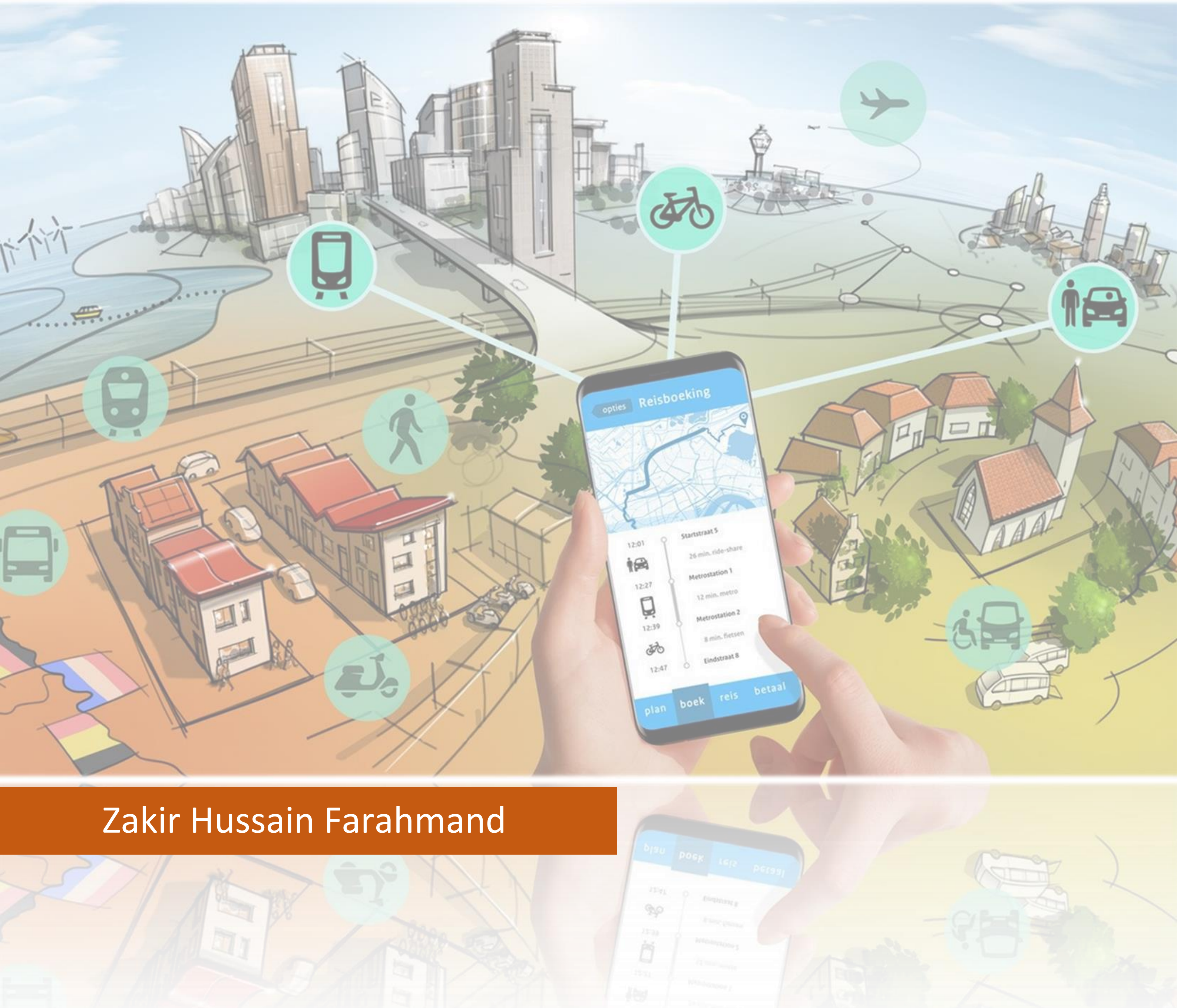
The Potential Role of Mobility as a Service as a Transport Demand Management Tool



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The Potential Role of Mobility as a Service (MaaS) as a Transport Demand Management Tool

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Preface

When I started looking for the subject of my master thesis, I was looking for something related to technological development in the transport era. The first time I heard about Mobility as Service (MaaS), I knew I want to dive into this topic. As a starting point, I did my 'Transport Research Project' about the effects of ride-sharing on reducing private car usage. However, it was not easy to find the right company interested in the topic of MaaS for management purposes or travel behavior changes in general. After meeting with several companies, MAP Traffic Management offered me this opportunity to investigate the potential of MaaS as a management tool.

In the beginning, I was supposed to perform my research on a specific case study, Amsterdam Zuidoost. When everything was going normal, the Covid-19 pandemic popped out from the middle of nowhere and smashed my whole plan. This was the time when the real challenge started. The best possible way to deal with this was to limit the scope of my study to commuting trips made by employees because they are easy to reach through their companies/organizations, it had its own difficulties, though. Despite all challenges, I am delighted that this overwhelming journey brought me here and the end product is something I am proud of.

This would not have been possible without the help of many people along the way. Prof. dr. ing. Karst Geurs, thank you so much for your feedback and guidance during several meetings we had, especially during the initial phase of my research. I appreciate our valuable discussions about the whole concept of MaaS. Those discussions helped me to identify my way in this research. I should also thank dr. Konstantinos Gkiotsalitis for being my supervisor and offering me constructive feedback whenever I needed it. Furthermore, I want to thank Patrick Hofman; you always made time and gave me your advice from questionnaire design to data collection and the final report. Dr. Jaap Vreeslijk, thank you so much for guiding me through my thesis and giving me this opportunity to complete my thesis at MAPtm.

Last not least, I would like to thank all my colleagues at MAPtm, friends, and everyone else who helped me along the way by giving feedback on the questionnaire and sharing the survey with your social and professional networks.

Zakir Hussain Farahmand,
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Abstract

For maintaining transport infrastructures as efficiently as possible, meanwhile, contributing to accessible and liveable cities, effective management of transport demands and resources is needed. In that sense, the Mobility as a Service (MaaS) concept is perceived as a promising solution to address the growing need for mobility. It is expected that MaaS would make travel more seamless. Moreover, it is expected that MaaS makes it possible to spread travel demand over time and modes, in favor of more sustainable modes. If these expectations come true, MaaS could be used as a tool to stimulate travel behavior. However, there is hardly any research focusing on this aspect of MaaS. The aim of this research was therefore to obtain insights on the potential role of MaaS as a transport demand management tool. An online survey including a Stated Choice experiment was conducted among employees in the Netherlands. Several Mixed logit models were performed to depict commuting mode choice behavior and underlying factors.

The result indicates that the inclusion of unlimited rides with train and e-bike sharing in the MaaS packages, as well as, car sharing attributes influence the mode choice behavior of employees. Furthermore, mode choice was significantly influenced by the price of the mobility packages and increasing parking tariffs. However, these effects were not equal for all types of employees. Young, low-income, multi-modal commuters and those who live near railway stations are more likely to change their commuting behaviors. On the other hand, MaaS might not be an effective management tool to change the commuting behaviors of old, high-income, car-dependent, and those who are living far from railway stations. Increasing parking tariffs on the other hand seemed to significantly influence car users who use street/garage parking spaces. This study concludes that MaaS could be seen as a promising transport management tool, but for specific types of employees. However, two unwanted consequences might hinder its effects. First, car users are very likely to substitute their car trips with car sharing, implying that the real nature of car-based traveling will not change with such modal shifts. Second, some employees who commute by public transport would switch to car sharing, and this could cross out the impact of MaaS on car users.

Summary

The rising demand for mobility increasingly puts pressure on transport infrastructures, and expansion is no longer be a sustainable solution, at least not in cities. For maintaining transport infrastructures as efficiently as possible, meanwhile, contributing to accessible and liveable cities, effective management of transport demands and resources is needed. In that sense, the Mobility as a Service (MaaS) concept is perceived as a promising solution to address the growing need for mobility. It is defined as an inter-modal mobility service that integrates the existing and new transport modes into a single interface, offers customized transport services and payment options. With this definition, MaaS aims to restructure the mobility distribution chain by integrating different transport services and supply them to individuals as a single service.

It is expected that MaaS would make travel more seamless. End-users and providers could communicate instantaneously via the platform and make the most out of transport infrastructures in efficient ways. Furthermore, accessibility to different modes would make it possible to use a more sustainable mode when it suits travel needs. This may lead to multi-modal traveling and efficient use of existing infrastructures, which is of particular interest to crowded cities. Moreover, it is expected that MaaS makes it possible to stimulate travel behavior towards off-peak traveling. Accordingly, travelers could be more spread throughout the day and reduce pressure during the rush hours. If these expectations come true, MaaS could be used as a transport demand management (TDM) tool to stimulate transport demand in favor of sustainable modes and reduce private car usage and/or ownership. However, there is hardly any research that studied its TDM aspects. MaaS is still an immature concept and many uncertainties and ambiguities exist related to its promises. Therefore, this study aimed to obtain insights into the potential role of MaaS as a TDM tool for work-related trips. The following research questions were formulated as:

RQ 1: What are the effects of mobility package elements and increasing parking tariffs on commuting mode choice behavior?

RQ 2: Which types of employees can be identified based on their current commuting patterns, and what are their characteristics?

RQ 3: What are the possible implications of investigated measures from the TDM perspective?

RQ 4: To what extent employees are willing to commute during off-peak hours?

By exploring employees' mode choice behavior and possible changes in their commuting patterns, the research provides insights if MaaS could be used as a TDM tool. This information

is valuable for both MaaS providers and public authorities to implement MaaS in a way that results in commuting behavior changes and hopefully increases in the use of environmentally friendly modes.

Furthermore, the research aimed to find out employees' attitudes towards MaaS characteristics and features. Since the concept of MaaS is not fully matured yet, end users might be carious about its characteristics (e.g. reliability, privacy, user-friendliness apps) and features (e.g. sharing subscriptions with family members, synchronization with personal agenda). Therefore, the fifth research question is:

RQ 5: What is the attitude of employees towards MaaS characteristics and features?

Literature research was done to identify underlying factors of mode choice behavior and the interests in using MaaS for commuting. A survey was then designed to investigate employees' mode choice and possible changes in their commuting behavior. This was done by the stated choice (SC) experiment. The SC design was based on 6 variables, namely the amount of ride with train, bus/tram/metro, car sharing, e-bike sharing, as well as, price and increase in parking tariffs (only for car users). Respondents were given six different choice questions, that were part of the SC experimental design with 54 profiles. They could select one of the three mobility packages, train+e-bike sharing, train+bus/tram/metro, car sharing+e-bike sharing. An opt-out or 'None' option was included to give respondents the freedom of choice since neither of the mobility packages could be desirable for a respondent. The 'None' option entailed that the person wants to continue using the current mode(s). When respondents selected their preferred mobility package, another question was displayed that asked them if they are willing to commute during off-peak hours by receiving a discount on their selected choice. This way, changes in commuting behavior was measured on two levels: change in commuting mode and change in commuting time. Furthermore, car users were asked if they are willing to substitute part of their car trips with other modes and if they think that MaaS can prevent them to reduce their car ownership/usage. Finally, respondents were asked about their attitude towards MaaS characteristics and features. This was done by telling the respondents to imagine that MaaS is available at the moment. The questionnaire also measured socioeconomic variables and current commuting patterns of respondents. This information was used to identify different categories of employees and compare their mode choice behaviors. In total, 236 respondents were found useful for further analyses.

To measure the effects of the attributes on mode choice, several Mixed Logit (ML) models were estimated. First, the models were estimated including only the mobility package elements. Latterly, the models were re-estimated per category of covariates, socioeconomic characteristics, and commuting-specific attributes. Since the increase in parking tariffs was displayed only for car users, relative ML models were estimated only for them, in which parking space and car necessity were inserted as covariates. Moreover, several scenarios have been composed based on the fitted models to obtain more insights into the combination of attributes. The scenarios split respondents into two groups: car users and non-car users. The first group refers to employees whose primary commuting mode is private/lease car. The second group refers to employees who mainly commute by other modes than cars. It must be noted that the sample was weighted to OViN 2017 and Wave 2016 data using the raking weights technique. This way, the sample bias was minimized to get more reliable results.

The results of the ML model estimations provided an understanding of the determinants of employees' mode choice behavior. Regarding the mobility package elements, unlimited rides with trains to working regions, and unlimited rides with e-bike sharing were found the most influential attributes. After that, car-sharing attributes were preferred in the MaaS packages. However, the inclusion of unlimited bus/tram/metro traveling did not significantly increase the choice probability of relative packages. The striking point was e-bike sharing outperformed bus/tram/metro as a last-mile travel mode. Moreover, the price of the mobility packages was found significantly influential in employees' mode choice. Even though most employees receive (partial) reimbursement from their employees for work-related trips, they still prefer cheaper transport modes. Likewise, the mode choice behavior of car users was influenced by increasing parking tariffs, but not very strongly. Overall, employees were found cost-sensitive, even if it is paid by a third party (employer).

However, a substantial difference existed in the mode choice behavior of different types of employees. Young (under 30) and low-income respondents were found to have more willingness in changing their commuting modes. On the other hand, older and high-income employees are less likely to replace their current modes, at least not with the provided mobility packages. Perhaps their long time established commuting habits made it difficult for them to change their habits, especially if they drive to work. However, education level and gender did not significantly affect employees' mode choice behavior.

Regarding the effect of current commuting patterns, commuting modes played a significant role in mode choice. To simplify the model estimation, respondents were categorized into three groups, car users, non-car users, and multi modal-commuters. The first group refers to respondents who drive private/lease cars to work. Basically, they do not use public transport for work-related trips. The non-car user group refers to respondents who commute mainly by public transport and partially with car sharing or bike sharing. In between, respondents who commute by car, in the meantime, by public transport are classified as multi-modal commuters. The results revealed that car users are less likely to replace their cars with other modes. For these respondents, car-sharing and e-bike sharing attributes were found influential in their mode choice. On the other hand, non-car users are more likely to choose train+e-bike sharing and train+bus/tram/metro. For them, subscribing to MaaS packages might not result in a major modal shift since they use more or less the same modes. The interesting category of respondents was multi-modal commuters. Their mode choice behavior was found similar to non-car users rather than car users. They showed more interest in train+e-bike sharing and train+bus/tram/metro packages, and less interest in car sharing+e-bike sharing. In addition to commuting modes, travel time and distance to railway stations were also found influential factors in mode choice. For longer travel time, respondents preferred packages with public transport. Furthermore, those who were living close to a railways station showed more willingness to commute by public transport. For shorter travel time, on the other hand, car-sharing and e-bike sharing were found preferred options. As well as, respondents who lived far from a railway station preferred car sharing+e-bike sharing. Regarding the travel distance and commuting frequency, no indication was found that these variables affect employees' mode choice behavior.

