguments: name, starting value, lower bound., upper bound., fixed(1) or not(0)
```

```
ASC_SHBIKE_12KM = Beta('ASC_SHBIKE_12KM',0,-1000,1000,0)
#ASC_SHBIKE_2KM = Beta('ASC_SHBIKE_2KM',0,-1000,1000,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-1000,1000,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-1000,1000,0)
B_COST_SHBIKE = Beta('B_COST_SHBIKE',0,-1000,1000,0)
B_UNLOCK_SHBIKE = Beta('B_UNLOCK_SHBIKE',0,-1000,1000,0)

B_WAIT = Beta('B_WAIT',0,-1000,1000,0)
B_COST_BTM = Beta('B_COST_BTM',0,-1000,1000,0)

ASC_SHCAR = Beta('ASC_SH_CAR',0,-1000,1000,0)
B_SEARCH_SHCAR = Beta('B_SEARCH_SH_CAR',0,-1000,1000,0)
B_COST_SHCAR = Beta('B_COST_SH_CAR',0,-1000,1000,0)
B_UNLOCK_SHCAR = Beta('B_UNLOCK_SH_CAR',0,-1000,1000,0)

# Utility functions

# Walking alt.
V1 = ASC_WALK_1KM * DIST1_DUMMY + ASC_WALK_2KM * DIST2_DUMMY

# Own bike alt.
V2 = ASC_STEP_1KM * DIST1_DUMMY + ASC_STEP_2KM * DIST2_DUMMY      +
B_SEARCH_STEP * STEP_TIME_SEARCH      + B_COST_STEP * STEP_COSTS      +
B_UNLOCK_STEP * STEP_UNLOCK

# Shared bike alternative (without access comp. for now)
V3 = ASC_SHBIKE_12KM * DIST1_DUMMY + ASC_SHBIKE_12KM * DIST2_DUMMY +
ASC_SHBIKE_4KM * DIST4_DUMMY      + B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH
+ B_COST_SHBIKE * SH_BIKE_COSTS      + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT      + B_COST_BTM * BTM_COSTS

V5 = ASC_SHCAR      + B_SEARCH_SHCAR * SH_CAR_TIME_SEARCH      + B_COST_SHCAR
* SH_CAR_COSTS      + B_UNLOCK_SHCAR * SH_CAR_UNLOCK


# Associate utility functions with the numbering of alternatives
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternatives
#AV1 = 1
#AV2 = 1
#AV3 = 1
#AV4 = 1

av = {1: AV_WALK, 2: AV_STEP, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_SHCAR}

# Define the contribution to the log likelihood function
logprob = bioLogLogit(V,av,CHOICE)


# ## Model estimation

biogeme = bio.BIOGEME(database,logprob)
biogeme.modelName = "Estimations_MNL_AB124_BASE02"

# Running the estimation

results = biogeme.estimate()