The effect of increasing parking was found to be dependent on the type of parking spaces that employees are currently using. Respondents who were parking on the street/garage were very likely to switch to alternative modes, especially to car sharing+e-bike sharing, when parking tariffs increased. On the other hand, those who used P+R locations were more interested in train+ e-bike sharing and train+ bus/tram/metro. Perhaps, they might subscribe to these packages for their last-mile travel, from P+R locations to workplaces and vice versa. However, the impact of increasing parking tariffs was limited for those who used their employers' parking space, which makes sense because they currently do not pay for parking. Notably is that respondents who had to drive cars due to personal reasons (e.g. carrying a baby seat) expressed less willingness to replace their cars. Perhaps, driving is the only feasible option for them until they have such constraints.

From the scenario analysis, it was found that the best configuration of the mobility package for non-car users is the package that includes unlimited train traveling to working regions and unlimited e-bike sharing traveling at €140/month. With this configuration, 48% of them would choose train+ e-bike sharing and 49.6% train+ bus/tram/metro. The result corresponds to the studies of Matyas and Kamargianni (2018b) and De Viet (2019), who found that MaaS adoption is strongly affected by unlimited access to public transport. For car users, on the other hand, the best configuration was found 60 minutes of car-sharing per day and unlimited rides with e-bike sharing at €140/month. 36.7% of them preferred this package with such a configuration. It was also found the unlimited rides with train and 60 minutes of car-sharing driving have the highest WTP and bus/tram/metro attributes have the lowest WTP. It means that employees pay more for having unlimited access to train and longer driving with car sharing.

However, changing commuting mode is not the only solution to reduce pressures on transport infrastructures. Shifting commuting demand to off-peak hours could also contribute to the TDM potential of MaaS. The results of this study revealed that multi-modal commuters are more likely to shift away from rush hours if they are given discounts on their preferred mobility packages. Around 52% of them expressed a willingness to commute during off-peak hours. Next to that, around 1/3 of car users who selected one of the mobility packages showed willingness in off-peak commuting. While non-car users are found less willing to change their time of commuting. Nevertheless, shifting them to off-peak commuting will only reduce pressures on public transport systems during rush hours, and will not affect traffic flow or congestion on roads.

Regarding the MaaS characteristics, it was found that limiting MaaS services to a single region is not desirable to employees. More than 70% of respondents wanted their packages to be usable throughout the whole Netherlands, not only in their working regions. Moreover, from the employees' perspective, the integration of real-time information (e.g. congestion, disruptions) and parking information could add value to MaaS services. Next to that, using subscriptions for other purposes than work and sharing subscriptions with family members, friends, and colleagues are preferred features of MaaS. The results also revealed that the reliability and privacy of the service are of high importance to employees. Since MaaS is still a developing concept, people need to be ensured that the new mobility service is reliable enough and does not violet their privacy norms. After that, flexibility, app user-friendliness, and app synchronization with personal agendas were rated valuable characteristics in MaaS services.

Concluding, MaaS seems to be a promising TDM tool in favor of sustainable transport modes, especially if other TDM measures like increasing parking tariffs are introduced alongside. Withstanding the small modal shift of car users, changes in their commuting mode did happen. A proportion of car users, even small, might reduce car usage and car-ownership in long term. Moreover, increasing parking tariffs can speed up modal shifts and hopefully promote the uptake of MaaS. However, the TDM potential of MaaS might be hindered by some undesirable consequences. First, car-sharing appears to be the most preferred substitute for private/lease cars. If so, the real nature of car-based trips does not change by switching to car-sharing because people still drive cars on roads. Second, the undesirable modal shift of non-car users to car-sharing will further increase the number of car-based trips, which might cross out its impact on car users. Third, the mobility packages were found to be more appealing to current public transport users. For them, using MaaS will not cause a major modal shift since they use more or less the same transport modes.

The findings of this research suggest a couple of recommendations for MaaS providers and public authorities. It is recommended that MaaS providers customize their packages concerning different types of employees and target them by their interests and travel needs. Expanding this to a broader context, different types of travelers will have different preferences and tastes of MaaS. Therefore, a better understanding of their mode choice behavior makes it possible to design a tailor-based service suited to the interest of identified groups. The second recommendation is related to the integration of TDM measures with MaaS services. Not only increasing parking tariffs and discounts on transport modes that investigated in this research but also several other measures could also be introduced alongside. These measures could be prioritizing parking space for car sharers, companies car initiatives (e.g. shifting from lease car to shared car), and optimizing the usage of existing parking spaces (e.g. booking parking spots beforehand). Last but not least, it is advised to take into account the undesirable consequences of the modal shift from public transport to car sharing.

Contents

List of Figures

List of Tables

List of abbreviations

AIC	Akaike Information Criterion
ASC	Alternative specific constant
BIC	Bayesian information criterion
CBS	Statistics Netherlands (Dutch: Centraal Bureau voor de Statistiek)
CI	Confidence Interval
e-bike	Electric bike
KiM	Netherlands Institute for Transport Policy Analysis
MaaS	Mobility as a Service
ML	Mixed Logit
MNL	Multinomial Logit
OViN	Onderzoek Verplaatsingen in Nederland
P+R	Park and Rides
RQ	Research Question
SC	Stated Choice
TDM	Transport Demand Management
WTP	Willingness to Pay

1 Introduction

The rising demand for mobility increasingly puts pressure on transport infrastructures. And conventional approaches where travel needs are countered by expanding infrastructures like roads, railways, parking, and airports are no longer a sustainable solution, at least not in crowded cities. Thus, dealing with the rise of mobility demand requires strategies that effectively manage (reduce) transport demand, as well as, change travel behaviors of people (Rodrigue et al., 2016).

One of the promising approaches that promote sustainable transport, in the meantime, deal with the growth of transport demand is 'integrated mobility', particularly Mobility as a Service (MaaS) (Kamargianni et al., 2016). MaaS refers to a digital platform that provides multiple transport modes, as well as, planning, booking, and payment options as part of a single service (Kamargianni, 2015). In other words, MaaS is an intermodal mobility service providing a combination of different transport modes including, public transport, car-sharing, ride-sharing, car rental, bike-sharing, and taxi through a single interface. It aims to restructure the mobility distribution chain by integrating multiple transport services and supply them to individuals as a single service (Kamargianni et al., 2018). As a result, users and providers communicate instantaneously via a digital service platform and make the most appropriate and efficient journey matches (Djavadian and Chow, 2017).

The key point in MaaS is that users can buy transport services based on their needs, not necessarily the means of transport (Kamargianni et al., 2016). This gives several supremacies to MaaS over conventional transport services. (1) Transport operators can find out, by looking at the platform records, what exactly the characteristics of users are, e.g. origins and destinations, time of travel, degree of flexibility, preferred price, and level of required comfort. (2) Service providers can arrange their offers based on transport demands. (3) Mobility operators, providers, and users can monitor the availability of transport modes; hence, adjust their services to travel needs accordingly (Enoch, 2018). (4) MaaS gives the possibility of actively managing both supply and demand in real-time and in parallel (Hensher, 2017).

It is expected that the MaaS services could be provided in favor of more sustainable transport with the hope that this will promote the uptake of public transport and shared modes. If so, MaaS could be used as a transport demand management (TDM) tool that leads to changes in travel behavior and reduction of car-based trips. This way, MaaS could reduce pressures on transport infrastructures and increase the use of more environmentally friendly modes. However, there is hardly any information in the literature about the TDM aspects of MaaS. There is only one other research that explored the potential of MaaS as a TDM tool by surveying Londoners (Matyas and Kamargianni, 2018a). Though the study concluded that MaaS is a promising TDM tool; however, the authors did not go beyond studying the willingness of travelers to use shared modes. This minimal evidence leaves space for further research to fill the gap between MaaS and TDM. Having said that, this research focuses on the TDM aspects of MaaS for commuting trips.

1.1 Research objectives

The main aim of this research is to obtain insights into the potential role of MaaS as a TDM tool, particularly for commuting trips. Introducing TDM measures alongside MaaS will potentially result in changes in mode choice behavior and hence scattering commuting demand over transport modes or time of the day will reduce pressures on transport infrastructures. Furthermore, the research aims to find out what characteristics and features of MaaS are valued by users. Since MaaS is in its initial stage, there is no consensus on what features should be included in the service that contributes to its uptake. Finally, the study intends to provide recommendations on the better practice of MaaS and how it could be used as a TDM tool.
Some of the terms used in the research objectives are defined in table 1.1.

Table 1.1: Definition of terms used in the research objective

Term	**Definition**
Mobility-as-a-Service (MaaS)	MaaS is an inter-modal mobility service that integrates the existing and new transport modes into a single platform, where users get customized transport services and payment options. With this definition, MaaS aims to restructure the mobility distribution chain by integrating different transport services and supply them to individuals as a single service (I and W, 2017; Matyas and Kamargianni, 2018a).
Transport demand Management (TDM)	TDM is a general term for the application of strategies that increase the efficient use of transport resources, most often by encouraging modal shifts from single-occupant auto to public transport and shared modes. TDM seeks to modify individuals' travel behavior by providing incentives or restricting auto trips (Habibian and Kermanshah, 2011).

1.2 Research questions

To achieve the research objectives of this study, the research questions are formulated as follows:
RQ 1: What are the effects of mobility package elements and increasing parking tariffs on commuting mode choice behavior?

RQ 2: Which types of employees can be identified based on their current commuting patterns, and what are their characteristics?
RQ 3: What are the possible implications of investigated measures from the TDM perspective?
RQ 4: To what extent employees are willing to commute during off-peak hours?

The first research questions refer to the intention of employees to choose transport modes for work-related trips in relation to the elements of MaaS packages and increasing parking tariffs. In this study, both encouraging measures, e.g. unlimited rides with trains, and discouraging measures (increasing parking tariffs) are examined. Giving incentives and disincentives along with MaaS packages could act as the 'carrot and stick' role, which is an important strategy in the TDM era. The second research question refers to identifying different categories of employees based on their current commuting patterns and socioeconomic characteristics, and how their mode choice behavior differs. Answering the first two research questions will provide a complete overview of employees' preferences and their commuting choice behavior. Research question 3 refers to the possible implications of the investigated measures from the TDM perspective. This will be done by composing several scenarios based on different configurations of mobility packages. The fourth research question refers to the distribution of commuting demands across the time of the day (shifting to off-peak hours). Of relevance to reducing pressures on transport infrastructures, this question reflects the willingness of employees to shift away from rush hours.

Concerning the MaaS characteristics, the following research question is formulated in this study:
RQ 5: What is the attitude of employees towards MaaS characteristics and features?

The fifth research question refers to employees' attitudes towards MaaS characteristics (e.g. reliability, privacy, user-friendliness apps) and features (e.g. sharing subscriptions with family members, synchronization with personal agenda).

1.3 Research scope

Individuals choose travel modalities that satisfy their needs and give them the maximum utility, known as mode choice behavior (De Vos et al., 2016). In this sense, many factors that influence travel behavior concerning travel mode, time and route. The scope of this research is set to work-related trips of employees in the Netherlands when mobility alternatives are provided through MaaS.

1.4 Managerial and scientific relevance

The research initiator is MAP Traffic Management, a Dutch consultancy company located in Utrecht, the Netherlands. They offer consultancy/advisory services to government, road authorities on the strategic, tactical, and operational levels of traffic management. Furthermore, they also take action to execute advises on a daily management basis. The ambition of the MAPtm is to explore smart and innovative solutions for traffic and mobility management. Therefore, it is of high interest to the company to deepen their understanding of MaaS markets and factors that determine the uptake of MaaS among end-users. This research aims to provide the company with useful insights into the implications of MaaS for management purposes so that the company could use the generated knowledge for undermining their decisions in the design and realization of MaaS services.

Furthermore, the study contributes to the nascent knowledge of the MaaS concept in several ways. First, the research contributes to the academic understanding relationship between MaaS services and TDM measures. Focusing on demand-side factors as well as supply-side attributes will contribute to the expansion of the MaaS concept to more practical utilization of MaaS as a TDM tool. This way the study partially fills the gap between TDM and the MaaS concept, which is still largely unexplored in transportation researches. Second, incentives and disincentives measures introduced with mobility packages in this study will give a better understanding of how we can influence commuters' choice behavior. There is barely any study that has investigated the 'stick' aspect of MaaS. Therefore, this study provides productive insights on how to stimulate commuting mode choice through MaaS.

1.5 Structure of the report

This is the end of the first chapter - a brief introduction to the subject, the research objectives, and the research questions. The next chapter represents the theoretical background of the research, particularly the MaaS concept and how MaaS is related to transport demand management. The research methodology is discussed in chapter 3 - a stated choice experiment targeted employees in the Netherlands. Chapter 4 presents the data analysis and results; meanwhile, all research questions are answered in this chapter. Chapter 5 concludes this research by summarizing the main findings, providing recommendations to MaaS providers and public authorities who are involved in such projects, and discussing the limitations of the research, as well as, recommendations for further research. Figure 1.1 presents the thesis outline.

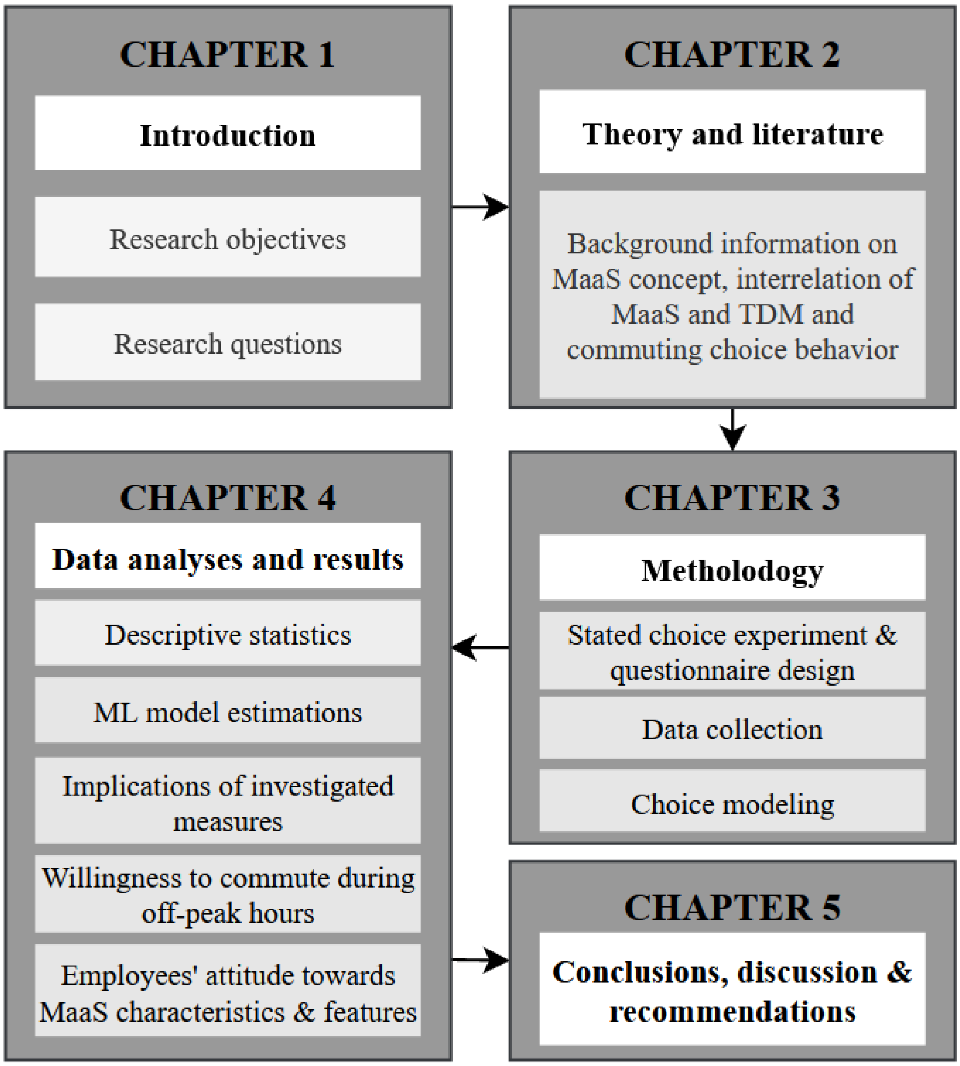

Figure 1.1: Thesis outline

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2 Theory and literature

This chapter reviews relevant literature regarding the concept of MaaS, institutional and integration levels, TDM measures, and travel mode choice behavior.