# Read the results

pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations

pandasGeneralStat = results.getGeneralStatistics()
pandasGeneralStat
```

Estimation report - AB MNL Base

Number of estimated parameters:	18
Sample size:	8808
Excluded observations:	0
Init log likelihood:	-11371.6
Final log likelihood:	-8282.534
Likelihood ratio test for the init. model:	6178.132
Rho-square for the init. model:	0.272
Rho-square-bar for the init. model:	0.27
Akaike Information Criterion:	16601.07
Bayesian Information Criterion:	16728.57
Final gradient norm:	1.6157E-01
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	149
Iterations:	127
Data processing time:	0:00:00.000003
Optimization time:	0:00:03.444062
Nbr of threads:	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_SHBIKE_12KM	-0.707	0.143	-4.96	7.15e-07	0.145	-4.87	1.13e-06
ASC_SHBIKE_4KM	-0.595	0.167	-3.56	0.000377	0.169	-3.53	0.000421
ASC_SH_CAR	-1.58	0.249	-6.33	2.38e-10	0.262	-6.01	1.91e-09
ASC_STEP_1KM	-0.556	0.216	-2.57	0.0102	0.224	-2.48	0.013
ASC_STEP_2KM	-0.984	0.248	-3.96	7.48e-05	0.245	-4.02	5.81e-05
ASC_WALK_1KM	0.411	0.0948	4.34	1.42e-05	0.0947	4.34	1.4e-05
ASC_WALK_2KM	-1.25	0.103	-12.2	0	0.104	-12	0
B_COST_BTM	-0.413	0.0546	-7.57	3.8e-14	0.055	-7.51	6e-14
B_COST_SHBIKE	-0.678	0.0556	-12.2	0	0.0565	-12	0
B_COST_SH_CAR	-0.558	0.056	-9.96	0	0.0583	-9.57	0
B_COST_STEP	-0.936	0.111	-8.41	0	0.112	-8.32	0
B_SEARCH_SHBIKE	-0.037	0.0186	-1.99	0.047	0.0188	-1.97	0.0491
B_SEARCH_SH_CAR	-0.0795	0.0436	-1.83	0.0679	0.0427	-1.86	0.0622
B_SEARCH_STEP	-0.161	0.037	-4.33	1.47e-05	0.0386	-4.15	3.25e-05
B_UNLOCK_SHBIKE	0.0105	0.0608	0.172	0.863	0.0606	0.173	0.863
B_UNLOCK_SH_CAR	0.0255	0.143	0.178	0.859	0.144	0.177	0.86
B_UNLOCK_STEP	0.0525	0.119	0.441	0.659	0.118	0.445	0.657
B_WAIT	-0.0433	0.00718	-6.03	1.66e-09	0.00719	-6.02	1.79e-09

F.3 MNL models with interactions

Best fitting interaction variables were identified by testing multiple combinations of interaction parameters on the base model. First, all possible interactions between the base model and each interaction variable are tested separately. Next, all significant interactions are combined into one model, which is then improved via iterations. Interactions that become insignificant are removed until the final model is obtained. In addition to checking significant also the Likelihood Ratio Test was used (top of the table) to test whether the interactions are significantly contributing to a better fit on the data.

Tested interaction variables:

Name	AB	HB	Dummy coding	Levels	# sign. AB	# sign. HB
Age	Yes	Yes	16-35 = 0, 36-65=1, 65+=2	3	10	10
Gender	Yes	Yes	M=0, V=1	2	1	1
Income	Yes	Yes	< modaal = 0, modaal = 1, > modaal = 2	3	3	4
Education lvl	Yes	Yes	≤MBO = 0, HBO = 1, WO = 2	3	2	6
Train travel frequency	Yes	Yes	1 of 2 dagen in de afgelopen 12 maanden = 0 3 tot 5 dagen in de afgelopen 12 maanden = 0 1 tot 3 dagen per maand = 1 6 tot 11 dagen in de afgelopen 12 maanden = 1 1 tot 3 dagen per week = 2 4 dagen per week of meer = 2	3	0	3
Train travel motive	Yes	Yes	sociaal-recreatief = 0, werk/school/zakelijk = 1	2	2	3
Duration train trip	Yes	Yes	meer dan 40 minuten = 1 (60 min in exp.) minder dan 40 minuten = 0 (30 min in exp.)	2	0	3
Usage shared bike	Yes	Yes	Never heard of = 0 Head of, never used = 1 Used = 2	3	1	4
Usage shared car	Yes	No	Never heard of = 0 Head of, never used = 1 Used = 2	3	1	-
Usage shared e-scooter	Yes	No	Never heard of = 0 Head of, never used = 1 Used = 2	3	1	-
Drivers license	Yes	Yes	No = 0, Yes = 1	2	3	2
Smartphone possession	Yes	Yes	No = 0, Yes = 1	2	2	1
Openness to new technology	Yes	Yes	Mean sum score			
Urban density of residence	No	Yes	0=1, 1=2, 2=3 (higher is lower density)	3	-	8

Home based trip MNL with interactions

Table 0-18 Last part of the iterations made to come to a final interaction model (from left to right). P-values in green are significant on a 95% confidence level.

LL	-9.239		-9.239		-9.264		-9.270		-9.314		-9.339		-9.333	
# parameters	36		35		34		33		29		25		25	
LRS	1,6		-0,098		-49,708		-11,786		-88,616		-50,36		12,208	
Chi square	3,8		3,8		3,8		3,8		9,48		9,48		5,9	
Name	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob, p-value**	**Value**	**Rob. p-value**
ASC_OWNBIKE_2KM	0.603	3,11E-07	0.603	3,12E-07	0.615	1,81E-07	0.615	1,84E-07	0.608	2,50E-07	0.667	1,07E-08	0.667	1,06E-08
ASC_OWNBIKE_4KM	0.185	0,134	0.185	0,134	0.192	0,122	0.193	0,119	0.187	0,131	0.261	0,0328	0.261	0,0329
ASC_OWNCAR_4KM	-1.8	0	-1.8	0	-1.79	0	-1.78	0	-1.91	0	-1.86	0	-1.86	0
ASC_SHBIKE_2KM	-0.845	0,0063	-0.845	0,00633	-0.805	0,00918	-0.809	0,00872	-0.806	0,00904	-0.789	0,0105	-1.02	0,000128
ASC_SHBIKE_4KM	-1.26	4,31E-05	-1.26	4,35E-05	-1.22	7,68E-05	-1.22	7,08E-05	-1.21	9,20E-05	-1.19	0,000111	-1.4	2,05E-07
ASC_WALK_2KM	-0.165	0,2	-0.184	0,102	-0.183	0,105	-0.182	0,107	-0.185	0,101	-0.184	0,103	-0.185	0,101
B_AGE2_ASC_SHBIKE	-1.09	2,22E-16	-1.09	2,22E-16	-1.19	0	-1.19	0	-1.23	0	-1.24	0	-1.18	0
B_AGE2_COST_OWNCAR	0.2	6,11E-13	0.2	6,12E-13	0.176	1,42E-10	0.176	1,54E-10						
B_AGE2_WAIT_BTM	0.0597	2,14E-12	0.0598	2,01E-12										
B_COST_BTM	-0.228	3,04E-05	-0.228	3,06E-05	-0.225	3,64E-05	-0.224	4,05E-05	-0.225	3,54E-05	-0.226	3,35E-05	-0.225	0,0000342
B_COST_OWNBIKE	-0.402	0	-0.402	0	-0.394	0	-0.384	0	-0.382	0	-0.294	0	-0.294	0
B_COST_OWNCAR	-0.339	2,32E-12	-0.339	2,37E-12	-0.327	9,49E-12	-0.328	9,15E-12	-0.123	2,42E-08	-0.122	2,82E-08	-0.122	2,82E-08
B_COST_SHBIKE	-1.07	0	-1.07	0	-1.07	0	-1.07	0	-1.07	0	-1.06	0	-1.07	0
B_EDUCATION1_COST_OWNBIKE	0.145	3,65E-05	0.145	3,69E-05	0.147	2,78E-05	0.124	0,000307	0.12	0,000488				
B_EDUCATION2_WAIT_BTM	-0.0276	0,00412	-0.0275	0,00417	-0.0324	0,000682								
B_FAM_SHBIKE2_ASC_OWNBIKE	1.03	0	1.03	0	1.06	0	1.08	0	1.09	0	0.858	0	0.858	0
B_FAM_SHBIKE2_ASC_SHBIKE	0.714	2,32E-12	0.715	2,22E-12	0.722	1,12E-12	0.747	1,57E-13	0.75	1,26E-13	0.754	9,10E-14	0.721	1,48E-12
B_FAM_SHBIKE2_COST_OWNBIKE	-0.182	0,00478	-0.182	0,00474	-0.185	0,00413	-0.185	0,00413	-0.185	0,00419				
B_FREQUENCY2_COST_OWNCAR	-0.175	5,41E-06	-0.175	5,42E-06	-0.174	5,16E-06	-0.173	6,07E-06						
B_INCOME1_COST_OWNBIKE	0.0801	0,0179	0.0801	0,0179	0.0754	0,0251	0.0786	0,0193	0.0765	0,023				
B_MOTIVE_ASC_WALK	-1.01	0	-1	0	-0.967	0	-0.955	0	-0.954	0	-0.951	0	-0.948	0
B_MOTIVE_COST_OWNCAR	0.168	3,81E-07	0.168	3,87E-07	0.167	3,84E-07	0.169	3,39E-07						
B_NEW_TECH_ASC_SHBIKE													0.273	0,00000982
B_PARK_OWNBIKE	-0.0227	0,0338	-0.0227	0,0338	-0.023	0,0313	-0.0229	0,0318	-0.0227	0,0342	-0.0214	0,0457	-0.0213	0,0463
B_PARK_OWNCAR	-0.0303	0,242	-0.0303	0,243	-0.0292	0,259	-0.029	0,264	-0.0249	0,331	-0.0242	0,344	-0.0242	0,344
B_PARK_SHBIKE	-0.0704	0,00145	-0.0705	0,00143	-0.0703	0,00147	-0.0703	0,00146	-0.0704	0,00145	-0.0712	0,00125	-0.0711	0,00126
B_SEARCH_SHBIKE	-0.0617	0,0266	-0.0617	0,0266	-0.0614	0,0271	-0.0613	0,0275	-0.061	0,0283	-0.0608	0,0289	-0.0607	0,0291
B_SMARTPHONE_ASC_SHBIKE	0.714	0,0059	0.714	0,00591	0.714	0,00582	0.72	0,0054	0.718	0,00557	0.704	0,00657		
B_TRIP_DURATION_ASC_WALK	-0.0258	0,758												
B_TRIP_DURATION_COST_OWNCAR	0.121	0,00115	0.121	0,00116	0.12	0,00115	0.121	0,00113						
B_UNLOCK_SHBIKE	-0.0855	0,338	-0.0858	0,336	-0.0873	0,328	-0.0877	0,326	-0.0886	0,321	-0.0913	0,306	-0.0971	0,276
B_URBAN_DENS1_ASC_OWNCAR	0.849	2,57E-08	0.852	2,37E-08	0.839	3,91E-08	0.825	6,29E-08	0.883	3,33E-09	0.779	1,23E-07	0.777	1,31E-07
B_URBAN_DENS1_COST_OWNBIKE	0.177	1,39E-06	0.177	1,37E-06	0.166	5,18E-06	0.159	1,16E-05	0.16	1,08E-05				
B_URBAN_DENS2_ASC_OWNBIKE	0.303	4,95E-06	0.303	4,81E-06	0.286	1,61E-05	0.271	4,11E-05	0.271	4,14E-05	0.188	0,00272	0.189	0,0025
B_URBAN_DENS2_ASC_OWNCAR	1.43	0	1.43	0	1.41	0	1.39	0	1.48	0	1.43	0	1.43	0
B_URBAN_DENS2_ASC_WALK	0.364	0,000518	0.366	0,000479	0.361	0,000578	0.348	0,000913	0.347	0,000951	0.343	0,00106	0.344	0,001
B_WAIT	-0.0449	9,54E-07	-0.0449	9,40E-07	-0.0204	0,0128	-0.0288	0,000243	-0.0288	0,000232	-0.0283	0,000287	-0.0283	0,000287

Estimation results of final interactions HB MNL model

Number of estimated parameters	25
Sample size	8808
Excluded observations	0
Init log likelihood	-12210.48
Final log likelihood	-9332.892
Likelihood ratio test for the init. model	5755.177
Rho-square for the init. model	0.236
Rho-square-bar for the init. model	0.234
Akaike Information Criterion	18715.78
Bayesian Information Criterion	18892.87
Final gradient norm	1.8286E-01
Diagnostic	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings	233
Iterations	218
Data processing time	0:00:00.000006
Optimization time	0:00:08.698593
Nbr of threads	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_OWNBIKE_2KM	0.667	0.116	5.76	8.23e-09	0.117	5.72	1.06e-08
ASC_OWNBIKE_4KM	0.261	0.122	2.13	0.0329	0.122	2.13	0.0329
ASC_OWNCAR_4KM	-1.86	0.198	-9.39	0	0.2	-9.3	0
ASC_SHBIKE_2KM	-1.02	0.27	-3.79	0.000149	0.268	-3.83	0.000128
ASC_SHBIKE_4KM	-1.4	0.27	-5.17	2.36e-07	0.269	-5.19	2.05e-07
ASC_WALK_2KM	-0.185	0.112	-1.65	0.0987	0.113	-1.64	0.101
B_AGE2_ASC_SHBIKE	-1.18	0.135	-8.74	0	0.132	-8.96	0
B_COST_BTM	-0.225	0.0548	-4.11	3.91e-05	0.0544	-4.14	3.42e-05
B_COST_OWNBIKE	-0.294	0.0269	-10.9	0	0.0269	-10.9	0
B_COST_OWNCAR	-0.122	0.0216	-5.66	1.49e-08	0.022	-5.55	2.82e-08
B_COST_SHBIKE	-1.07	0.0976	-10.9	0	0.0995	-10.7	0
B_FAM_SHBIKE2_ASC_OWNBIKE	0.858	0.0554	15.5	0	0.0553	15.5	0
B_FAM_SHBIKE2_ASC_SHBIKE	0.721	0.103	7.01	2.44e-12	0.102	7.08	1.48e-12
B_MOTIVE_ASC_WALK	-0.948	0.088	-10.8	0	0.0889	-10.7	0
B_NEW_TECH_ASC_SHBIKE	0.273	0.0602	4.54	5.52e-06	0.0618	4.42	9.82e-06
B_PARK_OWNBIKE	-0.0213	0.0107	-2	0.046	0.0107	-1.99	0.0463
B_PARK_OWNCAR	-0.0242	0.0253	-0.956	0.339	0.0256	-0.945	0.344
B_PARK_SHBIKE	-0.0711	0.0223	-3.18	0.00147	0.022	-3.22	0.00126
B_SEARCH_SHBIKE	-0.0607	0.0274	-2.22	0.0267	0.0278	-2.18	0.0291
B_UNLOCK_SHBIKE	-0.0971	0.0901	-1.08	0.281	0.0892	-1.09	0.276
B_URBAN_DENS1_ASC_OWNCAR	0.777	0.147	5.27	1.34e-07	0.147	5.28	1.31e-07
B_URBAN_DENS2_ASC_OWNBIKE	0.189	0.0627	3.02	0.00251	0.0626	3.02	0.0025
B_URBAN_DENS2_ASC_OWNCAR	1.43	0.155	9.23	0	0.154	9.25	0
B_URBAN_DENS2_ASC_WALK	0.344	0.103	3.34	0.000852	0.105	3.29	0.001
B_WAIT	-0.0283	0.00784	-3.62	0.0003	0.00781	-3.63	0.000287

Activity based trip MNL with interactions

Table 0-19 Last part of the iterations made to come to a final interaction model (from left to right).

LL	-8.005		-8.006		-8.008		-8.013		-8.020		-7.952		-7.955	
# parameters	33		32		30		28		26		29		27	
LRS			-3,26		-4,2		-10		-13,6		122,57		0	
chi-square	5,9		3,8		5,9		5,9		5,9		7,8		5,9	
Name	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**	**Value**	**Rob. p-value**
ASC_SHBIKE_12KM	-1.03	2,91E-10	-1.03	2,95E-10	-1.04	1,63E-10	-1.04	1,29E-10	-1.15	2,46E-14	-1.43	2,02E-13	-1.16	1,51E-14
ASC_SHBIKE_4KM	-0.8	1,31E-05	-0.799	1,33E-05	-0.811	8,81E-06	-0.817	7,56E-06	-0.927	7,96E-08	-1.21	1,66E-08	-0.934	6,03E-08
ASC_SHCAR	-1.44	1,78E-07	-1.45	1,67E-07	-1.6	1,27E-09	-1.6	1,23E-09	-1.59	1,57E-09	-4.13	0	-4.05	0
ASC_STEP_1KM	-0.856	0,000387	-0.856	0,000392	-0.858	0,000378	-0.62	0,00562	-0.612	0,00639	-2.99	3,33E-15	-2.96	2,66E-15
ASC_STEP_2KM	-1.26	9,63E-07	-1.26	9,84E-07	-1.26	9,57E-07	-1.04	2,37E-05	-1.03	2,94E-05	-3.35	0	-3.33	0
ASC_WALK_1KM	0.145	0,234	0.145	0,231	0.134	0,264	0.136	0,258	0.166	0,16	0.203	0,0861	0.19	0,108
ASC_WALK_2KM	-1.53	0	-1.53	0	-1.54	0	-1.54	0	-1.51	0	-1.48	0	-1.49	0
B_AGE1_ASC_WALK	0.247	0,00112	0.247	0,00114	0.247	0,00114	0.244	0,00128	0.245	0,00123	0.211	0,00536	0.222	0,00347
B_AGE2_ASC_SHBIKE	-0.623	0,0186	-0.623	0,0187	-0.582	0,0251	-0.57	0,0282						
B_AGE2_ASC_SHCAR	-0.649	0,0628	-0.65	0,0622										
B_AGE2_ASC_WALK	0.795	1,16E-09	0.794	1,20E-09	0.836	1,19E-12	0.843	7,07E-13	0.752	7,33E-15	0.639	6,92E-11	0.667	7,29E-12
B_AGE2_COST_BTM	0.427	4,07E-09	0.427	4,17E-09	0.458	1,04E-14	0.463	4,66E-15	0.388	0	0.332	6,66E-16	0.346	0
B_AGE2_COST_SHBIKE	0.416	0,00146	0.416	0,00148	0.422	0,00119	0.422	0,00121						
B_AGE2_COST_SHCAR	0.25	0,057	0.252	0,0548										
B_COST_BTM	-0.566	0	-0.565	0	-0.574	0	-0.577	0	-0.551	0	-0.534	0	-0.538	0
B_COST_SHBIKE	-0.812	0	-0.812	0	-0.814	0	-0.814	0	-0.715	0	-0.712	0	-0.713	0
B_COST_SHCAR	-0.564	4,64E-13	-0.623	0	-0.563	0	-0.563	0	-0.561	0	-0.574	0	-0.574	0
B_COST_STEP	-0.807	6,05E-11	-0.807	5,95E-11	-0.806	6,22E-11	-0.944	0	-0.943	0	-0.955	0	-0.954	0
B_EDUCATION2_ASC_SHBIKE	0.266	9,71E-05	0.265	9,97E-05	0.265	0,000101	0.263	0,000112	0.261	0,000127	0.269	7,95E-05	0.279	4,10E-05
B_FAM_SHBIKE2_ASC_SHBIKE	0.974	0	0.975	0	0.975	0	0.974	0	0.96	0	0.964	0	0.978	0
B_FAM_SHCAR1_COST_SHCAR	-0.111	0,0794												
B_FAM_STEP2_ASC_STEP	0.84	0,0287	0.841	0,0286	0.838	0,0288	0.847	0,0268	0.865	0,0232	0.581	0,187		
B_INCOME2_ASC_STEP	1.25	0,00146	1.25	0,00147	1.25	0,00151								
B_INCOME2_COST_STEP	-0.737	0,00836	-0.737	0,00839	-0.74	0,00818								
B_MOTIVE_ASC_WALK	-0.365	2,98E-07	-0.364	3,05E-07	-0.365	2,80E-07	-0.374	1,39E-07	-0.371	1,66E-07	-0.339	1,85E-06	-0.346	1,07E-06
B_MOTIVE_WAIT_BTM	-0.0235	0,00858	-0.0234	0,00901	-0.0236	0,00822	-0.0243	0,00641	-0.0237	0,0079	-0.0188	0,0363	-0.0198	0,0267
B_SEARCH_SHBIKE	-0.0372	0,0551	-0.0372	0,0552	-0.0372	0,0551	-0.0372	0,0551	-0.0374	0,0541	-0.0374	0,0537	-0.0373	0,0538
B_SEARCH_SHCAR	-0.0815	0,0612	-0.0811	0,0622	-0.0824	0,0561	-0.0826	0,0557	-0.082	0,0563	-0.0805	0,0656	-0.0808	0,0647
B_SEARCH_STEP	-0.163	2,50E-05	-0.163	2,50E-05	-0.163	2,51E-05	-0.162	2,89E-05	-0.161	2,97E-05	-0.163	2,87E-05	-0.163	2,89E-05
B_UNLOCK_SHBIKE	0.007	0,911	0.00709	0,91	0.00773	0,902	0.00803	0,898	0.0075	0,905	0.00646	0,917	0.00698	0,911
B_UNLOCK_SHCAR	0.0121	0,934	0.0104	0,943	0.0189	0,897	0.0193	0,894	0.023	0,874	0.0339	0,818	0.0334	0,821
B_UNLOCK_STEP	0.0387	0,743	0.0387	0,744	0.0387	0,743	0.0467	0,693	0.0473	0,689	0.0511	0,669	0.0528	0,658
B_WAIT	-0.0355	1,29E-05	-0.0355	1,26E-05	-0.0353	1,39E-05	-0.035	1,61E-05	-0.0352	1,55E-05	-0.0373	4,92E-06	-0.0369	5,82E-06
B_NEW_TECH_ASC_SHBIKE											0.0877	0,0354		
B_NEW_TECH_ASC_SHCAR											0.768	2,88E-13	0.701	4,44E-16
B_NEW_TECH_ASC_STEP											0.707	8,88E-16	0.742	1,23E-12

For the AB interaction model, the same iteration strategy was used as described at the HB interaction model (Table 0-18).

Estimation results of final interactions AB MNL model

Number of estimated parameters:	27
Sample size:	8808
Excluded observations:	0
Init log likelihood:	-11371.6
Final log likelihood:	-7955.112
Likelihood ratio test for the init. model:	6832.976
Rho-square for the init. model:	0.3
Rho-square-bar for the init. model:	0.298
Akaike Information Criterion:	15964.22
Bayesian Information Criterion:	16155.48
Final gradient norm:	2.2799E-01
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	317
Iterations:	279
Data processing time:	0:00:00.000006
Optimization time:	0:00:12.960033
Nbr of threads:	8

NAME	value	std err	t-test	p-value	rob. std err	rob. t-test	rob. p-value
ASC_SHBIKE_12KM	-1.16	0.149	-7.8	6e-15	0.151	-7.69	1.51e-14
ASC_SHBIKE_4KM	-0.934	0.172	-5.42	5.9e-08	0.172	-5.42	6.03e-08
ASC_SHCAR	-4.05	0.44	-9.19	0	0.445	-9.09	0
ASC_STEP_1KM	-2.96	0.357	-8.31	0	0.375	-7.9	2.66e-15
ASC_STEP_2KM	-3.33	0.373	-8.94	0	0.376	-8.86	0
ASC_WALK_1KM	0.19	0.121	1.57	0.116	0.118	1.61	0.108
ASC_WALK_2KM	-1.49	0.128	-11.6	0	0.127	-11.7	0
B_AGE1_ASC_WALK	0.222	0.0788	2.81	0.00494	0.0758	2.92	0.00347
B_AGE2_ASC_WALK	0.667	0.0986	6.77	1.32e-11	0.0974	6.85	7.29e-12
B_AGE2_COST_BTM	0.346	0.0405	8.54	0	0.0407	8.5	0
B_COST_BTM	-0.538	0.057	-9.44	0	0.0572	-9.41	0
B_COST_SHBIKE	-0.713	0.0571	-12.5	0	0.0579	-12.3	0
B_COST_SHCAR	-0.574	0.057	-10.1	0	0.0595	-9.65	0
B_COST_STEP	-0.954	0.113	-8.47	0	0.113	-8.42	0
B_EDUCATION2_ASC_SHBIKE	0.279	0.068	4.1	4.07e-05	0.068	4.1	4.1e-05
B_FAM_SHBIKE2_ASC_SHBIKE	0.978	0.0661	14.8	0	0.0668	14.6	0
B_MOTIVE_ASC_WALK	-0.346	0.0715	-4.83	1.34e-06	0.0709	-4.88	1.07e-06
B_MOTIVE_WAIT_BTM	-0.0198	0.00898	-2.2	0.0277	0.00892	-2.22	0.0267
B_NEW_TECH_ASC_SHCAR	0.742	0.105	7.04	1.91e-12	0.104	7.1	1.23e-12
B_NEW_TECH_ASC_STEP	0.701	0.0801	8.75	0	0.0861	8.15	4.44e-16
B_SEARCH_SHBIKE	-0.0373	0.0192	-1.94	0.0519	0.0194	-1.93	0.0538
B_SEARCH_SHCAR	-0.0808	0.0446	-1.81	0.0696	0.0438	-1.85	0.0647
B_SEARCH_STEP	-0.163	0.0375	-4.34	1.44e-05	0.0389	-4.18	2.89e-05
B_UNLOCK_SHBIKE	0.00698	0.0627	0.111	0.911	0.0624	0.112	0.911
B_UNLOCK_SHCAR	0.0334	0.146	0.228	0.82	0.147	0.226	0.821
B_UNLOCK_STEP	0.0528	0.121	0.438	0.662	0.119	0.443	0.658
B_WAIT	-0.0369	0.00809	-4.57	4.99e-06	0.00814	-4.53	5.82e-06

F.4 Nested Logit models

As explained in Section 6.2.1, two significant nests were identified when extending the base MNL models to nested logit models. These nests are i) a nest between the private bike and shared bike alternative in the HB case and ii) a nest between the shared e-scooter and the shared bike alternative in the AB case. The model syntaxes and estimation reports are presented below.

Home based trip model

Biogeme syntax – HB

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.draws as draws
import biogeme.models as models
import numpy as np

# Hide all the warnings
import warnings
warnings.filterwarnings('ignore')

# Importing the data
choice_data2 = pd.read_csv('HB2choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data4 = pd.read_csv('HB4choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")

# Convert choices to numeric
def convert_HB2(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Lopen']] = 1
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen fiets']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

def convert_HB4(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen auto']] = 5
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen fiets']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

convert_HB2(choice_data2)
convert_HB4(choice_data4)

# Add dummy variables for distance
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions
def add_av2(df):
    df['AV_WALK'] = 1
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 0

def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 1

add_av2(choice_data2)
add_av4(choice_data4)

# Merge the data
choice_data = pd.concat([choice_data2, choice_data4], axis=0, sort=False)
choice_data = choice_data.replace(np.nan, 0)

# Convert data to biogeme format
database = db.Database("DATA", choice_data)
from headers import *


# ## Model specification

# Parameters to be estimated <br>
# Arguments: name, starting value, lower bound., upper bound., fixed(1) or not(0)

ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-1000,1000,0)

ASC_OWNBIKE_2KM = Beta('ASC_OWNBIKE_2KM',0,-1000,1000,0)
ASC_OWNBIKE_4KM = Beta('ASC_OWNBIKE_4KM',0,-1000,1000,0)
```

```
B_WAIT = Beta('B_WAIT',0,-1000,1000,0)
B_COST_BTM = Beta('B_COST_BTM',0,-1000,1000,0)

ASC_CAR_4KM = Beta('ASC_CAR_4KM',0,-1000,1000,0)
B_PARK_OWNCAR= Beta('B_PARK_OWNCAR',0,-1000,1000,0)
B_COST_OWNCAR = Beta('B_COST_OWNCAR',0,-1000,1000,0)


# Utility functions

# Walking alt.
V1 = ASC_WALK_2KM * DIST2_DUMMY

# Own bike alt.
V2 = ASC_OWNBIKE_2KM * DIST2_DUMMY + ASC_OWNBIKE_4KM * DIST4_DUMMY +
B_PARK_OWNBIKE * OWN_BIKE_TIME_PARK + B_COST_OWNBIKE * OWN_BIKE_COSTS

# Shared bike alternative.
V3 = ASC_SHBIKE_2KM * DIST2_DUMMY + ASC_SHBIKE_4KM * DIST4_DUMMY +
B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH + B_PARK_SHBIKE * SH_BIKE_TIME_PARK +
B_COST_SHBIKE * SH_BIKE_COSTS + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS

# Own car alt.
V5 = ASC_CAR_4KM * DIST4_DUMMY + B_PARK_OWNCAR * OWN_CAR_TIME_PARK +
B_COST_OWNCAR * OWN_CAR_COSTS


# Associate utility functions with the numbering of alternatives
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternative
av = {1: AV_WALK, 2: AV_OWNBIKE, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_OWNCAR}

# Definition of nests:
# 1: nests parameter
# 2: list of alternatives
NEST_OWNBIKE_OWNCAR = Beta('NEST_OWNBIKE_OWNCAR',1.5,1.0,10,0)
# NEST_OWNBIKE_SHBIKE = Beta('NEST_OWNBIKE_SHBIKE',1.5,1.0,10,0)

NOT_NEST1 = 1.0, [1]
NOT_NEST2 = 1.0, [3]
NOT_NEST3 = 1.0, [4]
NEST = NEST_OWNBIKE_OWNCAR, [2,5]
nests = NOT_NEST1, NOT_NEST2, NOT_NEST3, NEST

# Define the contribution to the log likelihood function
logprob = models.lognested(V,av,nests,CHOICE)


# ## Model estimation

biogeme = bio.BIOGEME(database,logprob)
biogeme.modelName = "Estimations_NestedLogit_HB24"

results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations

pandasGeneralStat = results.getGeneralStatistics()
pandasGeneralStat
```

Estimation report – HB

Number of estimated parameters:	17
Sample size:	8808
Excluded observations:	0
Init log likelihood:	-12493.71
Final log likelihood:	-9639.877
Likelihood ratio test for the init. model:	5707.656
Rho-square for the init. model:	0.228
Rho-square-bar for the init. model:	0.227
Akaike Information Criterion:	19313.75
Bayesian Information Criterion:	19434.17
Final gradient norm:	2.6720E-01
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	333
Iterations:	309
Data processing time:	0:00:00.000003
Optimization time:	0:00:44.117198
Nbr of threads:	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_CAR_4KM	-1.08	0.161	-6.74	1.55e-11	0.161	-6.73	1.7e-11
ASC_OWNBIKE_2KM	0.856	0.11	7.8	6.44e-15	0.111	7.73	1.07e-14
ASC_OWNBIKE_4KM	0.444	0.116	3.82	0.000136	0.116	3.82	0.000135
ASC_SHBIKE_2KM	0.452	0.114	3.97	7.08e-05	0.115	3.92	8.76e-05
ASC_SHBIKE_4KM	0.0259	0.121	0.215	0.83	0.12	0.215	0.83
ASC_WALK_2KM	-0.401	0.107	-3.76	0.000172	0.108	-3.72	0.000203
B_COST_BTM	-0.221	0.0542	-4.07	4.72e-05	0.0541	-4.08	4.53e-05
B_COST_OWNBIKE	-0.167	0.0288	-5.81	6.23e-09	0.0289	-5.8	6.56e-09
B_COST_OWNCAR	-0.118	0.0213	-5.54	3.09e-08	0.0217	-5.43	5.72e-08
B_COST_SHBIKE	-0.229	0.0485	-4.71	2.48e-06	0.0489	-4.67	2.98e-06
B_PARK_OWNBIKE	-0.0135	0.00491	-2.75	0.00595	0.00491	-2.75	0.00598
B_PARK_OWNCAR	-0.0212	0.0249	-0.854	0.393	0.0251	-0.847	0.397
B_PARK_SHBIKE	-0.0145	0.00572	-2.54	0.011	0.00574	-2.54	0.0112
B_SEARCH_SHBIKE	-0.0142	0.0066	-2.16	0.031	0.00665	-2.14	0.0321
B_UNLOCK_SHBIKE	-0.00851	0.0202	-0.421	0.674	0.0203	-0.418	0.676
B_WAIT	-0.028	0.00775	-3.61	0.00031	0.00776	-3.6	0.000315
NEST_OWNBIKE_SHBIKE	4.69	0.899	5.22	1.83e-07	0.902	5.2	1.99e-07

Activity based trip model

Biogeme syntax – AB

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.draws as draws
import biogeme.models as models
import numpy as np

# Hide all the warnings
import warnings
warnings.filterwarnings('ignore')

# Import the data
choice_data1 = pd.read_csv('AB1choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data2 = pd.read_csv('AB2choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data4 = pd.read_csv('AB4choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")

# Convert choices to numeric
def convert_AB12(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Lopen']] = 1
    df.CHOICE[df.index[df['Choice'] == 'Step']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

def convert_AB4(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Deelauto']] = 5
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

convert_AB12(choice_data1)
convert_AB12(choice_data2)
convert_AB4(choice_data4)

# Add dummy variables for distance
choice_data1['DIST1_DUMMY'] = 1
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions

def add_av12(df):
    df['AV_WALK'] = 1
    df['AV_STEP'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_SHCAR'] = 0

def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_STEP'] = 0
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_SHCAR'] = 1

add_av12(choice_data1)
add_av12(choice_data2)
add_av4(choice_data4)

# Merge the data
choice_data = pd.concat([choice_data1, choice_data2, choice_data4], axis=0,
sort=False)
choice_data = choice_data.replace(np.nan, 0)


# Convert to (special) dataframe for Biogeme

database = db.Database("DATA", choice_data)
from headers import *

# ## Model specification

# Parameters to be estimated <br>
# Arguments: name, starting value, lower bound., upper bound., fixed(1) or not(0)

ASC_WALK_1KM = Beta('ASC_WALK_1KM',0,-1000,1000,0)
ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-1000,1000,0)

ASC_STEP_1KM = Beta('ASC_STEP_1KM',0,-1000,1000,0)
ASC_STEP_2KM = Beta('ASC_STEP_2KM',0,-1000,1000,0)
B_SEARCH_STEP = Beta('B_SEARCH_STEP',0,-1000,1000,0)
B_COST_STEP = Beta('B_COST_STEP',0,-1000,1000,0)
B_UNLOCK_STEP = Beta('B_UNLOCK_STEP',0,-1000,1000,0)

ASC_SHBIKE_12KM = Beta('ASC_SHBIKE_12KM',0,-1000,1000,0)
#ASC_SHBIKE_2KM = Beta('ASC_SHBIKE_2KM',0,-1000,1000,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-1000,1000,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-1000,1000,0)
```

```
# Utility functions

# Walking alt.
V1 = ASC_WALK_1KM * DIST1_DUMMY + ASC_WALK_2KM * DIST2_DUMMY

# Step alt.
V2 = ASC_STEP_1KM * DIST1_DUMMY + ASC_STEP_2KM * DIST2_DUMMY +
B_SEARCH_STEP * STEP_TIME_SEARCH + B_COST_STEP * STEP_COSTS +
B_UNLOCK_STEP * STEP_UNLOCK

# Shared bike alternative
V3 = ASC_SHBIKE_12KM * DIST1_DUMMY + ASC_SHBIKE_12KM * DIST2_DUMMY +
ASC_SHBIKE_4KM * DIST4_DUMMY + B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH +
B_COST_SHBIKE * SH_BIKE_COSTS + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS

# Shared car alt.
V5 = ASC_SHCAR + B_SEARCH_SHCAR * SH_CAR_TIME_SEARCH + B_COST_SHCAR *
SH_CAR_COSTS + B_UNLOCK_SHCAR * SH_CAR_UNLOCK


# Associate utility functions with the numbering of alternatives
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternatives
av = {1: AV_WALK, 2: AV_STEP, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_SHCAR}

# Definition of nests:
# 1: nests parameter
# 2: list of alternatives
NEST_STEP_SHBIKE = Beta('NEST_STEP_SHBIKE',1.5,1.0,10,0)
#  NEST_SHCAR_SHBIKE = Beta('NEST_SHCAR_SHBIKE',1.5,1.0,10,0)

NOT_NEST1 = 1.0, [1]
NOT_NEST2 = 1.0, [2]
NOT_NEST3 = 1.0, [4]
NEST = NEST_SHCAR_SHBIKE, [3,5]
nests = NOT_NEST1, NOT_NEST2, NOT_NEST3, NEST