Section 2.1 elaborates on the definition of MaaS. In section 2.2, the supply side of the MaaS concept, institutional and integration levels, and TDM measures are discussed. Section 2.3 discusses the demand side of MaaS, including mode choice behavior and travel behavior changes based on pilot projects. Section 2.4 elaborates on the conceptual model developed in this study. And the chapter concludes by summarizing the literature review.

2.1 Definition of MaaS

The novelty nature of MaaS makes it difficult to fully define what MaaS is and what implications accompany this concept. It can be thought of as an innovative concept (a new idea for conceiving mobility), a new phenomenon (occurring with the emergence of new behaviors and technologies), or as an innovative mobility solution (integrating transport modes and mobility services) (Jittrapirom et al., 2017). Therefore, several definitions have been discussed in the literature. The very first comprehensive definition is provided by Hietanen (2014) in which MaaS is defined as “a single interface that combines different transport modes to offer a tailored mobility package, similar to a monthly mobile phone contract, which could include other complementary services, such as trip planning, reservation, and payment." Based on this definition, the core specifications of MaaS are bundling, integration of transport modes, and customers' need-based services. A similar definition has been given by Gould et al. (2015), in which MaaS is defined as “an opportunity to shift the interest from private car ownership/usage to alternative modes, e.g. electric vehicles to mitigate the adverse impact of transport systems on urban contexts and the environment”. This definition brings the expectation that MaaS will replace the existing ownership-based transport with an access-based system. Giesecke et al. (2016) include the sociological level and sustainability dimensions into the MaaS definition. Users' acceptance and adoption, as well as, its role for travel behavior changes are of relevance to this definition.

Another comprehensive definition of MaaS is provided by Holmberg et al. (2016), in which MaaS is thought as a new way to facilitate the movement of people from origin to destination by offering available transport modes in a completely integrated way. Furthermore, it gives the possibility to plan, book, and pay for multiple modes that are required in a journey, all through a single platform (Holmberg et al., 2016). This definition focuses on the personalized, on-demand, and flexible characteristics of MaaS services. This way, mobility services could be framed around individuals' preferences which are missing in conventional transport systems

(Atasoy et al., 2015). Some authors emphasize the role of Information and Communication Technologies (ICTs) in MaaS services. Schlingensiepen et al. (2016), for instance, mention the collection, transmission, process, and presentation of information that is necessary for advising the best transport solution relative to users' needs. Other definitions consider the user-centric perspective that MaaS is aimed to provide door-to-door mobility for users (Ghanbari et al., 2015; Kamargianni et al., 2016; Rantasila, 2015). This requires technological advances, high cooperation of different transport operators, and the integration of several transport modes.

The literature review reveals that despite diversities in the definition of the MaaS concept, some characteristics are common in most definitions such as customization, tariff options, multi-modality, basic functionality (real-time information, planning, booking, and ticketing), and employed technologies. Table 2.1 represents some of the core characteristics of MaaS.

Table 2.1: MaaS core characteristics

Core characteristics	**description**
Multi-modal mobility	MaaS create multi-modal transportation systems and allowing users to choose the ones that fulfill their needs. Most MaaS platforms include public transport (bus, train, tram, and metro), care-sharing, ride-sharing, car-rental, bike-sharing, and on-demand bus service.
Subscription and payment	MaaS offers are mostly provided as "monthly packages" or "pay-as-you-go." The packages can cover different transport modes based on km/time/points/tickets that can be used in exchange for using the service. The pay-as-you-go refers to the payment based on a single journey. There is also another type of tariff in which the travel expense bills are sent to users at the end of each month. All the payments can be done via the app/website.
Single platform	MaaS service requires a platform that combines multiple functionalities into one integrated interface. A major enabler for MaaS is therefore the development of ICT. Mobile apps and websites are the communication tools between end-users and MaaS providers through which users can access to the service. Additionally, other features like the weather forecast, synchronization with personal calendar, travel history, and feedback could be included alongside with mobility services.
Demand orientation	MaaS could be called a need-based mobility paradigm. It offers multi-modal transport solutions that suit users' needs and travel preferences.
Customization	MaaS service consider the uniqueness of individual users by giving them recommendations and tailor-made solutions based on a user profile, travel preferences, budget limits, and past behaviors. It should give users the possibility to change their subscriptions based on their preferences. Furthermore, the MaaS provider ensures, due to an unforeseen event, the availability of alternative options or if the user requires an alternative mode during a journey or in the package.

Decision influence	Certain MaaS schemes could be designed to influence users' travel decisions by giving incentives to promote more sustainable transport modes, e.g. public transport, e-vehicle, and bike. As well as, disincentives, e.g. increase in parking tariff, could be introduced through MaaS. These features could be beneficial in the positive contribution of MaaS to sustainability and societal goals.

2.2 MaaS and supply side

2.2.1 Institutional levels

The institutional level refers to the involvement and/or benefits of parties in the realization of MaaS services. There are three institutional levels identified in the literature. Macro-level refers to national visions, action plans, and goals, legislation, subsidies, and taxes. Meso-level indicates the variety of institutions, regional and local public authorities, and private organizations. And micro-level refers to the individual customers and end-users of MaaS. Figure 2.1 represents the institutional levels of MaaS.

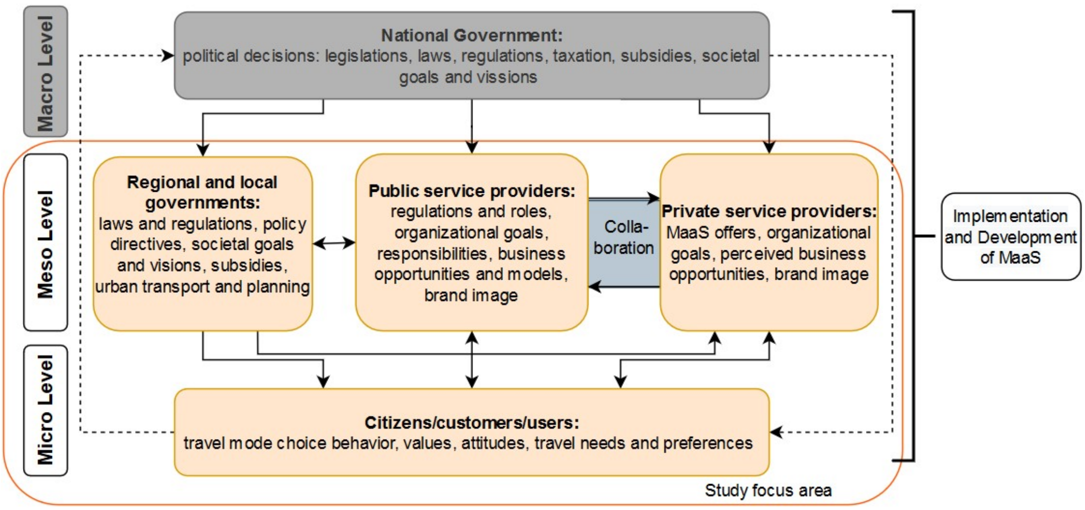


Figure 2.1: Institutional levels of MaaS; adopted from Karlsson et al. (2020)

Macro-level

The macro-level is like an umbrella under which the meso- and micro-levels can operate. It refers to the legal structure for public and private actors, as well as, encompasses informal factors like national goals and missions through the development of MaaS (Karlsson et al., 2020). In this level, the government has a critical role regarding the integration of mobility services in terms of creating preconditions for the implementation of MaaS and safeguarding public interests, safety, and privacy, as well as, environmental concerns (Lund et al., 2017). The government has to ensure the societal benefits of MaaS services by increasing mobility by other means than cars. A potential risk here is that private sectors will tend to attract strong customer demands for car-sharing and car-rental travel and hence increase the number of car-based trips. In this case, MaaS counteracts transport goals that focus on reducing car trips (Datson, 2016). This may hinder the support of policy-makers at different levels of MaaS development.

However, the government should find a balance between societal goals and business benefits. Regulations should be appropriate enough, in which public interest is served, meanwhile, private sectors find it easy to join the MaaS ecosystem (Goodall et al., 2017). It is of relevance to MaaS pilots in the Netherland where public transport tickets are subsidized by the government. It raises the question of how public transport operators are allowed to sell their tickets; furthermore, for which mobility services, e.g. public transport, car-sharing, or bike-sharing, it is reasonable for the government to subsidize.

Meso-level

The meso-level refers to involved parties, including public authorities and private sectors, as well as, non-profit organizations (Karlsson et al., 2017b). An important antecedent of well-functioning MaaS is the institutional coordination for the integration of information, ticketing, scheduling, and planning. Another aspect of integration is providing the necessary infrastructure for shared modes in the neighborhood of public transport stations, which requires public authorities' support (Lund et al., 2017).

Within the business ecosystem where several actors need to transform from their core businesses to the MaaS platform, multiple private actors need to collaborate for a scaled integrated mobility service ((Holmberg et al., 2016). Though there is a large market to attract customers to new and innovative mobility solutions (Datson, 2016), little information exists on what types of business models fulfill the interests of involved parties. However, the role of public transport providers is viable in the integrated mobility services, serving as a backbone of the system (Karlsson et al., 2017b). In this case, the service could be designed in a way to maximize the use of public transport rather than improving users' satisfaction level by other modes, e.g. car sharing. This way, MaaS could contribute to mitigating pressures on transport infrastructures by reducing car-based trips. On the other side of the coin, if external and independent actors are free to arrange a new service combination focusing only on financial benefits (König et al., 2016), the MaaS service might not serve as it is expected to.

Micro-level

The micro-level refers to individual users known as potential customers or end-users (Karlsson et al., 2020, 2017a). On the micro-level, social trends, e.g. travel behavior changes support the concept of MaaS. Pilot trials have shown that certain groups of individuals could be attracted to MaaS as a new mobility service (Karlsson et al., 2017a). Previous studies highlight as least five potential benefits that MaaS can bring to its users:

- Personalized service: MaaS offers relevant travel choices depending on the travel preferences of a customer.
- Ease of transaction: convenient access to different modes of transport via a single platform.
- Ease of payment: customers can pay by different schemes such as pay-as-you-go, monthly subscription, pre-pay, and post-pay.
- Dynamic journey management: MaaS provides customers with real-time information on their journey.
- Journey planning: MaaS service allows customers to plan their journey based on their travel preferences, e.g. cost, time, comfort, etc.

According to Sochor et al. (2015), among six groups of travelers (traditional car-lovers, flexible car lovers, urban-oriented public transport-lovers, conventional bike-lovers, ecological public transport, and bike-lovers, innovative technology-lovers), only three groups are likely to use MaaS services. These groups are public transport- and bike-lovers, flexible car users, and innovative technology-lover. An ex-post study from the Ubigo pilot showed that the primary customers of the MaaS service would be 'Flexi travelers' who often travel by public transport but also need other modes of transport regularly. These travelers will experience MaaS services as a price-worthy alternative to private car ownership. While car-dependent and customers whose mobility needs are well addressed by public transport are found less likely to use the service (Sochor et al., 2015). However, such studies are limited concerning commuters, particularly employees to know their motives to change their current modality styles and adopt MaaS in general.

2.2.2 Integration levels

In addition to different institutional levels of MaaS, its integration level is also of high relevance to this study. MaaS integrates existing mobility services into a single interface and its integration level differs from project to project. Figure 2.2 shows different levels of integration: 0) no integration; 1) integration of information; 2) integration of booking and payment; 3) integration of the service offers; and 4) integration of societal goals (Sochor et al., 2018). It should be noted that the integration levels do not necessarily depend on each other, but societal benefits and business potentials are related to the levels that will be discussed in the following sub-sections.

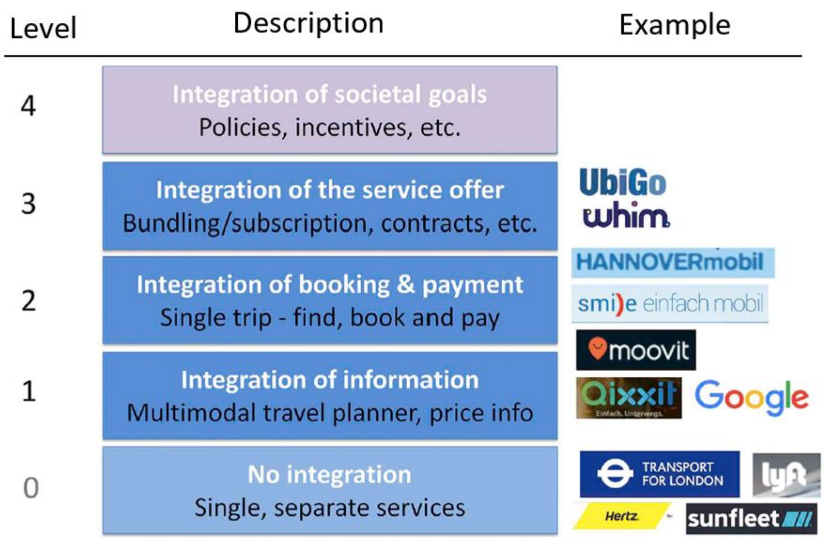


Figure 2.2: Integration level of MaaS, adapted from Sochor et al. (2018)

Level 0 - 1

In level 0, each transport system operates separately and therefore no integration occurs. Level 1 presents the integration of information like travel planning information and departure/arrival of public transport. Typically, end-users do not pay for travel information and therefore these apps/websites (e.g. google map, NS, 9292.nl, Qixxit) financially rely on ads and governmental subsidies. As such, level 1 has users rather than customers (Sochor et al., 2018). The added value of this level is decision assistance for finding the best mobility option in terms of travel time, cost, and convenience.