# Define the contribution to the log likelihood function

# nests component added
logprob = models.lognested(V,av,nests,CHOICE)

# ## Model estimation
biogeme  = bio.BIOGEME(database,logprob)
biogeme.modelName = "Estimations_NestedLogit_AB124"


# Running the estimation
results = biogeme.estimate()

# Read the results
pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations

pandasGeneralStat = results.getGeneralStatistics()
pandasGeneralStat
```

Estimation report – AB

Number of estimated parameters:	19
Sample size:	8808
Excluded observations:	0
Init log likelihood:	-10958.2
Final log likelihood:	-8277.67
Likelihood ratio test for the init. model:	5361.069
Rho-square for the init. model:	0.245
Rho-square-bar for the init. model:	0.243
Akaike Information Criterion:	16593.34
Bayesian Information Criterion:	16727.92
Final gradient norm:	1.8880E-01
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	166
Iterations:	149
Data processing time:	0:00:00.000005
Optimization time:	0:00:18.635585
Nbr of threads:	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_SHBIKE_12KM	-0.656	0.135	-4.88	1.07e-06	0.136	-4.82	1.41e-06
ASC_SHBIKE_4KM	-0.694	0.166	-4.17	3.06e-05	0.168	-4.14	3.49e-05
ASC_SH_CAR	-1.56	0.249	-6.28	3.42e-10	0.263	-5.95	2.66e-09
ASC_STEP_1KM	-0.702	0.184	-3.82	0.000133	0.193	-3.64	0.000275
ASC_STEP_2KM	-1.06	0.195	-5.45	4.96e-08	0.194	-5.46	4.83e-08
ASC_WALK_1KM	0.407	0.0945	4.31	1.62e-05	0.0942	4.32	1.53e-05
ASC_WALK_2KM	-1.23	0.103	-12	0	0.104	-11.8	0
B_COST_BTM	-0.404	0.0545	-7.42	1.18e-13	0.0548	-7.37	1.7e-13
B_COST_SHBIKE	-0.627	0.0561	-11.2	0	0.0564	-11.1	0
B_COST_SH_CAR	-0.558	0.056	-9.96	0	0.0583	-9.57	0
B_COST_STEP	-0.656	0.111	-5.9	3.54e-09	0.118	-5.56	2.75e-08
B_SEARCH_SHBIKE	-0.0337	0.0167	-2.01	0.0442	0.017	-1.98	0.0474
B_SEARCH_SH_CAR	-0.0793	0.0436	-1.82	0.0689	0.0427	-1.86	0.0633
B_SEARCH_STEP	-0.107	0.0299	-3.59	0.000336	0.0323	-3.32	0.000886
B_UNLOCK_SHBIKE	0.0167	0.0542	0.309	0.758	0.0542	0.309	0.757
B_UNLOCK_SH_CAR	0.0295	0.143	0.205	0.837	0.144	0.204	0.838
B_UNLOCK_STEP	-0.0142	0.0858	-0.165	0.869	0.0872	-0.162	0.871
B_WAIT	-0.043	0.00716	-6.01	1.86e-09	0.00716	-6.01	1.85e-09
NEST_STEP_SHBIKE	1.61	0.235	6.83	8.21e-12	0.249	6.45	1.11e-10

F.5 Panel Mixed Logit models

This section presents the model syntaxes and estimation reports of both (HB and AB) panel mixed logit models.

Home based trip model

Biogeme syntax

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.draws as draws
import biogeme.models as models
import numpy as np

# Hide all the warnings
import warnings
warnings.filterwarnings('ignore')

# Importing the data
choice_data2 = pd.read_csv('HB2choices_simple.csv',delimiter=',', encoding = "ISO-8859-1")
choice_data4 = pd.read_csv('HB4choices_simple.csv',delimiter=',', encoding = "ISO-8859-1")

# Convert choices to numeric
def convert_HB2(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Lopen']] = 1
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen fiets']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

def convert_HB4(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen auto']] = 5
    df.CHOICE[df.index[df['Choice'] == 'Uw eigen fiets']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

convert_HB2(choice_data2)
convert_HB4(choice_data4)

# Add dummy variables for distance
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions
def add_av2(df):
    df['AV_WALK'] = 1
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 0

def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 1

add_av2(choice_data2)
add_av4(choice_data4)

# Merge the data
choice_data = pd.concat([choice_data2, choice_data4], axis=0, sort=False)
choice_data = choice_data.replace(np.nan, 0)

# Convert data to biogeme format
database = db.Database("DATA", choice_data)

# Define panel variable (for ML panel effect)
database.panel("ID")

from headers import *

# ## Model specification
# Parameters to be estimated <br>
# Arguments: name, starting value, lower bound., upper bound., fixed(1) or not(0)

ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-1000,1000,0)

ASC_OWNBIKE_2KM = Beta('ASC_OWNBIKE_2KM',0,-1000,1000,0)
ASC_OWNBIKE_4KM = Beta('ASC_OWNBIKE_4KM',0,-1000,1000,0)
B_PARK_OWNBIKE = Beta('B_PARK_OWNBIKE',0,-1000,1000,0)
B_COST_OWNBIKE = Beta('B_COST_OWNBIKE',0,-1000,1000,0)

ASC_SHBIKE_2KM = Beta('ASC_SHBIKE_2KM',0,-1000,1000,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-1000,1000,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-1000,1000,0)
```

```
B_WAIT = Beta('B_WAIT',0,-1000,1000,0)
B_COST_BTM = Beta('B_COST_BTM',0,-1000,1000,0)

ASC_CAR_4KM = Beta('ASC_CAR_4KM',0,-1000,1000,0)
B_PARK_OWNCAR= Beta('B_PARK_OWNCAR',0,-1000,1000,0)
B_COST_OWNCAR = Beta('B_COST_OWNCAR',0,-1000,1000,0)

# Shared error parameters, fix the mean-parameter to 0
SIGMA_OWNBIKE_SHBIKE_M = Beta('SIGMA_OWNBIKE_SHBIKE_M',0,-100,100,1)
SIGMA_OWNBIKE_SHBIKE_STD = Beta('SIGMA_OWNBIKE_SHBIKE_STD',0,-100,100,0)

# Define a random parameter, normally distributed, designed to be used for Monte-Carlo simulation
SIGMA_OWNBIKE_SHBIKE = SIGMA_OWNBIKE_SHBIKE_M + SIGMA_OWNBIKE_SHBIKE_STD * bioDraws('SIGMA_OWNBIKE_SHBIKE','NORMAL')


# Utility functions

# Walking alt.
V1 = ASC_WALK_2KM * DIST2_DUMMY

# Own bike alt.
V2 = ASC_OWNBIKE_2KM * DIST2_DUMMY + ASC_OWNBIKE_4KM * DIST4_DUMMY + B_PARK_OWNBIKE * OWN_BIKE_TIME_PARK + B_COST_OWNBIKE * OWN_BIKE_COSTS + SIGMA_OWNBIKE_SHBIKE

# Shared bike alternative.
V3 = ASC_SHBIKE_2KM * DIST2_DUMMY + ASC_SHBIKE_4KM * DIST4_DUMMY + B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH + B_PARK_SHBIKE * SH_BIKE_TIME_PARK + B_COST_SHBIKE * SH_BIKE_COSTS + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK + SIGMA_OWNBIKE_SHBIKE

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS

# Own car alt.
V5 = ASC_CAR_4KM * DIST4_DUMMY + B_PARK_OWNCAR * OWN_CAR_TIME_PARK + B_COST_OWNCAR * OWN_CAR_COSTS


# Associate utility functions with the numbering of alternatives
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternatives
av = {1: AV_WALK, 2: AV_OWNBIKE, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_OWNCAR}

# Define the contribution to the log likelihood function
# is slightly different for the panel effects model
obsprob = models.logit(V,av,CHOICE)
condprobIndiv = PanelLikelihoodTrajectory(obsprob)
logprob = log(MonteCarlo(condprobIndiv))

# ## Model estimation
biogeme = bio.BIOGEME(database,logprob,numberOfDraws=100)
biogeme.modelName = "Estimations_PanelML_HB24"

results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations

pandasGeneralStat = results.getGeneralStatistics()
pandasGeneralStat
```

Estimation report

Number of estimated parameters:	17
Sample size:	1468
Observations:	8808
Excluded observations:	0
Init log likelihood:	-12210.48
Final log likelihood:	-7012.177
Likelihood ratio test for the init. model:	10396.61
Rho-square for the init. model:	0.426
Rho-square-bar for the init. model:	0.424
Akaike Information Criterion:	14058.35
Bayesian Information Criterion:	14148.31
Final gradient norm:	2.3424E-01
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	171
Iterations:	158
Data processing time:	0:00:00.000005
Number of draws:	1000
Draws generation time:	0:00:00.249947
Optimization time:	3:09:28.047750
Nbr of threads:	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_CAR_4KM	-1.33	0.188	-7.05	1.81e-12	0.18	-7.38	1.54e-13
ASC_OWNBIKE_2KM	1.81	0.303	5.98	2.21e-09	0.355	5.11	3.16e-07
ASC_OWNBIKE_4KM	1.72	0.306	5.63	1.75e-08	0.345	4.99	5.93e-07
ASC_SHBIKE_2KM	0.139	0.327	0.426	0.67	0.364	0.382	0.703
ASC_SHBIKE_4KM	-0.001	0.328	-0.00415	0.997	0.347	-0.00393	0.997
ASC_WALK_2KM	-0.682	0.13	-5.25	1.54e-07	0.135	-5.05	4.37e-07
B_COST_BTM	-0.343	0.0685	-5	5.61e-07	0.0485	-7.07	1.52e-12
B_COST_OWNBIKE	-0.681	0.043	-15.9	0	0.0455	-15	0
B_COST_OWNCAR	-0.133	0.0229	-5.8	6.74e-09	0.0204	-6.51	7.41e-11
B_COST_SHBIKE	-1.1	0.099	-11.1	0	0.0982	-11.2	0
B_PARK_OWNBIKE	-0.0501	0.0161	-3.11	0.00185	0.0136	-3.68	0.000233
B_PARK_OWNCAR	-0.0215	0.0269	-0.8	0.424	0.0199	-1.09	0.278
B_PARK_SHBIKE	-0.0667	0.023	-2.9	0.00375	0.0208	-3.21	0.00134
B_SEARCH_SHBIKE	-0.066	0.0281	-2.34	0.0193	0.0244	-2.69	0.0071
B_UNLOCK_SHBIKE	-0.0638	0.0928	-0.688	0.492	0.0818	-0.78	0.435
B_WAIT	-0.0428	0.00983	-4.35	1.34e-05	0.00673	-6.36	2.04e-10
SIGMA_OWNBIKE_SHBIKE	5.83	0.262	22.3	0	0.286	20.4	0

Activity based trip model

Biogeme syntax

```
import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.draws as draws
import biogeme.models as models
import numpy as np

# Hide all the warnings
import warnings
warnings.filterwarnings('ignore')

# Import the data
choice_data1 = pd.read_csv('AB1choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data2 = pd.read_csv('AB2choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")
choice_data4 = pd.read_csv('AB4choices_simple.csv',delimiter=',', encoding = "ISO-
8859-1")

# Convert choices to numeric
def convert_AB12(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Lopen']] = 1
    df.CHOICE[df.index[df['Choice'] == 'Step']] = 2
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

def convert_AB4(df):
    df['CHOICE'] = 0
    df.CHOICE[df.index[df['Choice'] == 'Deelauto']] = 5
    df.CHOICE[df.index[df['Choice'] == 'Deelfiets']] = 3
    df.CHOICE[df.index[df['Choice'] == 'BTM']] = 4
    del df['Choice']

convert_AB12(choice_data1)
convert_AB12(choice_data2)
convert_AB4(choice_data4)

# Add dummy variables for distance
choice_data1['DIST1_DUMMY'] = 1
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions

def add_av12(df):
    df['AV_WALK'] = 1
    df['AV_STEP'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_SHCAR'] = 0

def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_STEP'] = 0
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_SHCAR'] = 1

add_av12(choice_data1)
add_av12(choice_data2)
add_av4(choice_data4)

# Merge the data
choice_data = pd.concat([choice_data1, choice_data2, choice_data4], axis=0,
sort=False)
choice_data = choice_data.replace(np.nan, 0)

# Convert to (special) dataframe for Biogeme
database = db.Database("DATA", choice_data)

# Define panel variable (for ML panel effect)
database.panel("ID")

from headers import *

# ## Model specification

# Parameters to be estimated <br>
# Arguments: name, starting value, lower bound., upper bound., fixed(1) or not(0)

ASC_WALK_1KM = Beta('ASC_WALK_1KM',0,-1000,1000,0)
ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-1000,1000,0)
```

```
ASC_SHBIKE_12KM = Beta('ASC_SHBIKE_12KM',0,-1000,1000,0)
#ASC_SHBIKE_2KM = Beta('ASC_SHBIKE_2KM',0,-1000,1000,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-1000,1000,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-1000,1000,0)
B_COST_SHBIKE = Beta('B_COST_SHBIKE',0,-1000,1000,0)
B_UNLOCK_SHBIKE = Beta('B_UNLOCK_SHBIKE',0,-1000,1000,0)

B_WAIT = Beta('B_WAIT',0,-1000,1000,0)
B_COST_BTM = Beta('B_COST_BTM',0,-1000,1000,0)

ASC_SHCAR = Beta('ASC_SH_CAR',0,-1000,1000,0)
B_SEARCH_SHCAR = Beta('B_SEARCH_SH_CAR',0,-1000,1000,0)
B_COST_SHCAR = Beta('B_COST_SH_CAR',0,-1000,1000,0)
B_UNLOCK_SHCAR = Beta('B_UNLOCK_SH_CAR',0,-1000,1000,0)

# Shared error parameters, fix the mean-parameter to 0
SIGMA_STEP_SHBIKE_M = Beta('SIGMA_STEP_SHBIKE_M',0,-100,100,1)
SIGMA_STEP_SHBIKE_STD = Beta('SIGMA_STEP_SHBIKE_STD',0,-100,100,0)

# Define a random parameter, normally distributed, designed to be used for Monte-
Carlo simulation
SIGMA_STEP_SHBIKE = SIGMA_STEP_SHBIKE_M + SIGMA_STEP_SHBIKE_STD *
bioDraws('SIGMA_STEP_SHBIKE','NORMAL')


# Utility functions

# Walking alt.
V1 = ASC_WALK_1KM * DIST1_DUMMY + ASC_WALK_2KM * DIST2_DUMMY

# Step alt.
V2 = ASC_STEP_1KM * DIST1_DUMMY + ASC_STEP_2KM * DIST2_DUMMY +
B_SEARCH_STEP * STEP_TIME_SEARCH + B_COST_STEP * STEP_COSTS +
B_UNLOCK_STEP * STEP_UNLOCK + SIGMA_STEP_SHBIKE

# Shared bike alternative
V3 = ASC_SHBIKE_12KM * DIST1_DUMMY + ASC_SHBIKE_12KM * DIST2_DUMMY +
ASC_SHBIKE_4KM * DIST4_DUMMY + B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH +
B_COST_SHBIKE * SH_BIKE_COSTS + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK +
SIGMA_STEP_SHBIKE

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS

# Shared car alt.
V5 = ASC_SHCAR + B_SEARCH_SHCAR * SH_CAR_TIME_SEARCH + B_COST_SHCAR *
SH_CAR_COSTS + B_UNLOCK_SHCAR * SH_CAR_UNLOCK


# Associate utility functions with the numbering of alternatives
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternative
av = {1: AV_WALK, 2: AV_STEP, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_SHCAR}

# Define the contribution to the log likelihood function
# is slightly different for the panel effects model
obsprob = models.logit(V,av,CHOICE)
condprobIndiv = PanelLikelihoodTrajectory(obsprob)
logprob = log(MonteCarlo(condprobIndiv))Probab\' '

# ## Model estimation
biogeme = bio.BIOGEME(database,logprob,numberOfDraws=1000)
biogeme.modelName = "Estimations_PanelML_AB124"

# Running the estimation
results = biogeme.estimate()

# Read the results
pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations

pandasGeneralStat = results.getGeneralStatistics()
pandasGeneralStat
```

Estimation report

Number of estimated parameters:	19
Sample size:	1468
Observations:	8808
Excluded observations:	0
Init log likelihood:	-11371.6
Final log likelihood:	-7055.234
Likelihood ratio test for the init. model:	8632.731
Rho-square for the init. model:	0.38
Rho-square-bar for the init. model:	0.378
Akaike Information Criterion:	14148.47
Bayesian Information Criterion:	14249.01
Final gradient norm:	9.5405E-02
Diagnostic:	b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings:	184
Iterations:	162
Data processing time:	0:00:00.000004
Number of draws:	1000
Draws generation time:	0:00:00.252820
Optimization time:	3:14:38.470431
Nbr of threads:	8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_SHBIKE_12KM	-2.2	0.246	-8.93	0	0.228	-9.64	0
ASC_SHBIKE_4KM	-1.38	0.294	-4.7	2.65e-06	0.289	-4.79	1.68e-06
ASC_SH_CAR	-1.76	0.259	-6.79	1.16e-11	0.23	-7.63	2.35e-14
ASC_STEP_1KM	-2.49	0.305	-8.14	4.44e-16	0.316	-7.87	3.55e-15
ASC_STEP_2KM	-3.02	0.331	-9.11	0	0.315	-9.58	0
ASC_WALK_1KM	0.232	0.104	2.23	0.0259	0.121	1.91	0.056
ASC_WALK_2KM	-1.49	0.117	-12.8	0	0.137	-10.8	0
B_COST_BTM	-0.521	0.062	-8.41	0	0.0523	-9.97	0
B_COST_SHBIKE	-1.19	0.0785	-15.2	0	0.0821	-14.5	0
B_COST_SH_CAR	-0.57	0.0565	-10.1	0	0.0673	-8.47	0
B_COST_STEP	-1.13	0.123	-9.19	0	0.131	-8.65	0
B_SEARCH_SHBIKE	-0.062	0.0256	-2.42	0.0155	0.0258	-2.4	0.0163
B_SEARCH_SH_CAR	-0.0931	0.0442	-2.11	0.0353	0.0319	-2.92	0.00355
B_SEARCH_STEP	-0.193	0.0414	-4.67	3.08e-06	0.0402	-4.8	1.62e-06
B_UNLOCK_SHBIKE	0.00154	0.0831	0.0185	0.985	0.0805	0.0191	0.985
B_UNLOCK_SH_CAR	0.0357	0.145	0.245	0.806	0.115	0.31	0.756
B_UNLOCK_STEP	0.0155	0.135	0.115	0.908	0.125	0.124	0.901
B_WAIT	-0.053	0.00801	-6.61	3.82e-11	0.00616	-8.6	0
SIGMA_STEP_SHBIKE_STD	-3.64	0.164	-22.2	0	0.168	-21.7	0

F.6 (final) Panel Mixed Logit with interactions

HB final model

Biogeme syntax

```
# # ML estimation: home-based 1+2+4 km with panel and shared error comp.

import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.draws as draws
import biogeme.models as models
import numpy as np

# Importing the data
choice_data2 = pd.read_csv('HB2choices_full.csv',delimiter=',', encoding = "ISO-8859-1")
choice_data4 = pd.read_csv('HB4choices_full.csv',delimiter=',', encoding = "ISO-8859-1")

# Load interaction variables

# CHOICE_DATA2
cols = list(range(0,(choice_data2.columns.get_loc("BTM_COSTS")+1))) +
list(range(choice_data2.columns.get_loc("AGE_CATEGORY"),(choice_data2.columns.get_loc
("AGE_CATEGORY")+1))) +
list(range(choice_data2.columns.get_loc("MOTIVE"),(choice_data2.columns.get_loc("MOTIV
E")+1))) +
list(range(choice_data2.columns.get_loc("URBAN_DENS"),(choice_data2.columns.get_loc("U
RBAN_DENS")+1))) +
list(range(choice_data2.columns.get_loc("FAM_SHBIKE"),(choice_data2.columns.get_loc("FA
M_SHBIKE")+1))) +
list(range(choice_data2.columns.get_loc("NEW_TECH"),(choice_data2.columns.get_loc("NE
W_TECH")+1))) +
list(range(choice_data2.columns.get_loc("CHOICE"),(choice_data2.columns.get_loc("CHOIC
E")+1)))

choice_data2 = choice_data2.iloc[:,cols]

choice_data2['AGE2']=0
choice_data2['URBAN_DENS1']=0
choice_data2['URBAN_DENS2']=0
choice_data2['FAM_SHBIKE2']=0

choice_data2.loc[choice_data2['AGE_CATEGORY'] == 2, ['AGE2']] = 1
choice_data2.loc[choice_data2['URBAN_DENS'] == 1, ['URBAN_DENS1']] = 1
choice_data2.loc[choice_data2['URBAN_DENS'] == 2, ['URBAN_DENS2']] = 1
choice_data2.loc[choice_data2['FAM_SHBIKE'] == 2, ['FAM_SHBIKE2']] = 1

# CHOICE_data4
cols = list(range(0,(choice_data4.columns.get_loc("BTM_COSTS")+1))) +
list(range(choice_data4.columns.get_loc("AGE_CATEGORY"),(choice_data4.columns.get_loc
("AGE_CATEGORY")+1))) +
list(range(choice_data4.columns.get_loc("MOTIVE"),(choice_data4.columns.get_loc("MOTIV
E")+1))) +
list(range(choice_data4.columns.get_loc("URBAN_DENS"),(choice_data4.columns.get_loc("U
RBAN_DENS")+1))) +
list(range(choice_data4.columns.get_loc("FAM_SHBIKE"),(choice_data4.columns.get_loc("FA
M_SHBIKE")+1))) +
list(range(choice_data4.columns.get_loc("NEW_TECH"),(choice_data4.columns.get_loc("NE
W_TECH")+1))) +
list(range(choice_data4.columns.get_loc("CHOICE"),(choice_data4.columns.get_loc("CHOIC
E")+1)))
choice_data4 = choice_data4.iloc[:,cols]

choice_data4['AGE2']=0
choice_data4['URBAN_DENS1']=0
choice_data4['URBAN_DENS2']=0
choice_data4['FAM_SHBIKE2']=0

choice_data4.loc[choice_data4['AGE_CATEGORY'] == 2, ['AGE2']] = 1
choice_data4.loc[choice_data4['URBAN_DENS'] == 1, ['URBAN_DENS1']] = 1
choice_data4.loc[choice_data4['URBAN_DENS'] == 2, ['URBAN_DENS2']] = 1
choice_data4.loc[choice_data4['FAM_SHBIKE'] == 2, ['FAM_SHBIKE2']] = 1

# Add dummy variables for distance
choice_data2['DIST2_DUMMY'] = 1
choice_data4['DIST4_DUMMY'] = 1

# Add availability conditions
def add_av2(df):
    df['AV_WALK'] = 1
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 0
def add_av4(df):
    df['AV_WALK'] = 0
    df['AV_OWNBIKE'] = 1
    df['AV_SHBIKE'] = 1
    df['AV_BTM'] = 1
    df['AV_OWNCAR'] = 1

add_av2(choice_data2)
add_av4(choice_data4)

# Merge the data
choice_data = pd.concat([choice_data2, choice_data4], axis=0, sort=False)
choice_data = choice_data.replace(np.nan, 0)

choice_data.NEW_TECH = choice_data.NEW_TECH - 1
choice_data.NEW_TECH.head(3)
```

```
# Define panel variable (for ML panel effect)
database.panel("ID")
from headers import *

# ## Model specification
ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-100,100,0)

ASC_OWNBIKE_2KM = Beta('ASC_OWNBIKE_2KM',0,-100,100,0)
ASC_OWNBIKE_4KM = Beta('ASC_OWNBIKE_4KM',0,-100,100,0)
B_PARK_OWNBIKE = Beta('B_PARK_OWNBIKE',0,-100,100,0)
B_COST_OWNBIKE = Beta('B_COST_OWNBIKE',0,-100,100,0)

ASC_SHBIKE_2KM = Beta('ASC_SHBIKE_2KM',0,-100,100,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-100,100,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-100,100,0)
B_PARK_SHBIKE = Beta('B_PARK_SHBIKE',0,-100,100,0)
B_COST_SHBIKE = Beta('B_COST_SHBIKE',0,-10,100,0)
B_UNLOCK_SHBIKE = Beta('B_UNLOCK_SHBIKE',0,-100,100,0)

B_WAIT = Beta('B_WAIT',0,-100,100,0)
B_COST_BTM = Beta('B_COST_BTM',0,-100,100,0)

ASC_OWNCAR_4KM = Beta('ASC_OWNCAR_4KM',0,-100,100,0)
B_PARK_OWNCAR= Beta('B_PARK_OWNCAR',0,-100,100,0)
B_COST_OWNCAR = Beta('B_COST_OWNCAR',0,-100,100,0)

# Shared error parameters, fix the mean-parameter to 0
SIGMA_OWNBIKE_SHBIKE_M = Beta('SIGMA_OWNBIKE_SHBIKE_M',0,-100,100,1)
SIGMA_OWNBIKE_SHBIKE_STD = Beta('SIGMA_OWNBIKE_SHBIKE_STD',0,-100,100,0)

# Define a random parameter, normally distributed, designed to be used for Monte-
Carlo simulation
SIGMA_OWNBIKE_SHBIKE = SIGMA_OWNBIKE_SHBIKE_M + SIGMA_OWNBIKE_SHBIKE_STD
* bioDraws('SIGMA_OWNBIKE_SHBIKE','NORMAL')

# Interaction variables
B_MOTIVE_ASC_WALK = Beta('B_MOTIVE_ASC_WALK',0,-100,100,0)
B_FAM_SHBIKE2_ASC_OWNBIKE = Beta('B_FAM_SHBIKE2_ASC_OWNBIKE',0,-100,100,0)
B_AGE2_ASC_SHBIKE = Beta('B_AGE2_ASC_SHBIKE',0,-100,100,0)
B_FAM_SHBIKE2_ASC_SHBIKE = Beta('B_FAM_SHBIKE2_ASC_SHBIKE',0,-100,100,0)
B_NEW_TECH_ASC_SHBIKE = Beta('B_NEW_TECH_ASC_SHBIKE',0,-100,100,0)
B_URBAN_DENS1_ASC_OWNCAR = Beta('B_URBAN_DENS1_ASC_OWNCAR',0,-100,100,0)
B_URBAN_DENS2_ASC_OWNCAR = Beta('B_URBAN_DENS2_ASC_OWNCAR',0,-100,100,0)

# Utility functions

# Walking alt.
V1 = ASC_WALK_2KM * DIST2_DUMMY + B_MOTIVE_ASC_WALK * MOTIVE
# + B_URBAN_DENS2_ASC_WALK * URBAN_DENS2

# Own bike alt.
V2 = ASC_OWNBIKE_2KM * DIST2_DUMMY + ASC_OWNBIKE_4KM * DIST4_DUMMY +
B_PARK_OWNBIKE * OWN_BIKE_TIME_PARK + B_COST_OWNBIKE * OWN_BIKE_COSTS +
B_FAM_SHBIKE2_ASC_OWNBIKE * FAM_SHBIKE2 + SIGMA_OWNBIKE_SHBIKE

# Shared bike alternative.
V3 = ASC_SHBIKE_2KM * DIST2_DUMMY + ASC_SHBIKE_4KM * DIST4_DUMMY +
B_SEARCH_SHBIKE * SH_BIKE_TIME_SEARCH + B_PARK_SHBIKE * SH_BIKE_TIME_PARK +
B_COST_SHBIKE * SH_BIKE_COSTS + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK +
B_AGE2_ASC_SHBIKE * AGE2 + B_FAM_SHBIKE2_ASC_SHBIKE * FAM_SHBIKE2 +
B_NEW_TECH_ASC_SHBIKE * NEW_TECH + SIGMA_OWNBIKE_SHBIKE

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS

# Own car alt.
V5 = ASC_OWNCAR_4KM * DIST4_DUMMY + B_PARK_OWNCAR * OWN_CAR_TIME_PARK +
B_COST_OWNCAR * OWN_CAR_COSTS + B_URBAN_DENS1_ASC_OWNCAR * URBAN_DENS1
+ B_URBAN_DENS2_ASC_OWNCAR * URBAN_DENS2


# Associate utility functions with the numbering of alternatives
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternatives
av = {1: AV_WALK, 2: AV_OWNBIKE, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_OWNCAR}

# Define the contribution to the log likelihood function
# is slightly different for the panel effects model
obsprob = models.logit(V,av,CHOICE)
condprobIndiv = PanelLikelihoodTrajectory(obsprob)
logprob = log(MonteCarlo(condprobIndiv))

# ## Model estimation
biogeme = bio.BIOGEME(database,logprob,numberOfDraws=10000)
biogeme.modelName = "Estimations_PanelML_HB24_extended"

results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
pandasResults

pandasCorrelations = results.getCorrelationResults()
pandasCorrelations
```

Estimation report HB final model

Number of estimated parameters: 24
Sample size: 1468
Observations: 8808
Excluded observations: 0
Init log likelihood: -12210.48
Final log likelihood: -6825.923
Likelihood ratio test for the init. model: 10769.12
Rho-square for the init. model: 0.441
Rho-square-bar for the init. model: 0.439
Akaike Information Criterion: 13699.85
Bayesian Information Criterion: 13826.84
Final gradient norm: 2.5394E-01
Diagnostic: b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings: 244
Iterations: 221
Data processing time: 0:00:00.000004
Number of draws: 10000
Draws generation time: 0:00:13.259858
Optimization time: 19:40:40.834111
Nbr of threads: 8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_OWNBIKE_2KM	1.24	0.295	4.2	2.72e-05	0.275	4.51	6.6e-06
ASC_OWNBIKE_4KM	1.1	0.302	3.64	0.000275	0.284	3.87	0.000109
ASC_OWNCAR_4KM	-2.14	0.224	-9.55	0	0.286	-7.48	7.33e-14
ASC_SHBIKE_2KM	-0.808	0.356	-2.27	0.0233	0.379	-2.13	0.0329
ASC_SHBIKE_4KM	-0.972	0.359	-2.71	0.00682	0.384	-2.53	0.0112
ASC_WALK_2KM	-0.443	0.135	-3.29	0.00101	0.151	-2.93	0.00334
B_AGE2_ASC_SHBIKE	-1.11	0.138	-8.02	1.11e-15	0.195	-5.69	1.3e-08
B_COST_BTM	-0.353	0.0693	-5.1	3.45e-07	0.0497	-7.11	1.13e-12
B_COST_OWNBIKE	-0.693	0.0433	-16	0	0.0464	-14.9	0
B_COST_OWNCAR	-0.14	0.0234	-5.97	2.32e-09	0.021	-6.66	2.8e-11
B_COST_SHBIKE	-1.13	0.1	-11.3	0	0.0996	-11.4	0
B_FAM_SHBIKE2_OWNBIKE	3.11	0.402	7.73	1.11e-14	0.398	7.81	5.55e-15
B_FAM_SHBIKE2_SHBIKE	3.01	0.412	7.31	2.59e-13	0.404	7.46	8.62e-14
B_MOTIVE_ASC_WALK	-0.883	0.107	-8.25	2.22e-16	0.209	-4.22	2.4e-05
B_NEW_TECH_ASC_SHBIKE	0.288	0.0637	4.52	6.29e-06	0.102	2.81	0.00499
B_PARK_OWNBIKE	-0.0511	0.0163	-3.14	0.00167	0.0139	-3.69	0.000223
B_PARK_OWNCAR	-0.0225	0.0276	-0.814	0.415	0.0207	-1.08	0.278
B_PARK_SHBIKE	-0.0682	0.0233	-2.93	0.00338	0.021	-3.25	0.00117
B_SEARCH_SHBIKE	-0.0692	0.0284	-2.44	0.0148	0.0249	-2.78	0.00549
B_UNLOCK_SHBIKE	-0.0798	0.0937	-0.851	0.395	0.083	-0.962	0.336
B_URBAN_DENS1_OWNCAR	0.785	0.158	4.98	6.38e-07	0.303	2.59	0.0096
B_URBAN_DENS2_OWNCAR	1.53	0.165	9.26	0	0.319	4.79	1.69e-06
B_WAIT	-0.0437	0.00995	-4.4	1.11e-05	0.00689	-6.34	2.23e-10
SIGMA_OWNBIKE_SHBIKE	-5.65	0.255	-22.1	0	0.266	-21.2	0