Level 2

This level refers to the integration of planning, booking, and payment for a single trip. Customers' can access multiple transport modes with some additional features that could support travelers in finding their preferred mobility options. Such services will make travel easier through a single mobility marketplace or a one-stop-shop. Still, users are less likely to pay additional fees for such a service if some extra incentives and services are not provided alongside. Therefore, the business opportunity for the MaaS providers would be generated from brokerage fees, commission fees, fixed membership of transport operators (e.g. car-sharing companies), or selling information to cities the same as level 1(Sochor et al., 2018).

Level 3

This level indicates the integration of mobility services with a focus on the customers' complete mobility needs that transport providers cannot fulfill solely. Unlike level 2, transport services are bundled, usually subscription-based, not necessarily a single trip from A to B. At this level, an ICT platform is required to run the business. MaaS in this level involves a two-way responsibility from end-users to suppliers and vice versa, at least during the subscription. In that sense, the role of a MaaS provider is more than a broker or an open marketplace. It works with different suppliers to not only run a profitable business but also create value for suppliers and better address travel needs (Sochor et al., 2018). Thus, the service is financed by the bottom-line difference between packages and the amount of contract with transport service providers. The bottom-line difference refers to the 'swings and roundabouts' principle where some trips or modes are sold with high margins and some at loss. People may make fewer trips than they have subscribed for or the price model is different from what suppliers themselves market to their customers (Sochor et al., 2018).

Level 4

Level 4 represents the integration of local, regional, and national policies and goals into the MaaS context. The involvement of public authorities on local, regional, or national levels influences the societal and ecological impact of transport services and travel behavior through incentives/disincentives and setting conditions for transport operators. These actors should ensure that mobility solutions not only fulfill travel needs but also societal goals. Developing a contractual model for private-public cooperation, as well as, influencing users' travel behavior while running a 'profitable business' are discussed at this level (Sochor et al., 2018).

2.2.3 Current practice of MaaS

So far, there is no consensus on how MaaS should operate. Usually, every MaaS project has an exclusive way of practice. Depending on the integration level and available modes, the MaaS scheme differs across companies, cities, or pilot projects. In the case of Ubigo in Stockholm - launched in the spring of 2019 after its trial in Gothenburg - MaaS was provided in bundles, starting from a monthly subscription fee of 99€ (1050 SEK) for a small package and 397€ (4206 SEK) for big packages. Users also had the option to pause or change their plan at any time, transfer unused credit to the next month and share their plan with family members and friends. However, public transport and bike sharing were not included after the trial phase. The reason was that public transport providers could no longer continue with the regular business ecosystem of MaaS when subsidies ended (Sochor et al., 2016). In fact, the service turned out to become a private business like carpooling companies rather than a real MaaS service.

Similar to Ubigo, Whim in Helsinki provides MaaS service on a monthly subscription-based, which included public transport, city bike, taxi, rental car, and E-scooter and was only valid in the HSL area. Depending on the frequency of ridership, the price ranges from €59.7 to €499 per month (Whim, 2020). In the Netherlands, BEAMRZ – a Dutch MaaS operator - tried different schemes within the pilot project in the Paleiskwarteir area. Initially, the service integrated OV-bike, taxi, and parking with three offers, two of which were based on monthly subscriptions. Later on, the pricing scheme has been altered to pay-as-you-go.

Concerning level 1 and level 2 of integration, no information can be found in the literature or website of the companies concerning the price settings. Within the Smile app, the mobility platform offers individualized options for a trip from A to B and options are filtered concerning transport, time, price, and CO2 emission. The price differs according to the duration of usage and the distance driven (Smile, 2020). A similar principle is being utilized in the Hannovermobil in Hanover city, Germany. The service covers public transport, bike- and car-sharing, and taxi that users can book and pay through a single app (GVH, 2020). However, the price does not differ from using each mode separately.

2.2.4 Service design and technology acceptance

The user-friendliness design of MaaS services is of utmost importance for attracting people and locking them in (Kamargianni et al., 2018). Elderly people would feel uneasy about multiple characteristics of MaaS services and would be afraid of strict commitment to a MaaS subscription. On the other hand, the lack of previous experiences with multi-modality could be an obstacle to MaaS adoption. From the user side, MaaS services are accessible via a smartphone application, and hence having sufficient ICT skills is crucial (Strömberg et al., 2016). One of the reasons why Ubigo trial was successful in attracting new customers was the simplicity of its ICT system - easy enough to use (Karlsson et al., 2016). Therefore, the user-friendliness of the system is a key to enable users to navigate and understand, cancel, transfer unused credits to the next month, change plans, and so forth (Kamargianni et al., 2018).

2.2.5 MaaS and TDM measures

Mobility management (MM) and TDM refers to strategies that are aimed to change the way people perceive mobility services, instead of physically altering the infrastructures themselves (Matyas and Kamargianni, 2018a). Meyer (1999) defines TDM as ‘any action or set of actions aimed at influencing people’s travel behavior in such a way that sustainable mobility options are presented and/or auto trips are reduced. It refers to the development of a set of mechanisms influencing individuals’ behavior by mode, time, cost, or route in a such a way that sustainable modes are promoted (Ison and Rye, 2008; Meyer, 1999). Hard measures on the other hand refer to physical changes like infrastructure improvement or prohibiting parking in certain areas (Bamberg et al., 2011).

TDM measures usually include incentives for showing the desired behavior and disincentives for an undesirable behavior (Matyas and Kamargianni, 2018a), performing as the ’carrot and stick’ rule. Often the carrots and sticks rules are used in combination in the mobility management context. The primary purpose of TDM measures is changing travel behavior and reduce car-based trips while providing a wide variety of mobility options to everyone who wishes to travel (Robinson et al., 1997). Meyer (1999) grouped these measures into three broad categories. (1) Offering alternative modes or service that results in higher per vehicle occupancy. (2)

Giving incentives/disincentives to reduce the number of trips or to push trips to off-peak hours. (3) Accomplishing trip purposes via non-transport means, e.g. use of telecommunication for work or shopping. Smith (2008) added two other categories, namely parking and land-use management and policy reforms. Some of the widely used TDM measures are summarized in table 2.2.

Table 2.2: Examples of TDM measures; compiled from Meyer (1999) & Smith (2008)

Transport options	Incentives & disincentives	Parking and land-use management	Policy reforms
Providing generic and tailored public transport information Liaise with the local operator for new or better services and cheaper prices Pay for new services Alternative work schedules Integration of public transport and shared modes Prioritization of parking spaces for car sharers	Incentives for using greener modes Providing subsidies on public transport Reducing parking supply Car fleet management Company car initiatives (replacing lease cars with car sharing) Parking pricing and Road pricing	Bicycle parking Car free districts and pedestrianized streets Location-efficient development Parking management Shared parking Transit-oriented development	Access management Campus transport Car-free planning Institutional reforms Least-cost planning Special event management Transport demand management Tourist transport management

From the above measures, several of them could be introduced alongside MaaS services. Referring to the first and second categories of TDM measures, MaaS is a perfect interface to integrate public transport and shared modes, incorporate multiple transport providers, and provide travel information to end-users. In many industries like telecommunication and medical devices, the 'bundling solution' is used and is proved to be more competitive than standalone products or services (Cusumano et al., 2014). In the context of MaaS, bundling different transport modes will potentially accelerate travel behavior changes (Matyas and Kamargianni, 2018a). In fact, this is the primary idea behind the concept of MaaS to integrate separated transport services into a single interface. Furthermore, prioritizing parking spots on certain areas for car sharers, or at least for MaaS users, would contribute to travel behavior changes. Regarding the second category of TDM measures, the MaaS pricing scheme could be considered as the carrot to persuade individuals towards public transport and other shared modes or shift them to off-peak hours. For instance, travel costs during off-peak hours could be reduced so that travelers are encouraged to avoid rush hours. Providing favored alternatives with persuasive prices while increasing the price of other alternatives through MaaS could be an effective measure to influence mode choice behaviors. Moreover, increasing parking tariffs is another measure (as a stick rule) that could be introduced alongside the MaaS application. At the moment, this is applied as a standalone TDM measure to reduce car traffic inside the cities. The combination of these measures (increasing parking tariffs and incentivizing public transport and shared modes) with the MaaS application would result in major travel behavior changes. As a result, a new aspect will be added to MaaS and that is its potential role as a TMD tool, the primary focus of this study.

It must be noted that investigating measures related to parking and land-use management and policy reforms is beyond the scope of this study. Furthermore, the application of these measures requires the approval of high-level policy-makers and their integration with MaaS projects is very difficult, if not impossible.

2.3 Demand side

This section elaborates on the MaaS from the demand side or end-users'. The adoption of MaaS is highly dependent on the attitudes and preferences of potential users. Due to the novelty of the concept, there is limited evidence regarding the effect of MaaS on travel behavior changes. To obtain better insights into individuals' motivations for choosing a modality, this section elaborates on mode choice behavior and travel behavior changes that have occurred throughout pilot projects.

2.3.1 Travel mode choice behavior

To develop environmentally sustainable and socially desirable mobility service, understanding the individual and contextual determinants of mode choice behavior (De Vos et al., 2016). Most studies highlight the role of instrumental factors such as travel time and travel costs. For instance, random utility theory (RUT) or random utility maximization model has been extensively used in literature, in which a particular modality is chosen based on its highest utility, e.g. travel costs and time (De Vos et al., 2016; Paulssen et al., 2014). The assumption is that individuals maximize their utility gained from a trip (Buehler, 2011). Another assumption is that individuals choose travel modes that satisfy their needs and desires after accounting for the costs. However, the RUT theory does not consider the context of travel. Car travel, for instance, could be less attractive in dense cities due to traffic congestion, parking supply, and parking cost (Buehler, 2011). In contrast, cars have a higher utility in suburban areas and spread-out cities (Schwanen and Mokhtarian, 2005). Another notion is that people select where to live that enables them to travel with their preferred transport mode as much as possible. Residential location is a choice that affects people's activities and travel patterns in time and space. A car lover, for instance, will likely prefer to live in suburban neighborhoods where car accessibility is good (De Vos et al., 2013). Moreover, individuals tend to develop travel habits, so they no longer consciously trade-off the costs and benefits of available transport modes due to repeated positive experiences (De Vos et al., 2013). That is to say, it is difficult to draw a concrete cause-and-effect relationship for mode choice behavior.

Recent studies focus more on the theory of 'planned behavior' and 'interpersonal behavior' when it comes to travel behavior. In these studies, social psychology aspects of travelers like attitude, lifestyle, environmental concerns, and habits have received considerable attention (Paulssen et al., 2014). Studies indicate that attitudes toward less tangible attributes like comfort, convenience, travel satisfaction, and environmental concerns could be better predictors of mode choice behavior than objectives measures (De Vos et al., 2016). In often case, people choose the travel mode that gave them the highest travel satisfaction in previous trips, at least if other considerations such as cost will not constrain the use of that transport mode. For instance, if traveling with a particular transport mode is satisfactory, the degree of shifting to similar choices will reduce over time (De Vos et al., 2016). It suggests that people try to maximize experienced happiness alongside monetary and time utilities by choosing a mobility option that minimizes remembered pain and maximizes remembered pleasure (De Vos et al., 2013). This also relates to built-environment factors. People who do not live in their preferred neighborhood would experience low travel satisfaction as their living locations make them ride undesired modes.

A large body of literature shows that personal characteristics such as age, gender, income, driving licenses, education level, car ownership, and household structure affect travel mode choice (De Vos et al., 2016; Li et al., 2012). Li et al. (2012) found that car usage decreases at very old ages as well as at a very young age in the UK. Concerning gender, women rely less on private cars than men (Cheng et al., 2019). Additionally, studies report that people with higher income levels are more likely to travel by car (Bhat and Lockwood, 2004; Cheng et al., 2019). Both factors, income, and car ownership are closely correlated with each other, where a higher income makes cars a feasible option. Moreover, having a higher income mitigates the effect of travel cost constraint and therefore a person seeks faster and convenient modes (De Vos et al., 2013). Education level is another variable influencing travel mode choice behavior. Highly educated people are also prone to make more trips by public transport than private cars (van den Berg et al., 2011). Finally, those who are living in a large household are less likely to use non-motorized modes compared to those living in a smaller household (Ryley, 2006).

According to Paulssen et al. (2014), the personal values of travelers are also influential determinants of travel mode choice behavior. Personal value has been defined as an enduring individuals' belief that reflects the most basic characteristics of adaptation from which attitudes and behaviors are subsequently generated. Power, security, and hedonism, for instance, can potentially influence individuals' attitudes toward comfort, convenience, pleasure, reliability, and ownership of different transport alternatives, which in result affect the individuals' travel patterns. For example, an individual who hungers for the feeling of freedom and driving pleasure might continue to use a private car, even when it is not the cheapest, fastest, or safest mode of transport for him/her. Like personal values, the theory of interpersonal behavior refers to the attitudes and habits of people. For instance, a pro-environment person might prefer to travel more with public transport, or at least an electric vehicle (Adjei and Behrens, 2012). Figure 2.3

presents the hierarchy of cognition for travel mode choice behavior based on previous studies.

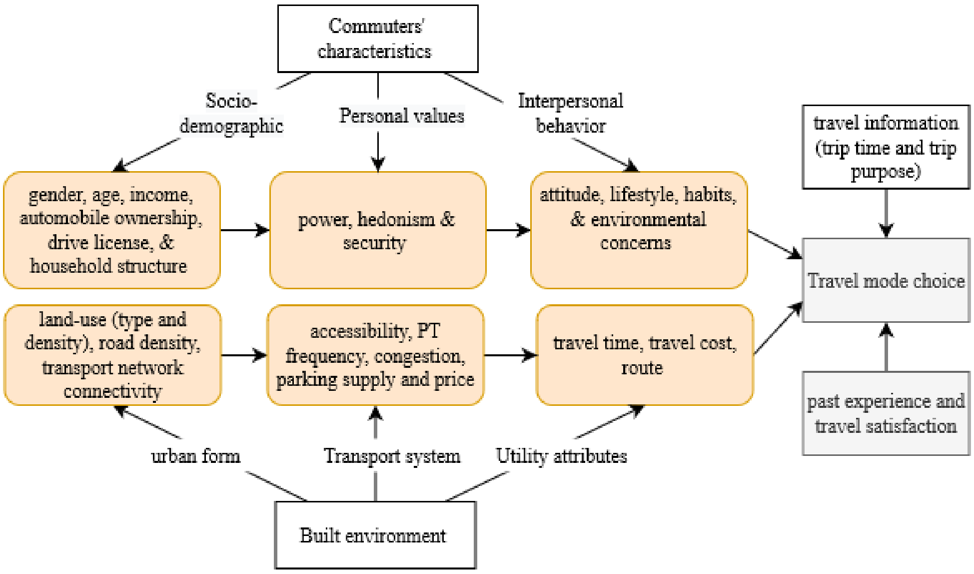


Figure 2.3: Travel mode choice behavior and explanatory factors

2.3.2 MaaS pilots and travel behavior changes

Frequent claims about positive contributions of MaaS to sustainability goals rely on research findings of pilot projects or qualitative studies. MaaS trials around the globe have revealed that it can reduce private car usage. In the case of Ubigo pilot in Gothenburg, Sweden, 44% of its users reduced their private car usage during the trial period (Karlsson et al., 2017b). As well as, it was found that 64% of Ubigo users had increased using alternative modes like car-sharing and bus/tram, of which 97% were satisfied with their mobility options (Karlsson et al., 2016). 48% of the participants in the Smile trial stated that their travel patterns had been changed since using the app. The service enabled them to take faster routes, combine multiple modes, and subscribe to new mobility options that they never used before (Smile-mobility, 2015). An ex-post study by Strömberg et al. (2018) on the Ubigo trial users identified several groups of travelers who showed different intentions for using MaaS. These groups are as follows:

- Car shedders: travelers who expressed willingness to stop owning their cars due to being expensive, inconvenient, and adverse impact on the environment. Around 95% reduced private car usage, of which 78% increased using car-sharing and 30% car rental.

- Car accessor: travelers who were interested in getting access to a car without owning it due to the same reasons that car shedders had. The study found that 37% of them reduced using their private cars.

- Simplifiers: travelers who showed willingness in using new ways of mobility; around 20% of them used fewer private cars by the end of the trial.

- Economizers: travelers who perceived MaaS as a way of saving money by reducing car-based trips. Around 53% of these travelers reduced their car usage.

The results of the Ubigo trial in Gothenborg and the Smile project in Vienna revealed that MaaS might contribute to higher use of public transport and shared modes, higher multi-modality, and lower use of private cars. However, the term ‘reduce’ is not defined in the aforementioned studies. It has not been clarified to what extent users reduced their private car usage, e.g. twice less or three times less. Furthermore, the authors do not consider the modal shift from public transport to car sharing and car rental. In that sense, the relationship between MaaS and travel behavior changes would be different. Additionally, half of the car owners of the Ubigo trial did not like the idea of having access to shared cars instead of owning one, which was not highlighted in the final results. Perhaps, MaaS could replace the second car ownership, not primarily the first cars (Karlsson et al., 2017a). Up to the knowledge of the author of this study, there is hardly any information about real travel behavior changes based on pilot projects except the Ubigo and Smile. It may be the novelty of the MaaS concept that constrains companies not to leak any information about their success or failure.

Nevertheless, there are many exploratory studies, mostly ex-ante analyses, on the expected travel behavior changes that could occur with MaaS. For instance, Kamargianni et al. (2018) found out that 35% of travelers in London are willing to replace their private cars with public transport if they are given unlimited access through MaaS. Gruijter (2019) found that people who frequently used train and travel planning applications are expected to adopt MaaS. However, the study does not highlight whether these people are willing to change travel behavior, especially from cars to public transport.

2.4 Conceptual model

Based on the literature review in section 2.1 - 2.3, the uptake of MaaS and its potential role as a TDM tool could be explained by the following variables:

- Socioeconomic characteristics (gender, age, income, and education level)
- Commuting-specific attributes (commuting modes, frequency, travel time, travel distance, distance to railway stations, and parking space for car users)
- Mobility package elements (amount of ride included in the packages, price)
- Increasing parking tariffs

Figure 2.4 represents the elements of the conceptual model developed in this study. It should be noted that the macro-level is beyond the interest of this study. This level refers to the national government that develops policies and regulations for the whole transport systems in the country.

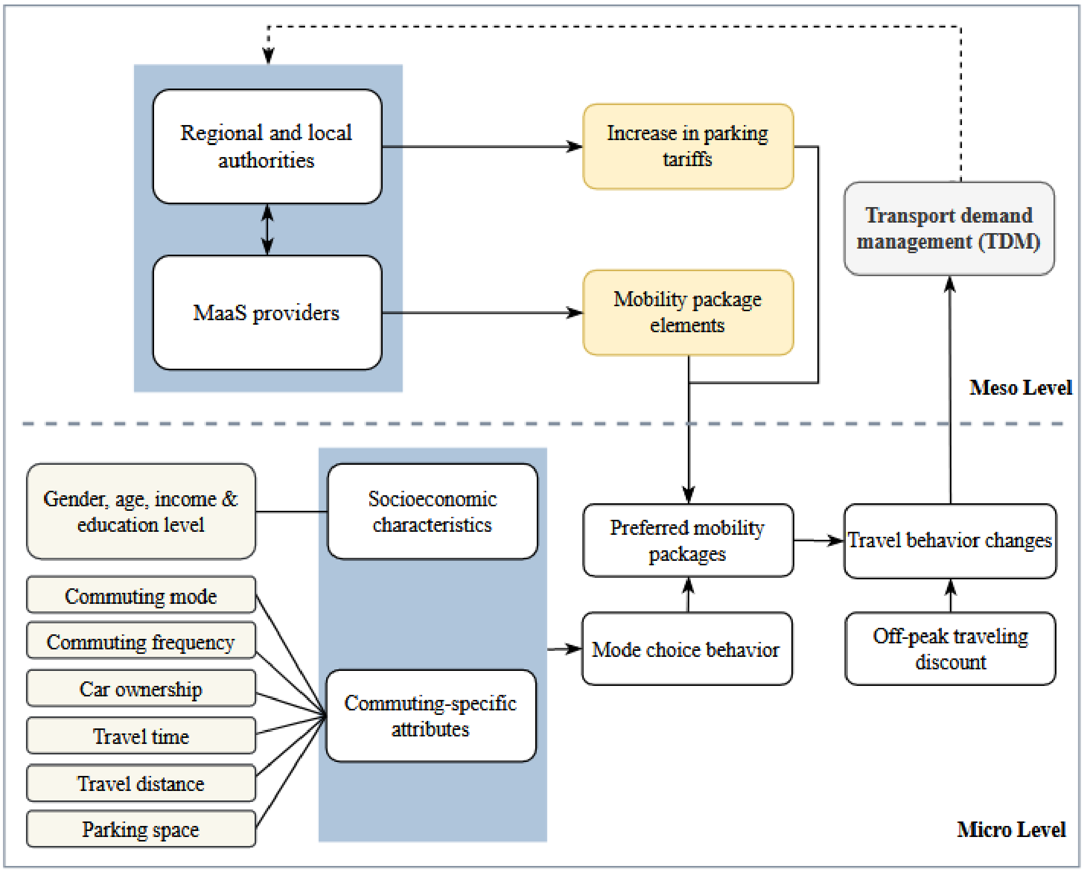


Figure 2.4: Conceptual model

2.4.1 The 'meso-level' of the conceptual model

The meso-level involves different institutions: regional and location authorities, public transport providers, private transport operators, MaaS providers, and civil society sectors. Of relevance to this study, regional and local authorities and MaaS providers are included in the meso-level. These two actors are mainly involved in developing the MaaS services, as well as, setting TDM measures. In the Netherlands, parking norms are decided upon by municipalities. Thereby, they have the authority to increase/decrease parking tariffs in their regions. Likewise, MaaS providers are responsible for designing mobility packages. The cooperation between local authorities and MaaS providers will lead to the integration of TDM measures and MaaS services. It must be noted that MaaS providers are not standalone regarding the specifications of mobility packages. Many actors like public transport operators and private mobility providers (e.g. car-sharing companies) are also involved in the process. However, this study does not discuss its role in the MaaS ecosystem.

2.4.2 The 'micro-level' of the conceptual model

The micro-level refers to the commuting mode choice behavior of end-users (employees) and their preferences for certain types of mobility options. In that sense, socioeconomic characteristics and commuting-specific attributes that influence the decision-making mechanism for choosing certain mobility options will be used as input to map employees' mode choice behavior. Furthermore, travel behavior changes (modes and time) will provide an insight into the benefits of MaaS and its applicability as a TDM tool.

2.5 Conclusion

This chapter provided background information on the topic of MaaS, mode choice behavior, and TDM. It showed that there is still no global consensus on what MaaS entails, neither a single definition exists for it. Therefore, the service has been broken down in terms of institutional and integration levels. Depending on the objectives of MaaS, the integration and institutional levels differ from project to project. Moreover, the chapter also explored how MaaS is currently being designed in different countries. Since the concept of MaaS is not matured enough, there is still limited information about its uptake among employees and underlying factors that drive their commuting choice behavior. Furthermore, MaaS is not yet perceived to be used for management purposes and little evidence exists to prove its potential as a TDM tool. The lack of information in literature motivated this research to partially fill the gap between MaaS and TDM.

3 | Research methodology

This chapter discusses the methodology to answer the research questions and achieve the ultimate objectives of this study. Using the conceptual model presented in section 2.4, the 'stated choice (SC) experiment' has been selected for this study. The SC methods are widely used in travel behavior studies to explore the intention of customers to purchase a product/service that is not available in the market yet (Hensher, 1994). Since MaaS is also not available in the Dutch transport market except for a handful of pilots, this technique is, therefore, suitable for investigating the commuting mode choice behavior with hypothetical scenarios.

The next section (3.1) discusses the design process of the SC experiment, identification of alternatives, attributes, and attribute levels. Section 3.2 describes the design of the survey questionnaire and sample recruitment. And the final section illustrates the choice modeling technique used for data analysis.

3.1 Stated choice experiment design

The very first phase of the research strategy aims to design the SC experiment. A set of attributes is selected through the literature review to design the experiment. Figure 3.1 shows the process of the SC experiment which is adapted from Hensher et al. (2005). It begins with problem refinement, followed by stimuli refinement (identification of alternatives, attributes, and attribute levels). The third stage includes the statistical properties of the experiment design, followed by generating experimental design employing statistical packages. The next stage refers to the allocation of attributes (identified in stage 2) to the design columns. Once the attributes are allocated to related columns, choice sets are constructed and then randomized. The final stage refers to the construction of the survey instrument. Each stage will be described in the upcoming subsections.

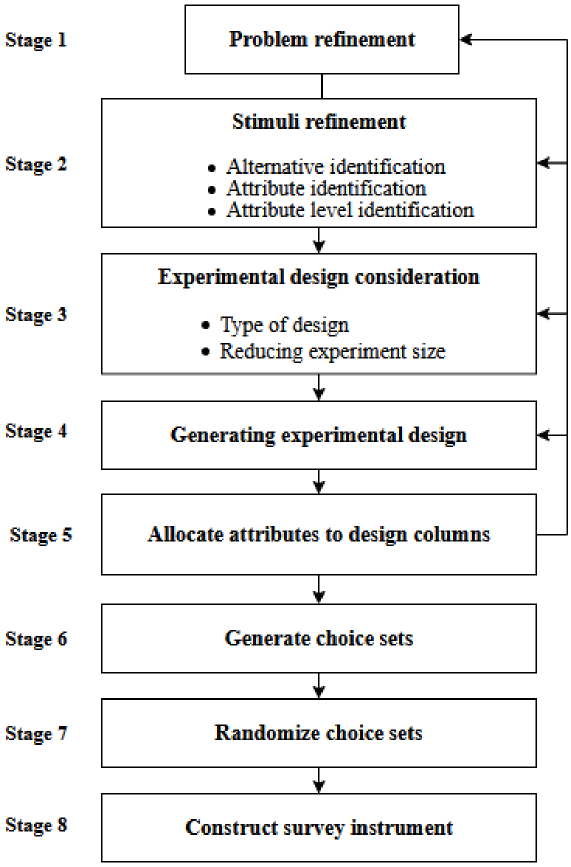


Figure 3.1: Experimental design process; adapted from Hensher et al. (2005)

3.1.1 Stage 1

The first stage of the SC design is to refine the problem. This stage has already been done through the literature review and developing the conceptual model. The hypothesis is that the mobility package elements and increasing parking tariffs affect the mode choice behavior of employees concerning work-related trips. For instance, increasing parking tariffs would get people out of their private cars and promote public transport ridership. Moreover, including unlimited access to public transport in the mobility packages might result in travel behavior changes.

3.1.2 Stage 2

The second stage of the experimental design process is ‘stimuli refinement’, which includes the identification of alternatives, attributes, and attribute levels. In the beginning, it was decided to include a wide range of transport modes such as public transport (train, bus, tram, metro), car-sharing, e-bike sharing, taxi, bicycle, on-demand bus, and car rental. Latterly, taxi, on-demand bus, and car rental were eliminated from the alternative list. The explanation is that the study mainly focuses on employees who commute several times per week to their works, and they would prefer transport modes that are suitable for regular commuting. Car rental was excluded

because the research mainly focuses on commuting between home and work. In that case, car rental is very similar to car sharing. Additionally, car rental has less flexibility compared to car sharing due to its fixed service location. Car rentals are usually available in specific areas and users need to collect and return the rented car to the same location. While car-sharing is much more flexible and the pickup points are dispersed around cities. Ridesharing, on the other hand, is based on individual agreements between supplier and customer. Since it is not a well-known form of transport mean, respondents may need many more details to understand what they are asked about.
In the next step, alternatives, attributes, and attributes are determined.

Alternatives

Though including all transport modes and multi-modal combinations from home to final destination provides more travel options to employees, it will result in too many combinations. This makes it difficult to create a practical choice experiment. Therefore, the list of alternatives should be culled (Hensher et al., 2015). Since there are many transport modes available in the Netherlands, it was necessary to subjectively select transport modes that are mostly used for commuting. This resulted in the inclusion of four transport modes in the mobility packages: train, bus/tram/metro, car-sharing, and e-bike sharing. Out of these alternatives, three combinations have been composed as follows:

- **Train + e-bike sharing** – in this package train serves as the main transport mode and then employees can transfer to a shared e-bike to reach their final destination (home or workplace). In this case, e-bike sharing is expected to act as a complement to train for the last-mile travel between railway stations and home and between stations and workplaces. The assumption is that e-bike sharing hubs are dispersed around a city and there are no accessibility constraints.

- **Train + bus/tram/metro** – in this package, train serve as the primary mean of commuting and bus/tram/metro as a complement for the last-mile travel.

- **Car sharing + e-bike sharing** - in this package, car-sharing serves as the main transport mode and e-bike sharing for the last-mile travel. The assumption is that people can find shared cars at car-sharing spots near their homes and working places, but they need to use e-bike sharing to reach car sharing.

Attributes and levels

In the SC experiment, it is required to determine attributes and attribute levels associated with each alternative. In total, six attributes are identified to be included in the SC design. These attributes are the amount of free ride with train, bus/tram/metro, e-bike sharing, car-sharing, the price of mobility packages, and increasing parking tariffs for car users.

Train and bus/metro/tram

Studies show that the amount of free ride with public transport and shared modes especially unlimited access is an influential factor in mode choice (Matyas and Kamargianni, 2018a). In this study, three attribute levels are defined for trains, "unlimited rides to working regions", "20 day-return tickets to working regions", "15 day-return tickets to working regions". The attribute levels for bus/metro/tram slightly differ from trains because the day-return ticket does not exist for these modes. However, many public transport providers like GVB in Amsterdam do offer day-ticket and multi-day tickets. Therefore, bus/tram/metro attribute levels are specified as "unlimited rides to working regions", "20 day-tickets to working regions", "15-day tickets to working regions".