AB final model

Biogeme syntax (shortened)

```
# # ML estimation: activity-based 1+2+4 km with panel, shared error comp., and
interactions

import pandas as pd
import biogeme.database as db
import biogeme.biogeme as bio
import biogeme.draws as draws
import biogeme.models as models
import numpy as np

# Import the data

[...]

# Convert to (special) dataframe for Biogeme
database = db.Database("DATA", choice_data)

# Define panel variable (for ML panel effect)
database.panel("ID")
from headers import *

# ## Model specification
# Parameters to be estimated <br>
ASC_WALK_1KM = Beta('ASC_WALK_1KM',0,-1000,1000,0)
ASC_WALK_2KM = Beta('ASC_WALK_2KM',0,-1000,1000,0)
ASC_STEP_1KM = Beta('ASC_STEP_1KM',0,-1000,1000,0)
ASC_STEP_2KM = Beta('ASC_STEP_2KM',0,-1000,1000,0)
B_SEARCH_STEP = Beta('B_SEARCH_STEP',0,-1000,1000,0)
B_COST_STEP = Beta('B_COST_STEP',0,-1000,1000,0)
B_UNLOCK_STEP = Beta('B_UNLOCK_STEP',0,-1000,1000,0)
ASC_SHBIKE_12KM = Beta('ASC_SHBIKE_12KM',0,-1000,1000,0)
ASC_SHBIKE_4KM = Beta('ASC_SHBIKE_4KM',0,-1000,1000,0)
B_SEARCH_SHBIKE = Beta('B_SEARCH_SHBIKE',0,-1000,1000,0)
B_COST_SHBIKE = Beta('B_COST_SHBIKE',0,-1000,1000,0)
B_UNLOCK_SHBIKE = Beta('B_UNLOCK_SHBIKE',0,-1000,1000,0)
B_WAIT = Beta('B_WAIT',0,-1000,1000,0)
B_COST_BTM = Beta('B_COST_BTM',0,-1000,1000,0)
ASC_SHCAR = Beta('ASC_SH_CAR',0,-1000,1000,0)
B_SEARCH_SHCAR = Beta('B_SEARCH_SH_CAR',0,-1000,1000,0)
B_COST_SHCAR = Beta('B_COST_SH_CAR',0,-1000,1000,0)
B_UNLOCK_SHCAR = Beta('B_UNLOCK_SH_CAR',0,-1000,1000,0)

# Shared error parameters, fix the mean-parameter to 0
SIGMA_STEP_SHBIKE_M = Beta('SIGMA_STEP_SHBIKE_M',0,-100,100,1)
SIGMA_STEP_SHBIKE_STD = Beta('SIGMA_STEP_SHBIKE_STD',0,-100,100,0)

# Define a random parameter, normally distributed, designed to be used for Monte-
Carlo simulation
SIGMA_STEP_SHBIKE = SIGMA_STEP_SHBIKE_M + SIGMA_STEP_SHBIKE_STD *
bioDraws('SIGMA_STEP_SHBIKE','NORMAL')

# Interaction variables
B_AGE2_COST_BTM = Beta('B_AGE2_COST_BTM',0,-1000,1000,0)
B_FAM_SHBIKE2_ASC_SHBIKE = Beta('B_FAM_SHBIKE2_ASC_SHBIKE',0,-1000,1000,0)
B_MOTIVE_ASC_WALK = Beta('B_MOTIVE_ASC_WALK',0,-1000,1000,0)
B_MOTIVE_WAIT_BTM = Beta('B_MOTIVE_WAIT_BTM',0,-1000,1000,0)
B_NEW_TECH_ASC_SHCAR = Beta('B_NEW_TECH_ASC_SHCAR',0,-1000,1000,0)
B_NEW_TECH_ASC_STEP = Beta('B_NEW_TECH_ASC_STEP',0,-1000,1000,0)

# Utility functions
# Walking alt.
V1 = ASC_WALK_1KM * DIST1_DUMMY + ASC_WALK_2KM * DIST2_DUMMY +
B_MOTIVE_ASC_WALK * MOTIVE

# E-scooter alt.
V2 = ASC_STEP_1KM * DIST1_DUMMY + ASC_STEP_2KM * DIST2_DUMMY +
B_SEARCH_STEP * STEP_TIME_SEARCH + B_COST_STEP * STEP_COSTS +
B_UNLOCK_STEP * STEP_UNLOCK + B_NEW_TECH_ASC_STEP * NEW_TECH +
SIGMA_STEP_SHBIKE

# Shared bike alternative
V3 = ASC_SHBIKE_12KM * DIST1_DUMMY + ASC_SHBIKE_12KM * DIST2_DUMMY +
ASC_SHBIKE_4KM * DIST4_DUMMY + B_COST_SHBIKE * SH_BIKE_COSTS +
B_FAM_SHBIKE2_ASC_SHBIKE * FAM_SHBIKE2 + B_SEARCH_SHBIKE *
SH_BIKE_TIME_SEARCH + B_UNLOCK_SHBIKE * SH_BIKE_UNLOCK + SIGMA_STEP_SHBIKE
# + B_EDUCATION2_ASC_SHBIKE * EDUCATION2 \

# BTM alt. (note: no ASC here)
V4 = B_WAIT * BTM_TIME_WAIT + B_COST_BTM * BTM_COSTS + B_MOTIVE_WAIT_BTM *
MOTIVE * BTM_TIME_WAIT
# + B_AGE2_COST_BTM * AGE2 * BTM_COSTS \

# Shared car alt.
V5 = ASC_SHCAR + B_COST_SHCAR * SH_CAR_COSTS + B_SEARCH_SHCAR *
SH_CAR_TIME_SEARCH + B_UNLOCK_SHCAR * SH_CAR_UNLOCK +
B_NEW_TECH_ASC_SHCAR * NEW_TECH
```

```
# Associate utility functions with the numbering of alternative
V = {1:V1, 2: V2, 3: V3, 4:V4, 5:V5}

# Associate the availability conditions with the alternatives
av= {1: AV_WALK, 2: AV_STEP, 3: AV_SHBIKE, 4:AV_BTM, 5:AV_SHCAR}

# Define the contribution to the log likelihood function
# is slightly different for the panel effects model
obsprob = models.logit(V,av,CHOICE)
condprobIndiv = PanelLikelihoodTrajectory(obsprob)
logprob = log(MonteCarlo(condprobIndiv))

# ## Model estimation
biogeme = bio.BIOGEME(database,logprob,numberOfDraws=10000)
biogeme.modelName = "Estimations_PanelML_AB124_extended"

# Running the estimation
results = biogeme.estimate()

pandasResults = results.getEstimatedParameters()
pandasResults
```

Estimation report AB final model

Number of estimated parameters: 24
Sample size: 1468
Observations: 8808
Excluded observations: 0
Init log likelihood: -11371.6
Final log likelihood: -6936.624
Likelihood ratio test for the init. model: 8869.951
Rho-square for the init. model: 0.39
Rho-square-bar for the init. model: 0.388
Akaike Information Criterion: 13921.25
Bayesian Information Criterion: 14048.25
Final gradient norm: 1.3531E-01
Diagnostic: b'CONVERGENCE: NORM_OF_PROJECTED_GRADIENT_<=_PGTOL'
Database readings: 289
Iterations: 271
Data processing time: 0:00:00.000004
Number of draws: 10000
Draws generation time: 0:00:12.155912
Optimization time: 19:57:29.255556
Nbr of threads: 8

NAME	VALUE	STD ERR	T-TEST	P-VALUE	ROB. STD ERR	ROB. T-TEST	ROB. P-VALUE
ASC_SHBIKE_12KM	-2.46	0.242	-10.2	0	0.224	-11	0
ASC_SHBIKE_4KM	-1.59	0.285	-5.57	2.48e-08	0.268	-5.95	2.75e-09
ASC_SH_CAR	-4.56	0.456	-9.98	0	0.66	-6.9	5.19e-12
ASC_STEP_1KM	-4.62	0.446	-10.4	0	0.631	-7.33	2.29e-13
ASC_STEP_2KM	-5.11	0.464	-11	0	0.618	-8.26	2.22e-16
ASC_WALK_1KM	0.452	0.111	4.08	4.46e-05	0.136	3.33	0.000873
ASC_WALK_2KM	-1.29	0.122	-10.6	0	0.145	-8.85	0
B_COST_BTM	-0.525	0.0622	-8.44	0	0.0525	-10	0
B_COST_SHBIKE	-1.2	0.079	-15.2	0	0.0822	-14.6	0
B_COST_SH_CAR	-0.588	0.0576	-10.2	0	0.07	-8.4	0
B_COST_STEP	-1.18	0.126	-9.38	0	0.136	-8.68	0
B_FAM_SHBIKE2_ASC_SHBIKE	1.07	0.141	7.57	3.75e-14	0.221	4.82	1.46e-06
B_MOTIVE_ASC_WALK	-0.591	0.0965	-6.13	8.9e-10	0.154	-3.84	0.000124
B_MOTIVE_WAIT_BTM	-0.052	0.0132	-3.95	7.85e-05	0.0151	-3.45	0.000569
B_NEW_TECH_ASC_SHCAR	0.852	0.11	7.75	9.1e-15	0.184	4.64	3.48e-06
B_NEW_TECH_ASC_STEP	0.684	0.0997	6.86	6.94e-12	0.163	4.2	2.64e-05
B_SEARCH_SHBIKE	-0.0626	0.0257	-2.44	0.0147	0.0259	-2.42	0.0155
B_SEARCH_SH_CAR	-0.0952	0.0453	-2.1	0.0357	0.0332	-2.87	0.0041
B_SEARCH_STEP	-0.203	0.0422	-4.81	1.52e-06	0.042	-4.82	1.42e-06
B_UNLOCK_SHBIKE	0.00515	0.0834	0.0618	0.951	0.0812	0.0635	0.949
B_UNLOCK_SH_CAR	0.0531	0.149	0.358	0.721	0.117	0.453	0.651
B_UNLOCK_STEP	0.0235	0.137	0.172	0.864	0.127	0.185	0.853
B_WAIT	-0.0333	0.00948	-3.51	0.00044	0.00828	-4.02	5.74e-05
SIGMA_STEP_SHBIKE_STD	3.32	0.151	22	0	0.153	21.7	0

G Scientific paper

Shared mobility for the first and last mile: exploring the willingness to share

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Abstract

Over the past decade, the development of ICT and online platforms has provided the infrastructure for new ways of sharing on a scale never seen before which are causing a shift from ownership to access-based-consumption. This trend offers promising prospects for the case of mobility but the true magnitude of impact that the increasing popularity of shared mobility services will have on the total transportation system remains uncertain. For NS, as largest railway operator in the Netherlands, it is therefore relevant to investigate how these new services can contribute to better first and last mile transportation within the multimodal train trip, as most of these types of shared mobility operate on an urban scale. Accordingly, this study aims to explore and measure the factors that affect people's willingness to use shared mobility services as access or egress transport in multimodal train trips. A series of stated choice experiments was developed in which respondents were asked to choose their preferred mode from a set of alternatives for a given access- or egress trip. Next to conventional modes, included shared modes were bike, (standing) e-scooter, and car. By applying discrete choice modelling, separate mixed logit models were estimated for the home-based side trip (origin to railway station) and the activity based side trip (railway station to final destination) in order to assess the impact of choice factors related to characteristics of the available modes, trip, and traveler. Results show that the willingness to use shared modes is in the first place strongly affected by familiarity with these modes. As the overall observed familiarity and in particular experience with shared modes was low, intrinsic (negative) mode preferences were found to be the dominating choice factors. This was especially the cases for shared e-scooter and to a lesser extent also for the shared car. Traveler characteristics were found affect the magnitude of the fixed mode preference in a sense that young and higher educated travelers significantly appeared to be more open to try shared modes. Contrary to the e-scooter and car, the shared bike exemplifies a more familiar option which was found to results in a different hierarchy of mode related factors: the general fixed mode preference becomes less dominant and usage costs gains more importance.

Keywords

shared mobility, shared bike, shared e-scooter, shared car, first and last mile, door-to-door trip, mode choice, travel preferences, stated choice experiments, discrete choice modelling

---

1. Introduction

Over the past decade, the concept of sharing has attracted more and more attention. Although sharing itself is nothing new, the development of ICT and online platforms has provided the infrastructure for new ways of sharing on a scale never seen before, which are causing a shift from ownership to access-based-consumption (Belk, 2014; Hamari, Sjöklint, & Ukkonen, 2016). This trend offers promising prospects for the case of mobility (Standing, Standing, & Biermann, 2018)(KiM, 2018; Wong, Hensher, & Mulley, 2017) and a growing body of literature reveals how shared mobility services could help solving transportation problems related to congestion, parking, sustainability, and accessibility (Standing et al., 2018).

Despite an increasing amount of studies devoted to the topics of shared mobility and mobility as a service, the true magnitude of impact that this increasing popularity of shared mobility will have on the total transportation system remains uncertain (Cherry & Pidgeon, 2018; KiM, 2018; Standing et al., 2018). Contributing to this uncertainty is, among other things, the under-explored decision-making process of people regarding the use of shared mobility services (Böcker & Meelen, 2017; Cherry & Pidgeon, 2018; Tussyadiah, 2015). This requires additional research, which is not only relevant from a scientific point of view, but also for companies operating in the transportation sector.

As this research is conducted for NS, the largest railway operator in the Netherlands, it is in particular relevant to investigate how these new services can contribute to better first and last mile transportation within the multimodal train trip, as most of these types of shared mobility operate on an urban scale. The goal of this research is therefore to explore and measure the factors that affect people's willingness to use shared mobility services as access or egress transport in multimodal train trips.