Car sharing

In this study, three attribute levels are specified for car sharing, "60 free minutes per day then pay per minute", "50 free minutes per day then pay per minute", "40 free minutes per day then pay per minute". The standard fare is adopted from the Car2go [1] price setting, which is €0.26 per minute without any further registration fee. It must be noted that providing unlimited access to car-sharing is not feasible to include in the mobility package due to its high cost. Thus, the attribute levels have been limited to free minutes per day that could fulfill the travel needs of a normal employee traveling less that one hour per day.

E-bike sharing

Regarding the e-bike sharing, three attribute levels have been specified for the SC experiment. These levels are: "unlimited rides", "2 free hours per day then pay per hour", and "1 free hour per day then pay per hour". The hourly price of e-bike sharing is set based on Ubree [2], which is €2.0 per hour.

Price of mobility packages

This attribute refers to the price of the mobility packages. As discussed previously, each package combines two transport modes and is offered as a single mobility option to respondents. Attribute levels for the price have been created based on literature review and information on the websites of transport providers in the Netherlands. This resulted in three hypothetical prices, €140/month, €180/month, and €200/month.

Increasing parking tariffs

In the transport management era, parking cost has been found an important measure to reduce car traffic generated by employees. Parking tariffs and restriction are one of the most common 'stick' measures that influences travel mode choice and use of alternative transport modes (Kaths, 2011). The reason is that the duration of their stay is usually longer than other travelers. As a result, increasing parking tariffs is expected to enhance the selection of mobility packages. Because this attribute is the only stick measure in this study, its influence on the mode choice is

[1] Car2go is a car-sharing provider, that its shared cars are available in many big cities in the Netherlands. All cars are electric and cars do not need to be returned to a fixed point.

[2] Ubree is a bike-sharing company that provides electric bikes.

of particular interest.

Notably is that the parking tariffs differ relative to the location of parking. For some areas, the parking tariff starts from € 3.50 per hour and increases up to € 8.0 per hour. In addition to normal parking, P+R parking is also available in many cities where car drivers use their OV-Chipkaart or buy the P+R CFP card to ride bus, tram, or metro within one hour after entering the P+R location. Thus, the increase in parking tariffs is set as €1.0/hour, €1.5/hour, €2.0/hour on the existing parking costs. Since location is not included as an attribute in the SC experiment, the base parking tariff depends on how much car users currently pay for their parking.
Table 3.1 provides an overview of the attributes and attribute levels discussed previously.

Table 3.1: Overview of attributes and attribute levels

Alternative	Attributes	# levels	Levels
Train	amount of free ride	3	Unlimited rides to working regions 20 day-return tickets to working regions 15 day-return tickets to working regions
Bus/tram/metro	amount of free ride	3	Unlimited rides to working regions 20 day tickets to working regions 15 day tickets to working regions
Car sharing	amount of free ride	3	60 free minutes/day then pay per minute 50 free minutes/day then pay per minute 40 free minutes/day then pay per minute *standard fare: €0.26/minute*
E-bike sharing	amount of free ride	3	Unlimited rides 2 free hours/day then pay per hour 1 free hour/day then pay per hour *standard fare: €2/hour*
All alternatives	package price	3	€140/month €180/month €200/month
Current mode (private/lease car)	inc. in parking tariffs	3	€1.0/ hour €1.5/hour €2.0/hour
All mobility packages	Off-peak travel discount	3	20% discount 30% discount 40% discount

Table 3.2 represents covariates that are included in the survey questionnaire, but not in the SC design.

Table 3.2: Overview of covariates

Covariate	Levels
Gender	male, female, other
Age	[write down]
Annual net income	less than €10,000 €10,000-20,000 €30,000-40,000 more than €30,000 I'd rather not to say
Education level	secondary/vocational Bachelor Master/PhD/PDEng
Driving license	yes, no
Car ownership	yes, no
Commuting mode	car, train, bus/tram/metro, bicyle, car sharing, bike-sharing
Commuting frequency	[1, 2, 3, 4, & 5 times per week]
Travel time	[write down]
Departure time	[6:00 to 10:00, other]
Return time	[15:00 to 19:00, other]
Parking space	Employers parking, paid parking, P+R location
Travel allowance	fully, partially, don't receive
Work location	[write down]
Home post code (pc4)	[write down]

3.1.3 Stage 3, 4 and 5

After identifying the alternatives, attributes, and attribute levels, a number of different combinations could be generated. The full number of possible choice sets is equal to L^{MA}, where L indicates the number of levels, M number of alternatives, and A number of attributes. Since the number of combinations increases relatively with the number of levels and attributes, exploring all combinations here is impossible; therefore, the 'orthogonal factorial design' is used. In this case, the number of combinations could be reduced, where the sum of columns (not row) equals to each other. As a result, the risk of multidisciplinary is eliminated. Furthermore, the orthogonal arrays show balanced levels. It means that all the attribute levels appear with the same frequency, which maximizes the statistical power of the experiment (Dillingham, 2016). JMP (a software from SAS) is used to design the SC experiment. It should be noted that the generation of the SC design (stage 4) and allocation of attributes to the design columns (stage 5) are run simultaneously. In total, 54 profiles are generated within the orthogonal array. Latterly, the profiles are divided into 6 choice sets, with 9 profiles each. From each choice set, one random profile is displayed to each respondent. Appendix A contains the complete array of the SC experiment.

3.1.4 Stage 6, 7 and 8

Stage six, seven, and eight refers to the generation of choice sets, randomization of the profiles, and construction of the survey instrument. The survey is conducted via Qualtrics, an online survey platform adopted by the University of Twente.

3.2 Questionnaire design

This section illustrates the design and contents of the questionnaire. The questionnaire started with a short introduction to the context of the survey and the purpose of the study. Moreover, the introduction described what sort of questions will be asked and how long it takes to complete the questionnaire. It was also assured that the responses will be analyzed anonymous and used only for this research. It should be noted that the respondents could fill out the questionnaire in Dutch and in English.

The rest of the questionnaire was divided into four parts. The first part referred to the current commuting patterns of employees, e.g. commuting mode, commuting frequency, etc. Notably is that the questionnaire ended for respondents who commuted by bicycle/scooter or walk to their works. The reason is that these two groups of employees are unlikely to use MaaS and are therefore excluded from the target group of this study.

The second part of the questionnaire started with a short explanation of MaaS and a 57-second video introducing the MaaS concept in Dutch with English subtitles. The video was prepared by the Technical University of Eindhoven and clearly explains what MaaS is and how it works. Afterward, the way that choice questions should be selected was explained to participants. It must be noted that the formulation of these questions depended on whether a respondent commutes by car or other means of transport. For non-car users, the questions were formulated in a way that asked respondents to choose their desired mobility package: train+e-bike sharing, train+bus/tram, metro, and car sharing+e-bike sharing or "None". Choosing the 'None' implies that the person wanted to continue using his/her current mode(s). Figure 3.2 presents an example of choice questions for non-car users.

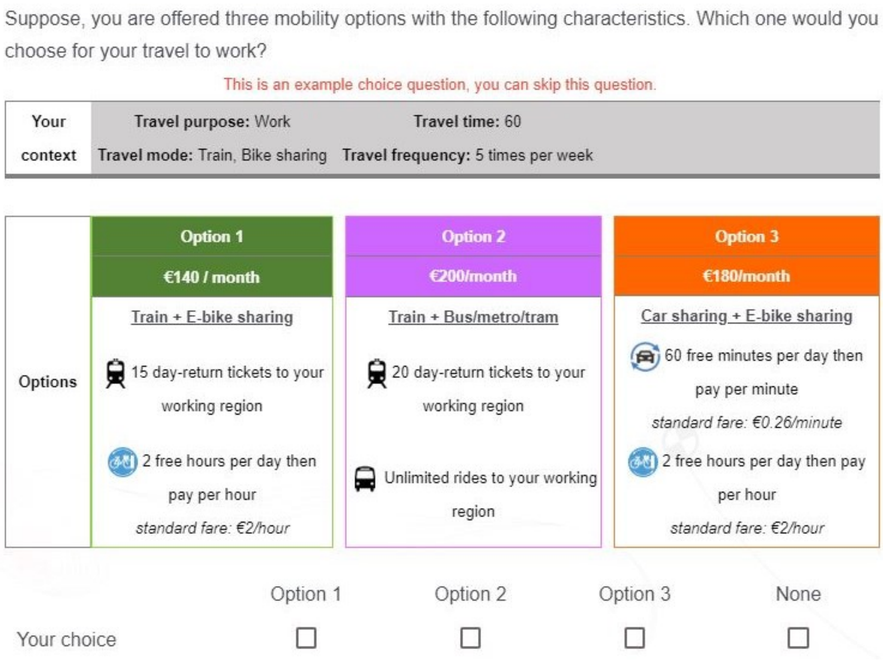


Figure 3.2: Choice question for non-car users

For car users, the choice questions were associated with the increase in parking tariffs. Since the parking tariffs differ depending on the parking space, the questions were phrased in a way that reflected the increase in current parking costs that car users pay. Each choice question was followed by another question that asked the willingness of car users to commute during off-peak hours if they are given a discount on their selected package. Again, selecting the 'None' option means the person did not want to replace his/her car with other modes. An example of choice questions is presented in figure 3.3.

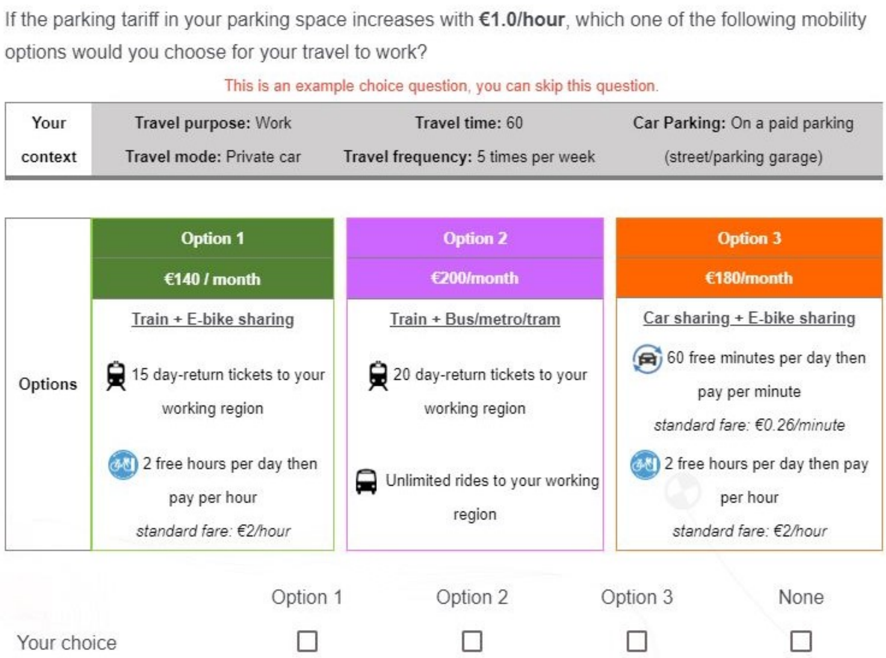


Figure 3.3: Choice question for private/lease car users

In the third part of the questionnaire, respondents were asked about their attitudes towards MaaS characteristics and additional features. Furthermore, some other questions were asked concerning their willingness to reduce car ownership and substitute part of their car trips with public transport and shared modes. The last part of the questionnaire focused on the socioeconomic characteristics of respondents, e.g. age, gender, income, and education. Figure 3.4 represents the overall structure of the questionnaire used in this study. The complete questionnaire can be found in appendix B.

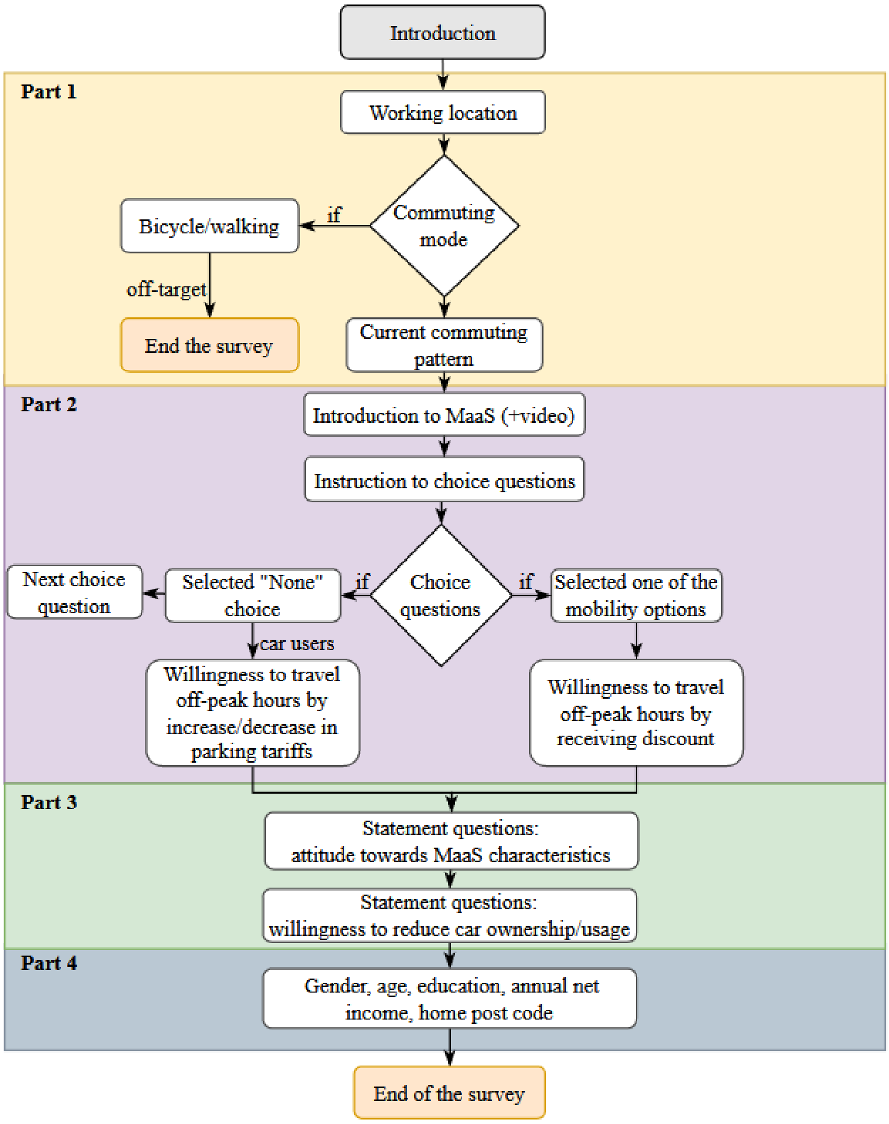


Figure 3.4: Questionnaire structure

Sample recruitment

The sample was recruited through an online survey among employees in the Netherlands. To recruit respondents, the questionnaire link was shared with 300 people who participated in another survey conducted by MAPtm in Amsterdam Southeast. Moreover, respondents were also recruited through social media, e.g. LinkedIn and Facebook, by posting the questionnaire link on personal profile and public/private groups. In total, it was targeted to get around 250 useful respondents in the survey. A useful respondent demonstrates a respondent who meets the requirements of the target group and completed the questionnaire in a reasonable time.