Shared mobility services can in general be conceptualized as innovative transportation strategies that enables travelers to gain temporary access to transportation modes on an "as-needed" basis (Shaheen et al., 2015). Many different types of shared mobility services exist and when categorizing them, an important split can be made in what the travelers gains access to, a vehicle or a ride. Given the popularity of cycling and walking in the current modal split of access and egress trips and the potential of the shared (standing) e-scooter and bike, shared vehicles are found to be the most relevant type of shared mobility to investigate in terms of mode choice factors. The included shared modes in this study are the shared bike, the shared (standing) e-scooter, and the shared car.

Using the stated preference approach, a series of five choice experiments was designed that covers a representative range of conventional- and shared access- and egress modes of transport and trip distances. For a given access or egress trip scenario, respondents were asked to choose their most preferred option. The experiments were conducted through an online questionnaire among a representative sample of NS-customers. Based on the collected choice data, preference parameters are estimated using a mixed logit framework. The results provide insights in the role of travel cost, travel time and traveler- and trip characteristics in the mode choice process of travelers when shared modes are included in their choice set.

The sections that follow address the research approach, including the design of the experiments and specification of the model, the survey and sample, and the results of model estimation. The final section concludes the paper by summarizing the main conclusions and discussing directions for future research.

2. Research approach

This research's main interest are the trade-offs that travelers make when choosing between shared mobility services and other options. The included alternatives in the stated choice experiments should therefore offer a choice between shared mobility options and conventional mode options. Multiple stated choice experiments were conducted to be able to measure a variety of trade-offs between conventional and shared mode options for access and egress trips.

Table 1 The five choice sets: split per distance class and type of trip.

	Mode options	Home-based trip		Activity based trip	
		2 km	4 km	1 or 2 km	4 km
conventional options	walk	•		•	
	private bike	•	•		
	private car		•		
	BTM	•	•	•	•
shared options	shared e-scooter			•	
	shared bike	•	•	•	•
	shared car				•

With respect to task feasibility for the respondents, choice experiments are conducted separately for the home-based- (access) and activity-based (egress) trip. Choosing between entire door-to-door trip chains that vary in modes for both the home-based- and the activity-based trip (with a fixed train part), including several varying attributes, is considered to result into a too complex choice task, which would decrease the validity of the experiment (Hess & Rose, 2009). Given the interest in the willingness to use of multiple shared modes, choice sets for multiple distances are constructed. Table 1 presents the choice set of the five different experiments. Respondents were assigned to one home-based- and to one activity-based experiment.

Three type of mode choice factors are included in the experiments. In the first place, mode characteristics are included as attributes of the alternatives in the choice sets and are presented in Table 2 and Table 3, including the different attribute level values. Since experiments are conducted for fixed distances, the in-vehicle times cannot be varied. Therefore transfer time components are included and varied over three levels. Since different types of travel times and costs are perceived differently (Arentze & Molin, 2013), all attributes are included as separate alternative specific attributes. Next to travel times and costs, for the shared mode, also an attribute linked to quality of service is included. Two types of unlock methods represent the convenience factor. The shared vehicle can either be opened via smartphone (easy) or via an acquired code on the docking station of the vehicle (difficult).

Table 2 Overview of the attributes and attribute levels of the home-based trip experiments.

Attribute	Level value 2 km	Level value 4 km
Walking		
Walking time (fixed) [min]	26	-
Private bike		
Biking time [min]	8	16
Parking time (fixed) [min]	1, 3, 6	1, 3, 6
Parking costs [€]	€ 0.00, € 1.20, € 1.80	€ 0.00, € 1.20, € 1.80
Shared bike		
Search time [min]	1,3,5	1,3,5
Biking time (fixed) [min]	8	16
Parking time [min]	1,3,6	1,3,6
Usage costs [€]	€0.50, €1.00, €1.60	€0.50, €1.00, €1.60
Unlock method	smartphone, code	smartphone, code
Bus/tram/metro (BTM)		
Waiting time [min]	2, 5, 10	2, 5, 10
In-vehicle time (fixed) [min]	12	24
Ticket cost [€]	€1.20, €1.60, €2.20	€1.40, €1.80, €2.30
Private car		
In-vehicle time (fixed) [min]	-	12
Parking time [min]	-	1, 3, 6
Parking costs [€]	-	€1.00, €4.00, €7.00

Table 3 Overview of the attributes and attribute levels of the activity-based trip experiments.

Attribute	Level value 1 km	Level value 2 km	Level value 4 km
Walking			
Walk_time [min]	13	26	-
Shared e-scooter			
Search time [min]	1, 3, 5	1, 3, 5	-
On-vehicle time (fixed) [min]	4	8	-
Parking time [min]	1	1	-
Usage costs	€ 1.00, € 1.60, € 2.10	€1.40, €2.00, €2.50	-
Unlock method	Smartphone, code	Smartphone, code	-
Shared bike			
Search time [min]	1, 3, 5	1, 3, 5	1, 3, 5
On-vehicle time [min]	4	8	16
Parking time [min]	1	1	1
Usage costs [€]	€ 1.00, € 1.60, € 2.10	€1.40, €2.00, €2.50	€1.50, €2.00, €2.60
Unlock method	Smartphone, code	Smartphone, code	Smartphone, code
Bus/tram/metro			
Waiting time [min]	2, 5, 10	2, 5, 10	2, 5, 10
In-vehicle time [min]	6	12	20
Ticket costs [€]	€0.90, €1.30, €1.80	€1.20, €1.60, €2.10	€1.40, €1.80, €2.30
Shared car			
Search time [min]	-	-	2, 4, 6
In-vehicle time [min]	-	-	12
Parking time [min]	-	-	1
Usage costs [€]	-	-	€2.00, €3.50, €5.50
Unlock method	-	-	Smartphone, code

The second type of mode choice factors are trip characteristics. The effect of such context variables can also be tested for in stated preference experiments (Molin & Timmermans, 2010). In this case, context variables are used to construct a number of train travel situations for which the respondents make their mode choices. The included variables are: duration of the train trip, travel purpose and time of day. The latter two are varied in a combined way as NS travel data shows that (train) trip purpose and whether people travel mostly during peak- or off-peak hours are strongly correlated (NS, 2019). Both train trip duration and trip purpose + time of day were varied over two levels resulting in 4 context profiles. For train trip duration the two levels are: 30 minutes and 60 minutes, which were derived from the total distribution of train trips made by NS customers. For trip purpose and time of day a distinction is made between traveling for business purposes during rush hour and traveling for leisure activities during off-peak hours.

The third and last type of mode choice factors addressed in this study are factors related to the traveler. These are measured via separate questions in the questionnaire. Apart from standard socio-demographics, also a number of factors specifically linked with the topic of access-based consumption and shared mobility is included. These are familiarity with shared modes, degree of digital literacy, and attitudes of the traveler towards sharing in general and towards trying new technologies.

In stated choice experiments, the use of imaginary scenarios may lead to bias in responses. Care was taken to avoid this bias as much as possible via realistic specification of attribute levels and by providing clear instructions to respondents, especially when introducing the shared modes. Travel times and prices are varied within realistic ranges considering the transport mode and trip distance. Additionally, assignment of respondents to the different context profiles and home-based trip experiments was based on several profiling questions at the beginning of the questionnaire and by using already available data of the respondents from the NS customer database. In doing so, the perceived realism of the choice sets can be increased which contributes to the goal of SP experiments of having respondents make informed choices (Hess & Rose, 2009).

The attribute levels were systematically varied by constructing an experimental design using software package *Ngene*. An orthogonal design of was used to construct a total of 36 choice set per experiments. These sets are divided into 6 blocks of each 6 choice sets. That way respondents make two times six choices: Six in the home-based choice experiment, and six in the activity-based choice experiment. As an example, Figure 1 present one of the choice sets of the home-based 2 km experiment.

Figure 1 Example of a choice set presented at the home-based 2 km experiment.

3. Survey and sample

Respondents were recruited from the NS customer database. A semi-random sample was drawn from this population in the sense that customers living in non-urbanized areas were excluded based on the urban density scale of their home address. This was done because the studied shared mobility services are assumed to operate in urbanized areas and excluding travelers that live in non-urbanized areas increases the perceived realism of the hypothetical choice situation to the respondents. Allocation of respondents to the choice experiments occurred on a semi-random base as well. Using respondents' home-address (available from the NS database), respondents were assigned to the home-based trip (1, 2, or 4km) experiment that matches best with the distance between their home-address and the nearest railway station. Allocation to the activity-based trip was random, allocation to the contexts was based on profiling questions regarding train travel behavior asked at the beginning of the survey.

The experiments were implemented into an online survey. A pilot survey was conducted (among 26 respondents) to check whether respondents understood the questionnaire and to test the setup of the experiments. The main survey was then conducted in May 2019. Of all 2870 respondents that started the survey, 1841 filled out the complete survey and after data cleaning, the sample that is used for this research consists of 1835 respondents. Table 4 presents the composition of the sample in terms of socio-demographic- and train travel variables. As can be noted, the sample contains both higher shares of elderly and of higher educated people. Besides, people that travel more often by train were more tempted to complete the survey compared to people that travel by train only a few times per year.

Each respondent received a total of 12 choice tasks: 6 tasks for one assigned home-based trip context, and 6 tasks for one activity-based trip experiment. A small number of simple questions on socio-demographic variables was asked in-between the two choice experiments to avoid respondent fatigue. Since choice models are separately estimated for the home-based- and the activity-based trip situation, the total number of observations available for each model is 11,010 (= 6 x 1835).

Table 4 Characteristics of the sample

Variable	Category	Sample	NS customers	Difference
Gender	Male	42%	47%	- 5%
	Female	58%	53%	+ 5%
Age	16-35	18%	37%	-19%
	36-65	49%	46%	+4%
	65+	34%	17%	+16%
Education	High	62%	35%	+27%
	Average	26%	39%	-13%
	Low	8%	27%	-19%
Travel purpose	Work/school	30%	22%	+8%
	Business	7%	6%	+1%
	Social/leisure	58%	58%	+0%
	Other	5%	14%	-9%
Travel frequency	≥1 day/week	33%	22%	+11%
	1-3 days/month	25%	17%	+8%
	6-11 days/year	26%	17%	+9%
	1-5 days/year	16%	43%	-27%

4. Results

In order to conclude on the importance of the selected mode choice factors, the results from the stated choice experiments are analyzed using descriptive statistics and discrete choice modelling.

Descriptive statistics

Descriptive statistics in the first place reveal that a large share of respondents (58%) had a fixed preference for one mode in either the home-based or the activity-based trip experiment. This suggests that fixed mode preferences played an important role in the hypothetical choice situations. In total, 41% of the respondents did not switch mode in both experiments. Analysis of this group revealed that especially elderly, lower educated and less frequent train travelers are more likely not to switch to another (shared) mode when transfer time and travel costs are varied.

Apart from choice distribution, experience with shared modes is found to be generally low, as can be noted in Figure 2. Besides, large differences exist between the different modes. Respondents are most familiar with shared bikes: 28% of the respondents has used a shared bike and only 14% has never heard of the concept while only 2% has experience with e-scooters which are new to almost half of the sample (47%). Though these differences are not surprising given the current availability of the different shared modes in the Netherlands, the familiarity distributions provide relevant background information when evaluating the results from the estimated choice models.

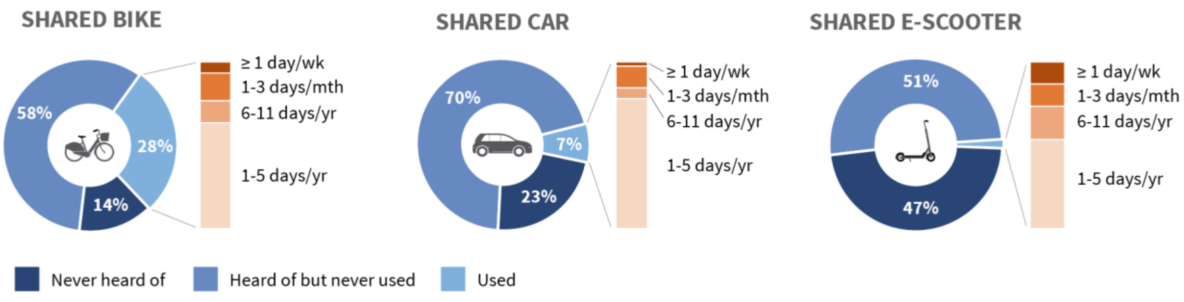

Figure 2 Respondents' familiarity with shared modes.

Discrete choice modelling

Due to the fundamental differences between the home-based (HB)- and the activity-based (AB) trip regarding (private) mode availability, route familiarity, and travel behavior inertia, the assessment of the effect of the selected factors was conducted via separate stated choice experiments for the home-based and the activity based trip. In order to come to two final models, one for the HB trip and one for the AB trip, several modelling steps were taken. The models were estimated using software package *Biogeme* (Bierlaire, 2018).

As a start, the multiple experiments for different trip distances were combined into one multinomial logit (MNL) model for the HB and one for the AB case (the base-models). To account for the differences in distance between the experiments, multiple separate alternative specific constants (ASCs) are estimated for the alternatives that were present in more than one experiment (HB: shared bike, BTM; AB: walking, shared e-scooter, shared bike, BTM). It was also checked whether alternative specific parameters of the same kind obtained similar values and thus possibly could be represented by a generic parameter. This was not the case. To investigate the impact of personal characteristics and context variables, these variables were added to the model as interaction variables. The interaction effects of each of these dummy coded variables were first tested separately, where after all significant interactions were included into one model (one for HB, one for AB) which was iterated until the solid significant interactions remained.

Since some of the presented alternative in the choice experiments have shared characteristics (like private and shared bikes both being bikes), the base MNL models were enhanced by testing for nest components that can account for the shared elements between alternatives (Train, 2009). One significant nest was found for each model: *nest private bike - shared bike* in the HB model and *nest shared e-scooter - shared bike* in the AB model. To correct for correlations across the choice of one respondent (panel effects), the multinomial logit models are replaced with panel mixed logit models which as a final step are extended with the earlier found significant interaction variables.

Table 5 shows some statistics of the model estimations. The final models obtain a rho-square value of 0.442 and 0.388, indicating a reasonable goodness-of-fit. Models for both types of trip are performing better after each step: loglikelihoods (LL) and rho-squared values both increase. Apart from the goodness-of-fit measures, the performance of the models was also measured via cross-validation. The choice data was split into two groups. A random 80% of the sample was used to estimate the models. Next, simulated choice predictions by the final models for both the 80% and the remaining 20% were compared as an attempt to validate performances. Table 6 presents the prediction rates. As can be noted, the correct prediction rates between the two subsamples are slightly different, but considered a sufficient proof of validation of the model.