3.3 Choice modeling

Discrete choice modeling is used to explain individuals' mode choice behavior concerning a set of alternatives. The goal is to find out what attributes drive them to prefer one alternative over another. The assumption is that individuals select an alternative which gives them the maximum utility considering its characteristics (de Dios Ortúzar and Willumsen, 2011). The relative contribution of each attribute to the overall utility of an alternative is calculated through the model estimations. Notably is that individuals' characteristics, e.g. socioeconomic characteristics, can be also inserted as covariates in the model (de Dios Ortúzar and Willumsen, 2011).

Suppose U_{jq} presents the utility of alternative j (j= 1, . . ., J) in choice set $A = \{A_1,...,A_j,...,A_N\}$ with particular attributes $x \in X$. Individual q encounters a full set of alternatives in choice set A and chooses the one that gives him/her the maximum utility. The utility associated with alternative j, chosen by individual q in choice set A, represents a discrete choice model by utility expression which is calculated by the following equation (de Dios Ortúzar and Willumsen, 2011; Hensher et al., 2005):

$$U_{jq} = V_{jq} + \varepsilon_{jq} = \sum_k \beta_{kj}\, x_{jqk} + \varepsilon_{jq} \qquad (1)$$

In this equation, the U_{jq} is represented by two components:

- V_{iq} refers to the observed/measured attributes X, and
- ε_{jq} refers to the random part which reflects residuals or observational errors

β is the alternative specific coefficient associated with observed attributes and ε shows the error term or random utility with the mean equal to zero and is assumed to be independently and identically distributed (IID) over alternatives. The most common choice model is the 'multinomial logit' (MNL) model (Hensher et al., 2005). In this model, observed components are assumed to be independent and have the same variance (identical). In this case, the probability that alternative i will be chosen by an individual is defined by the utility of the alternative. If the utility of alternative i is greater than the utility of alternative j (j = 1, ...i, ...J), it is likely that individuals choose alternative i. This can be written as:

$$p_i \;=\; p(U_i \geq U_j);\; \forall\; j \;=\; 1,\; ...i, ...\; J \qquad (2)$$

The probability that individual q will choose alternative i from the choice set of j alternatives is equal to:

$$p_{iq} = \frac{exp(V_{iq})}{\sum_{j=1}^{J} exp(V_{jq})}; \forall j = 1, ...i, ... J \quad (3)$$

3.3.1 Mixed logit model

A more advanced version of MNL is the 'mixed logit' (ML) model, which addresses the limitations of standard logit by allowing random taste variation, unrestricted substitution patterns, and correlation in unobserved factors (Train, 2009). It is defined based on the functional form of choice probabilities and the behavioral specification with this form of choice probabilities is called 'mixed logit' (ML), 'random parameter logit', 'mixed multinomial logit' (MML) or 'hybrid logit' model (Hensher et al., 2005; Train, 2009). It has been proven that ML provides a better interpretive power and model fit than other logit models (Ye and Lord, 2014). According to Hess et al. (2005), there are several advantages in using ML instead of MNL as follows:

- ML accounts for the possible correlation over repeated choices made by each individual. Therefore, it does not exhibit the 'independence of irrelevant alternatives' (IIA) property. IIA implies that the choice between two alternatives depends only on the characteristics of these two alternatives, not necessarily the characteristics of other alternatives.
- ML can be derived under several behavioral specifications with separate interpretations.
- ML can closely approximate the multinomial probit model, in which normal distribution is used for error term, instead of logistic distribution used for MNL. However, unlike the probit model, ML represents situations where the coefficients follow other distributions than the normal distribution.

Notably, the probability of all alternatives sums up to one; therefore, the ratio of choice probability for an individual is assumed to be unaffected by the systematic utilities of other alternatives. This is also known as IIA property, which makes the ML model easy to utilize and provide an approximation to reality (Train, 2009). Furthermore, using this model allows for similarities between alternatives in the unobserved part of the utility and hereby relaxing the IIA-property (error component). Moreover, the model can measure the effect of multiple observations per individual, meanwhile, detect heterogeneity in the parameters of an attribute across the population, known as random coefficient (Hensher et al., 2015; Train, 2009)

3.3.2 Model specification

In order to calculate the utility of alternatives, an assumption is made that an individual chooses the alternative from provided choice sets that give him/her the maximum utility considering its attributes. This is called ‘utility-maximizing behavior’, in which individuals behave as they are maximizing their overall utility when choosing the alternative (Hensher et al., 2015).

Let U_{jtq} presents the utility a alternative j (j= 1, . . ., J) in each of T choice set. Individual q consider a full set of alternatives in choice set t to choose an alternative that gives the maximum utility. The utility associated with each alternative j, chosen by individual q in choice situation t, represents a discrete choice model by utility expression(Hensher et al., 2015). The utility can be calculated as:

$$U_{jtq} = \sum_{k=1}^{k} \beta_{qk}\, x_{jtqk} + \varepsilon_{jtq} = \beta_q^{'} x_{jtq} + \varepsilon_{jtq} \tag{4}$$

In which x_{jtq} shows observed variables, including attributes of the alternatives, socio-economic characteristics of employees and decision context (trip-specific aspects). β_q is a vector of coefficients of explanatory variables for individual q which represents the person’s tastes and ε_{jtq} is a random term with IID extreme value distribution (Train, 2009).

The choice probabilities of ML model are the integral of standard logit probabilities over a density of parameters, which can be calculated as follows:

$$P_{iq} = \int L_{iq(\beta)} f(\beta) d\beta \tag{5}$$

In this equation, the logit probability of calculated at parameters β:

$$L_{iq(\beta)} = \frac{e^{V_{iq}(\beta)}}{\sum_j e^{V_{iq}(\beta)}} \tag{6}$$

$V_{iq}(\beta)$ is the observed portion the alternative utility, related to the parameters β. If the utility is assumed to be linear, then $V_{iq}(\beta) = \beta^{'} x_{iq}$. In this case, the probabilities of ML model are calculated using the following the equation (Train, 2009):

$$P_{iq} = \int \frac{e^{\beta^{'} x_{iq}}}{\sum_j e^{\beta^{'} x_{jq}}} f(\beta) d\beta \tag{7}$$

$f(\beta)$ is the choice density over the coefficient values, the so called mixing distribution. For the normal distributions N, the density takes the following form:

$$f_N(\beta|\mu,\sigma) = \frac{1}{\sqrt{(2\pi)}\sigma} exp(-\frac{(\beta-\mu)^2}{2\sigma^2}) \tag{8}$$

where μ and σ denote the mean and standard deviation, respectively. Since each respondents face 6 different choice questions (more than one observation for each individual), the probability that a person makes the sequence of choices is the result of logit formulas:

$$L_{iq()\beta} = \prod_{t=1}^{T}[\frac{e^{V_{iq}^{t}(\beta)}}{\sum_j e^{V_{iq}^{t}(\beta)}}] \tag{9}$$

3.4 Conclusion

This chapter illustrated the process of the SC experiment, questionnaire design, sample recruitment approaches, and choice modeling. The SC experiment has been chosen in order to investigate the mode choice behavior of employees. The data have been collected with an online questionnaire where the choice questions were repeated 6 times for each respondent on a random basis. Each time, the attribute levels differed per mobility package and choice questions.

To analyze the data, the Mixed Logit model has been used to estimate the coefficient of the attributes and the covariates. The model will also present detailed information on the explanatory factors which drive employees' mode choice decision. Furthermore, the attitude of employees towards MaaS characteristics and features was evaluated, which could be valuable information for better practice of the service. The next chapter elaborates on the results of data analysis.

4 Results

This chapter elaborates on data analyses and answering the research questions. Section 4.1 describes the collected data and descriptive statistics. Subsequently, section 4.2 elaborates on the ML model estimations. Section 4.3 discusses the implications of investigated matures, followed by section 4.4 that illustrates the willingness of employees to travel during off-peak hours. And, the last section discusses the attitude of employees towards MaaS characteristics.

4.1 Data

The data was collected through an online survey between May 13th and June 20th, 2020. To encourage participation, 10 hand sanitizers of 500ml were raffled among respondents who completed the questionnaire properly. The following channels were used to recruit respondents:

- Sharing the questionnaire with 300 people who had participated in a previous survey conducted by MAPtm in Amsterdam Southeast (SE).
- Sending the questionnaire link to HR managers of local companies whose contact details were provided by a student association at the University of Twente.
- Social media (LinkedIn & Facebook), where the questionnaire link was re-shared 26 times by friends, colleagues, and Ph.D. students. As well as, the questionnaire was posted in 58 LinkedIn and 14 Facebook groups.
- The questionnaire was also dispersed among personal networks via emails and LinkedIn messages.

Table 4.1 shows the number of respondents who opened, started, and completed the questionnaire. Of 487 people who opened the questionnaire link, 411 (84.4%) started and 307 (63%) completed the questionnaire.

Table 4.1: Questionnaire completion

Questionnaire			Clicked	Started	Completeted
Language	EN	Count	188	149	109
		% of total	100%	79.3%	58.0%
	NL	Count	270	234	177
		% of total	100%	86.7%	65.6%
Amsterdam SE		Count	29	28	21
		% of total	100%	96.6%	72.4%
Total		Count	487	411	307
		% of total	100.0%	84.4%	63.0%

4.1.1 Data cleaning

Not every respondent is useful to be included in the data analyses. Of 307 respondents who finished the questionnaire, 243 (79.2%) respondents could meet the sample requirements. As explained in section 3.2., employees who commute by bicycle/scooter and walking are not in the target group of this study. Table 4.2 shows the descriptive of in-target and off-target respondents.

Table 4.2: Descriptive of in-target and off-target the sample

Questionnaire			Off-target	In-target	Total
Language	EN	Count	29	80	109
		Percentage	26.6%	73.4%	100.0%
	NL	Count	35	163	198
		Percentage	17.7%	82.3%	100.0%
Total		Count	64	243	307
		Percentage	20.8%	79.2%	100.0%

Furthermore, the data has been checked for outliers, strange values, and incompleteness. Of 243 in-target respondents, seven respondents were found unreliable due to very short completion time, not working in the Netherlands, or not meeting the in-target requirements. In total, 71 responses were deleted and the other 236 were found reliable for further analyses. The complete process of data cleaning can be found in appendix C.

4.1.2 Sample profile

Table 4.3 shows the respondents' characteristics. The sample is being evaluated for its representativeness of the population. The distributions of gender, education level, and age are provided on the website of CBS, where the working population over 18 years old is around 8.324 million (CBS, 2019). To make the sample distributions comparable with CBS data, variables are being re-categorized. Afterward, the Chi-square test is performed to check if the sample is representative of the working population in the Netherlands. The test compares the observed number of

respondents in the sample with the expected numbers. If the chi-square value of a variable is insignificant (p-value>0.05), there is no (or insignificant) differences between the distribution of that variable in the sample and in the population. The test was conducted for gender, education level, and age. There was no data available about the annual net income of employees in the Netherlands or the data is not open to the public. The CBS data provides information on household income, not individual income and, therefore, this variable could not be tested for its representativeness.
The following points elaborate on the main characteristics of the sample.

- Regarding the gender, the male/female ratio of respondents is not completely representative of the population. The chi-square test shows that, for this variable, the sample distribution differs from the CBS statistics (p-value<0.05). The sample slightly over-represents female respondents (55.5%) over males (44.5%).

- Approximately 55.5% of the respondents have a high education level (master or PhD/PDEng), 32.2% middle level (bachelor degree), and 12.3% low level (secondary/vocational). Comparing to the CBS data, the sample over-represents highly-educated employees. The chi-square test also indicates significant differences between the sample distribution and the population distribution (p-value<0.05).

- Respondents with more than €40.000 and €30,000 to €40,000 of yearly net income account for 34.3% and 22%, respectively. While respondents with annual income between €10,000 to €30,000) account for 19.9% and respondents with very low income (less than €10,000) account for only 5.5% of the sample size. However, these percentages cannot be compared with the population because CBS does not provide information on the annual income of individual employees. It must be mentioned that 43 respondents (18.2%) did not want to say their income and, therefore, declared as 'I'd rather not to say'. This group of respondents is labeled as 'unknown'.

- The average age of the respondents is 40 years old, with a standard deviation of 11.66 years. For the ease of analysis, the age has been categorized into five groups. Comparing with the CBS data, the sample slightly over-represents younger employees (see table 4.3).

Table 4.3: Comparison of the sample with CBS statistics

Variable	Categories	# Respondents	Sample share	Population (CBS)
Gender	Male	105	44.5%	52.5%
	Female	131	55.5%	47.5%
	Total	236	100.0%	
Education level	Secondary/vocational	29	12.3%	21.0%
	Undergraduate	76	32.2%	40.0%
	Master, PhD or PDEng	131	55.5%	39.0%
	Total	236	100.0%	
Annual net income	Less than €10,000	13	5.5%	NA
	€10,000 - €20,000	9	3.8%	
	€20,000 - €30,000	38	16.1%	
	€30,000 - €40,000	52	22.0%	
	more than €40,000	81	34.3%	
	Unknown	43	18.2%	
	Total	236	100.0%	
Age	20-30	76	32.2%	23.3%
	31-40	46	19.5%	21.6%
	41-50	66	28.0%	22.5%
	51-60	40	16.9%	23.0%
	>60	8	3.4%	9.7%
	Total	236	100.0%	

The respondents have spread across 56 municipalities in terms of working locations. Figure 4.1 shows the geographic locations of the working and living of respondents. As can be seen in the figure, a large proportion of respondents work in Amsterdam, The Hague, Almere, Enschede, and Utrecht. However, the living locations are slightly more dispersed.