Table 5 Model estimation statistics

Model	# parameters	Final LL	Rho²	Halton draws
Home-based trip models				
0. Null	0	-12210	-	-
1. MNL HB24 base	16	-9681	0.207	-
2. NL HB24	17	-9640	0.228	-
3. MNL HB24 with interactions	25	-9339	0.235	-
4. Panel ML HB24 with error component (EC)	17	-7012	0.426	1,000
5. Panel ML HB24 EC extended (with interactions)	25	-6818	0.442	10,000
Activity-based trip models				
0. Null	0	-11372	-	-
1. MNL AB124 base	18	-8283	0.272	-
2. NL AB124	19	-8278	0.245	-
3. MNL AB124 with interactions	27	-7955	0.298	-
4. Panel ML AB124 EC	19	-7055	0.378	1,000
5. Panel ML AB124 EC extended (with interactions)	25	-6933	0.388	10,000

Table 6 Comparison of prediction rates

Model	% correct predictions 80% group	% correct predictions 20% group
Panel ML HB 24 EC	54.37 %	54.91%
Panel ML AB 124 EC	60.98 %	64.85 %

The detailed parameter estimations of the home-based trip model are presented in Table 7. Except for the parameters related to the unlock method of the shared bike and the parking costs of the private car, all parameters are significant on a significance level of 0.05. All presented parameter values are relative utility contributions compared to the ASC of the BTM alternative which is kept at zero.

Results related to the attribute parameters indicate the following. In the first place it can be noted that *traveler characteristics* have the largest impact on the willingness to use a shared bike as access mode. Especially whether travelers have previous experience with shared bikes strongly affects the mode choice process. Having used a shared bike before massively increases the preference for both the private and the shared bike alternative (increase of 3.11 and 3.01 utils). In that case, the private bike is still intrinsically preferred over the shared bike, but differences in mode related factors of parking/usage costs and, to a lesser extent, also parking time can cause a substantial amount of disutility to let the shared bike become the preferred option. Overall however, the private bike was strongly preferred over the shared bike (53% of all choices vs. 6%) which can be linked to fact that the majority of the respondents (72%) has no previous experience with using a shared bike.

Besides, compared to the included conventional modes, this relative unpopularity of the shared bike can also be matched with the shared bike in general scoring lowest on intrinsic mode preference (-0.81 and 0.97). These preferences play a substantial role, as was expected based on the discussed large share of respondents with a fixed preference and the fact that the in-vehicle times were not varied in the experiments and therefore load onto the fixed preference scores as well. The effect of *trip characteristics* travel purpose and urban density are found to change this preference order: The private car is least preferred for trips to railway stations in highly dense urban areas and travelers heading towards an important meeting (must-traveler) would quicker turn to using a shared bike compared to walking.

With respect *to mode characteristics*, costs and in particular (transfer) time attributes are found to be less important than the intrinsic mode preference interacting with traveler characteristics. In the case of the shared- and private bike alternatives, costs play a slightly less important role than the mode preferences, while the impact of search- and parking time is approximately five times smaller. Sensitivity to both costs and transfer time is both highest for the shared bike alternative, which could be linked to the familiarity issue: costs and time elements are weighed heavier for never tried alternatives. Lastly, the included qualitative element of accessibility – the unlocking method of the shared bike– appeared not to be a significantly considered factor in the choice process.

Table 7 Parameter estimations of the final home-based trip model

Name	Description	Value	Robust SE	Rob. t-test	p-value
Walk					
ASC_WALK_2KM	Alt. specific constant of walk alternative	-0,443	0,151	-2,93	0,003
Private bike					
ASC_OWNBIKE_2KM	Alt. specific constant private bike - 2km experiment	1,24	0,275	4,51	0,000
ASC_OWNBIKE_4KM	Alt. specific constant private bike - 4km experiment	1,1	0,284	3,87	0,000
B_PARK_OWNBIKE	Parking time private bike	-0,0511	0,0139	-3,69	0,000
B_COST_OWNBIKE	Parking costs private bike	-0,693	0,0464	-14,9	0,000
Shared bike					
ASC_SHBIKE_2KM	Alt. specific constant shared bike - 2km experiment	-0,808	0,379	-2,13	0,033
ASC_SHBIKE_4KM	Alt. specific constant shared bike - 4km experiment	-0,972	0,384	-2,53	0,011
B_SEARCH_SHBIKE	Search time shared bike	-0,0692	0,0249	-2,78	0,005
B_PARK_SHBIKE	Park time shared bike	-0,0682	0,021	-3,25	0,001
B_COST_SHBIKE	Cost usage shared bike	-1,13	0,0996	-11,4	0,000
B_UNLOCK_SHBIKE	Unlocking method shared bike	-0,0798	0,083	-0,962	0,336*
BTM					
B_WAIT_BTM	Waiting time BTM	-0,0437	0,00995	-4,4	0,001
B_COST_BTM	Trip fare BTM	-0,353	0,0497	-7,11	0,000
Private car					
ASC_OWNCAR_4KM	Alt. specific constant private car (only 4km)	-2,14	0,286	-7,48	0,000
B_PARK_OWNCAR	Parking time private car	-0,0225	0,0207	-1,08	0,278*
B_COST_OWNCAR	Parking costs private car	-0,14	0,021	-6,66	0,000
Interactions					
B_MOTIVE-MUST_WALK	Effect of being a must-traveler on utility walking	-0,883	0,209	-4,22	0,000
B_FAM_SHBIKE2_OWNBIKE	Effect of having used sh.bike on utility own bike	3,11	0,398	7,81	0,000
B_AGE2_SHBIKE	Effect being a 65+ traveler on utility sh.bike	-1,11	0,195	-5,69	0,000
B_FAM_SHBIKE2_SHBIKE	Effect of having used sh.bike on utility sh.bike	3,01	0,404	7,46	0,000
B_NEW_TECH_SHBIKE	Effect of attitude towards new tech on utility sh.bike	0,288	0,102	2,81	0,005
B_URB_DENS1_OWNCAR	Effects of urban density of utility private car	0,785	0,303	2,59	0,010
B_URB_DENS2_OWNCAR	Effects of urban density of utility private car	1,53	0,319	4,79	0,000
Shared error components					
SIGMA_OWNBIKE_SHBIKE	Shared error comp. between the bike alternatives	-5,65	0,266	-21,2	0,000

Table 8 presents the detailed parameter estimations of the activity-based trip model. All parameters have the expected sign, except for the unlocking attributes of all three included shared modes. These parameters are also highly insignificant and their values are close to zero. This indicates that the unlocking method of the shared modes did not play a role in the decision making process when choosing between the modes

Results of the significant parameters suggest the following. Similar to the home-based side, familiarity with the shared mode concepts emerged also here as a prominent factor in the mode choice process. Being unknown and therefore unpopular applies in particular to the shared e-scooter and shared car alternative. These alternatives score remarkable low on intrinsic mode preference (e-scooter: -4.5, -5.1; shared car: -2.14), which can be linked to the general observed low familiarity with these modes in the sample. The shared bike is a much more common egress mode to the respondents (due to the availability of OVfiets) which correspondents with a much less dominating intrinsic preference (-2.45 and -1.59) and a larger impact of costs and time attributes compared to the shared e-scooter and car.

Traveler characteristics related to one's openness to trying new technologies and (again) having experience with shared modes emerges as interaction variables that are significantly related with the intrinsic mode preference of the shared modes. The more respondents can be characterized as early adopters, the smaller the difference between the intrinsic mode preferences of shared and conventional modes.

Apart from these static preferences, the *trip characteristic* travel purpose is found to affect the sensitivity to travel time in such way that must travelers are more likely to consider a shared bike than lust travelers due to higher sensitivities to walking time and BTM waiting time. However, sensitivity to costs for shared bike usage is much stronger associated with disutility than is the case for costs of a BTM ticket.

Thus, regarding the impact of the tested factors on the willingness to use shared modes, it can be concluded that when the familiarity with the shared mode is too low (e-scooter and car), the role of time and cost attributes is in general too small to play a significant role. In case of a more familiar shared mode (shared bike), travel time- and especially costs attributes can make a differences. However, sensitivity to the tested cost attributes among the alternatives was found to be highest for the shared bike (and e-scooter), which means that for equal increase in travel costs, higher disutilities are associated with the shared modes compared to the conventional ones.

Table 8 Parameter estimations of the final activity-based trip model

Name	Description	Value	Robust SE	Rob. t-test	p-value
Walk					
ASC_WALK_1KM	Alt. specific constant of walk alternative - 1km	0,452	0,136	3,33	0,001
ASC_WALK_2KM	Alt. specific constant of walk alternative - 2km	-1,29	0,145	-8,85	0,000
Shared e-scooter					
ASC_STEP_1KM	Alt. specific constant of e-scooter alternative - 1km	-4,62	0,631	-7,33	0,000
ASC_STEP_2KM	Alt. specific constant of e-scooter alternative - 2km	-5,11	0,618	-8,26	0,000
B_SEARCH_STEP	Search time shared bike	-0,203	0,042	-4,82	0,000
B_COST_STEP	Cost usage shared bike	-1,18	0,136	-8,68	0,000
B_UNLOCK_STEP	Unlocking method shared bike	0,0235	0,127	0,185	0,853
Shared bike					
ASC_SHBIKE_1+2KM	Alt. specific constant of shared bike alternative - 1/2km	-2,46	0,224	-11	0,000
ASC_SHBIKE_4KM	Alt. specific constant of shared bike alternative - 4km	-1,59	0,268	-5,95	0,000
B_SEARCH_SHBIKE	Search time shared bike	-0,0626	0,0259	-2,42	0,016
B_COST_SHBIKE	Cost usage shared bike	-1,2	0,0822	-14,6	0,000
B_UNLOCK_SHBIKE	Unlocking method shared bike	0,00515	0,0812	0,0635	0,949
BTM					
B_WAIT	Waiting time BTM	-0,0333	0,00828	-4,02	0,000
B_COST_BTM	Trip fare BTM		0,0525	-10	0,000
Shared car					
ASC_SHCAR	Alt. specific constant of shared car alt.	-4,56	0,66	-6,9	0,000
B_SEARCH_SHCAR	Search time shared bike	-0,0952	0,0332	-2,87	0,004
B_COST_SHCAR	Cost usage shared bike	-0,588	0,07	-8,4	0,000
B_UNLOCK_SHCAR	Unlocking method shared bike	0,0531	0,117	0,453	0,651
Interactions					
B_MOTIVE_WALK	Effect of being a must traveler on pref. walking	-0,591	0,154	-3,84	0,000
B_NEW_TECH_STEP	Effect of attitude towards new technology on pref. sh.bike	0,684	0,163	4,2	0,000
B_FAM_SHBIKE2_SHBIKE	Effect of having used shared bike before on pref. sh. bike	1,07	0,221	4,82	0,000
B_MOTIVE_WAIT_BTM	Effect of being a must traveler on sens. to waiting time BTM	-0,052	0,0151	-3,45	0,001
B_NEW_TECH_SHCAR	Effect of attitude towards new technology on pref. sh.car	0,852	0,184	4,64	0,000
Shared error comp.					
SIGMA_STEP_SHBIKE	Shared error component between e-scooter and sh.bike	3,32	0,153	21,7	0,000

When comparing the home-based trip with the activity-trip, similarity can in the first place be noted with respect to the importance of familiarity with shared modes. In both cases, having tried before or being willing to try, plays an important role in the shared modes' chances of being picked by the respondents. Also the impact of cost and time attributes was in both trip-models found to be higher for the costs attributes. Because the estimated parameters of both models are relative values to the fixed alternative specific constant of the BTM alternative, direct detailed comparison between parameter values of the two models is not possible. However, by calculating willingness-to-pay (WTP) ratios (dividing time-parameter by cost-parameter), allows for a rough comparison. The WTP for reduced search time of a shared bike is slightly lower in the AB case (HB € 3.64/hour vs. AB € 3.12/hour), which also applies to the WTP related to BTM waiting time (€ 7.44/hour of HB vs (averaged) € 6.13/hour of the AB model). This suggests that more disutility is associated with these travel time components in case of the home-based trip than in the activity-based trip.

5. Conclusion and recommendations

In this study a series of stated choice experiments was developed to explore and measure the factors that affect people's willingness to use shared mobility services as access or egress transport in multimodal train trips. A large sample of NS customers participated in these experiments (n=1835). Based on the collected choice data, mixed logit models that correct for panel effect and take into account common error terms between alternatives were estimated to assess the mode preferences of the respondents. The impact of choice factors related to characteristics of the modes, trip, and traveler was tested separately for the home-based side (origin to railway station) and the activity based side (railway station to final destination) of the total multimodal journey.

From the results, it can be concluded that in general, the chances of shared modes are found to be strongly influenced by travelers' experience and familiarity with these mode which can be linked to the adoption time of these new modes. The less travelers are accustomed to having a particular shared mode in their choice set, the larger the dominance of an intrinsic dislike. The shared bike exemplifies a mode that is already a more familiar option, especially for the activity-based trip, which results in a different hierarchy of mode related factors. The intrinsic mode preference become less dominant and other mode characteristics such as search time and usage costs gain more importance.

In this adoption stadium of the shared bike, usage costs become the most decisive factor. Sensitivity to costs of using a shared modes are still high compared to other modes, but this could decrease as the familiarity-burden decreases and the benefits of shared modes in terms of speed increase in valuation. In such future stage, the ease of usage – like the tested unlocking methods – could also become a more relevant factor in the mode choice process, but for now such effect is completely overshadowed by the intrinsic dislike factor.

Naturally, the above made point is generalized and its applicability also depends on the type of traveler and the type of trip. The more a traveler can be identified as an early adopters of innovations, the smaller the dominance of the found intrinsic mode dislike in his mode choice process. In line with the findings from the presented modal portfolio's, in particular travel purpose and age show to affect the willingness to use shared modes. The type of traveler that is younger and travels often by train (commuting) is more likely to switch to or try a shared mode in his door-to-door trip.

The findings of this study provide some first insights in the mode choice process of using shared modes within the multimodal train trip. Further research could extend these insights in several ways. By focusing more specifically one shared mode, the effects of other relevant attributes (such as availability) can be tested, such attributes were excluded in this study because of the broad range of included modes and trip distances. Besides, the identified importance of familiarity advocates for using research methods that include pilots in future research.

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