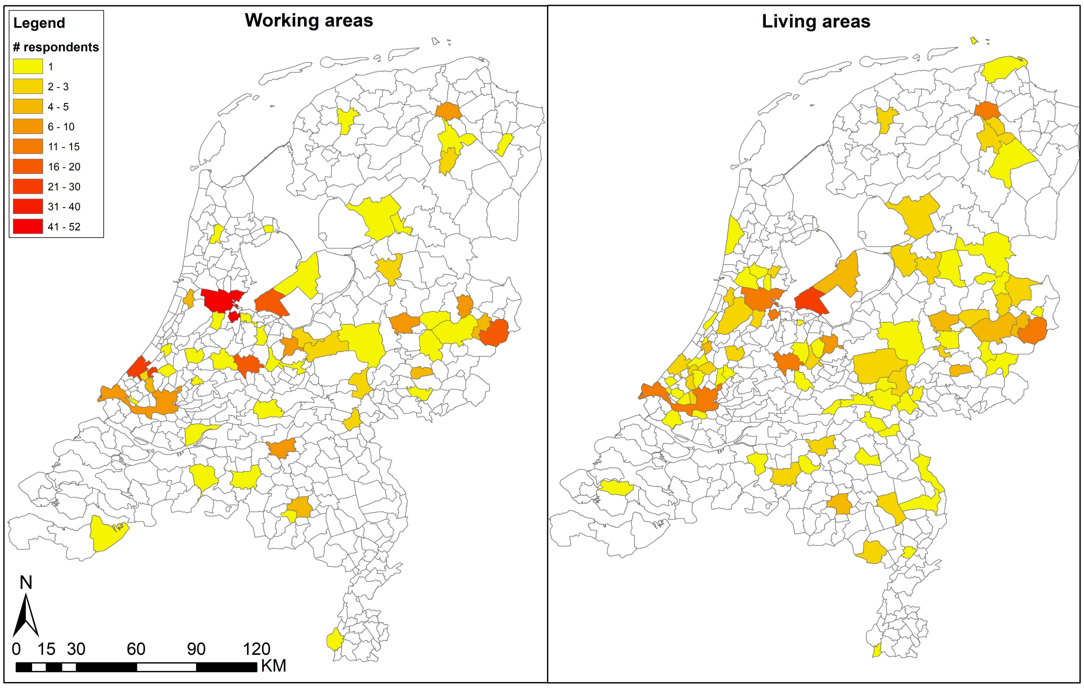


Figure 4.1: Working and living areas of the respondents

In addition to socio-economic characteristics, employees were also asked about their current commuting mode(s), frequency of commuting, private/lease ownership, travel allowance, and parking spaces. Table 4.4 represents an overview of the sample characteristics concerning the commuting patterns.

Table 4.4: Commuting patterns of respondents

Variable	Categories	# Respondents	Sample share
Car ownership	Yes	162	68.6%
	No	74	31.4%
Lease car	Yes	26	11.0%
	No	210	89.0%
Travel allowance	Yes, fully	91	38.6%
	Yes, partially	74	31.4%
	No	71	30.1%
Main commuting mode	Private/lease car	96	40.7%
	PT + Private/lease car	31	13.1%
	PT	100	42.4%
	PT + car sharing	1	0.4%
	Car sharing	2	0.8%
	Bike sharing	2	0.8%
	PT+car sharing+bike sharing	4	1.7%
Commuting frequency to work	5 times per week	97	41.1%
	4 times per week	78	33.1%
	3 times per week	33	14.0%
	Twice a week	14	5.9%
	Once a week	14	5.9%

As can be seen in the table, the majority respondents use public transport and private/lease car, of which 42.4% public transport (train, bus, tram, and metro), 40.7% private/lease car, and 13.1% use both. These three groups account for about 96% of the sample. Regarding the parking space of car users, the majority of respondents (90.4%) use their employers' parking spaces free of charge. While only 5.6% use street/garage parking and 4% P+R locations. This is of high relevance to the increase in parking tariffs, which will be discussed later in this chapter. Figure 4.2 shows the percentage of car users concerning their parking spaces.

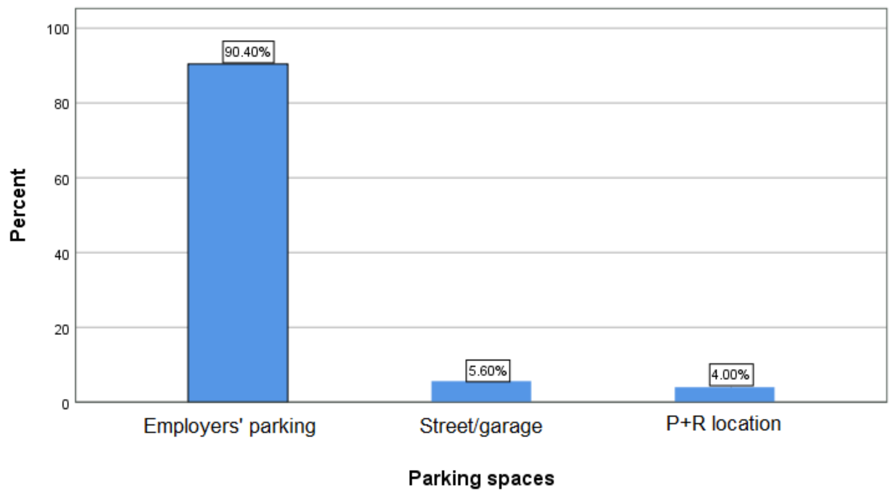


Figure 4.2: Parking spaces used by car users

In addition to commuting modes, the time of commuting is of high relevance to this study since part of the study refers to commuting during off-peak hours. Figure 4.3 shows the number of respondents versus departure and return time. As can be seen in the figure, most of the respondents commute during rush hours, 7:00 to 8:30 from home to work and 16:30 to 18:00 from work to home. Considering the fact that around 96% of the respondents use either public transport or car as their main commuting mode, one can imagine the pressure that employees' work-related trips put on transport infrastructures during rush hours.

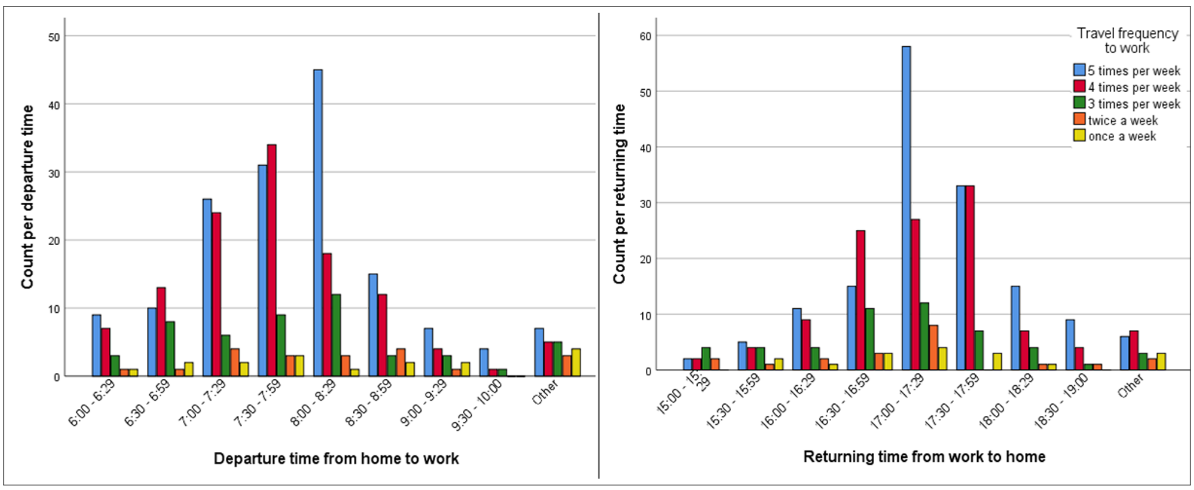


Figure 4.3: Commuting time during the day

4.2 Model estimations

This section illustrates the results of the Mixed Logit (ML) model estimations using Stata/MP 16 - powerful software for choice modeling. In order to estimate the ML models, the cmxtmixlogit command is used, which applicable for panel data. This command is being frequently used when individuals encounter several choices. In other words, several observations exist for each individual.

The first two research questions will be answered by the end of this section, "What are the effects of mobility package elements and increasing parking tariffs on commuting mode choice behavior of employees?", and "Which types of employees can be identified based on their current commuting patterns, and what are their characteristics?" Answering these questions provides information about the underlying determinants that influence employees' commuting mode choice behavior.

Sample weights

Before performing the ML models, the sample needs to be balanced to the population. As discussed in section 4.2.1, the sample is disproportionate to the population. As a result, under-presentation and/or over-presentation of the sample is a threat to the validity and accuracy of estimations (Royal, 2019). Therefore, it is required to bring some adjustments in the sample in order to minimize the sample bias and enhance the reliability of results.

A robust technique to balance the sample distributions with the population is raking, also known as 'proportional fitting', 'sample balancing', or 'ratio estimation' (Kalton and Flores Cervantes, 2003). This technique fits the sample distributions to the known distributions of the population in an iterative process. The sequence of variables might be multiple times until the convergence is reached. This way the distributions of the sample become more in line with the distributions of the population considering all introduced parameters (Kalton and Flores Cervantes, 2003). Applying the raking weights adjust the sample to reflect the population and makes the results more accurate and generalizable (Royal, 2019).

The auxiliary source for calculating raking weights could be population data (e.g CBS) or similar surveys (Royal, 2019). In this study, the sample is weighted to OViN-2017[1] and Wave-2016[2]. Since the sample represents employees, OViN data is being sorted to include only respondents who have made work-related trips. Three variables are used to define raking weights: gender, education level, and income level. Since the annual income in OViN 2017 is based on households, the income distribution is therefore compared with the Wave 2016 data. Table 4.5 presents the proportions of the OViN 2017, wave 2016, and the sample.

[1] data from a survey carried out by CBS between 2010 and 2017 as a successor to the Mobility Survey of the Netherlands (MON) that was conducted by Rijkswaterstaat from 2004 to 2009

[2] data from Mobility Panel of the Netherlands

Table 4.5: Sample and population distributions

		OViN 2017		Sample share		
Variable	Category	Count	Percentage	Count	Percentage	Ratio
Gender	Male	3116	52.2%	105	44.5%	1.174
	Female	2848	47.8%	131	55.5%	0.860
Education	Low	73	21.0%	29	12.3%	1.707
	Middle	139	40.0%	76	32.2%	1.242
	High	135	39.0%	131	55.5%	0.703
Annual net income		Wave 2016				
	Less than €10,000	346	9.0%	13	5.5%	1.638
	€10,000 - €20,000	1091	28.4%	9	3.8%	7.454
	€20,000 - €30,000	1273	33.2%	38	16.1%	2.059
	€30,000 - €40,000	428	11.2%	52	22.0%	0.506
	more than €40,000	155	4.0%	81	34.3%	0.118
	Unkown	545	14.2%	43	18.2%	0.779

To perform raking, the 'anesrake' package in R is used, which implements the ANES (American National Election Study) weighting algorithm. It generates multiplicative weights so that the sample distributions match with the population distributions for gender, education, and income. Table 4.6 shows the summary of raking weights. The complete syntax of the raking wight process is provided in appendix E.

Table 4.6: Raking weights summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.060	0.132	0.500	1.000	1.105	5.000
Design effect:	2.522				

Note: The complete convergence is achieved after 35 iterations.

After weighing the sample, the ML models are estimated based on both unweighted and weighted samples. Figure 4.4 presents an overview of the ML models that are discussed in the upcoming subsections. First, the model is estimated considering only the mobility package elements. Afterwards, socioeconomic characteristics like gender, age, education level, and annual net income are inserted in the model as covariates. Since socioeconomic characteristics are not the only explanatory factors, the effects of commuting-specific attributes is also estimated performing another ML model. Finally, the ML model is performed specifically for car users, in which the increase in parking tariffs is included the model estimation. It must be mentioned that another ML was run considering the working locations of respondents as a covariate. The output of this model can be found in appendix F.9.

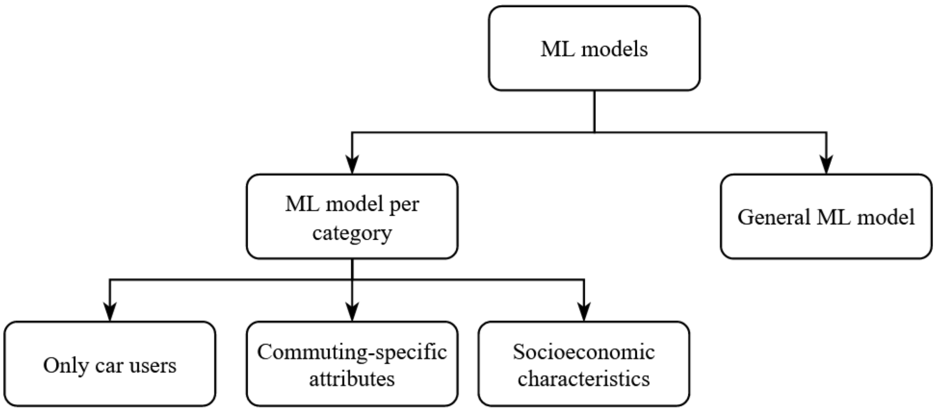


Figure 4.4: Overview of ML models

4.2.1 General ML model estimation

The general ML model incorporates with the mobility package elements - known as alternative-specific variables - that vary across alternatives and individuals. In this model estimation, the price of the packages is set as a random parameter with normally distributed coefficients (approximated using 1000 Halton draws). This means that the coefficient value of the price varies over respondents rather than being fixed. Specifying random coefficient reflects the correlation of choices across alternatives and thereby relaxes the IIA property of the ML model (Train, 2009). And the amount of free ride with train, bus/tram/metro, e-bike sharing, and car-sharing are considered to be fixed parameters. Table 4.7 presents the result of ML model estimations (unweighted and weighted) with the mobility package elements. The Wald chi-square test values of both models (unweighted and weighted) demonstrate that at least the coefficient of one attribute is significantly different from zero (prob>ch2) - so the null hypothesis rejected H0=0. The complete output of the models can be found in appendix F.1 and F.2.

Within the unweighted estimation, the coefficient value of the price is -0.031. It means that when the price of an alternative increases, the overall utility of the alternative reduces. The low standard deviation (0.03) of price indicates that heterogeneity does not exist in the preference of employees towards the price. However, the price still plays a significant role in mode choice, even though most employees do not pay by themselves. On the other hand, the attributes related to train, e-bike sharing, and car-sharing have positive coefficient values, 0.326, 0.17, 0.235, respectively. The positive values mean that increasing the amount of free ride has a positive contribution to the utility of the mobility packages. The coefficient related to bus/tram/metro on the other hand is very small and statistically insignificant. Only 3.6% of the variation in the mode choice can be explained by bus/tram/metro attributes. In the weighted estimation, the coefficient values of train and car-sharing become stronger compared to the unweighted estimation. However, the coefficient values of the e-bike sharing become statistically insignificant.

Table 4.7: General ML model estimations

Parameter		Unweighted		Weighted	
		Value	P>z	Coef.	P>z
Non-random	train	0.326	**0.000**	0.461	**0.001**
	bus/tram/metro	0.036	0.679	0.055	0.623
	e-bike sharing	0.170	**0.007**	0.103	0.300
	car sharing	0.235	**0.009**	0.258	0.065*
Random	price	-0.031	**0.000**	-0.029	**0.000**
	sd_{price}	0.031		0.031	
Cont. using current mode		Base alternative			
Train+ e-bike sharing	ASC	4.738	**0.000**	4.917	**0.000**
Train +bus/tram/metro	ASC	4.937	**0.000**	4.922	**0.000**
Car sharing+ e-bike sharing	ASC	4.662	**0.000**	4.885	**0.000**
	# cases	1416		1416	
	LL	-1419.93		-1450.21	
	Wald chi2(5)	132.84		43.52	
	Prob > chi2	0.000		0.000	
	# Halton draws	1000		1000	
	AIC	2857.85		2918.428	
	BIC	2905.15		2965.729	

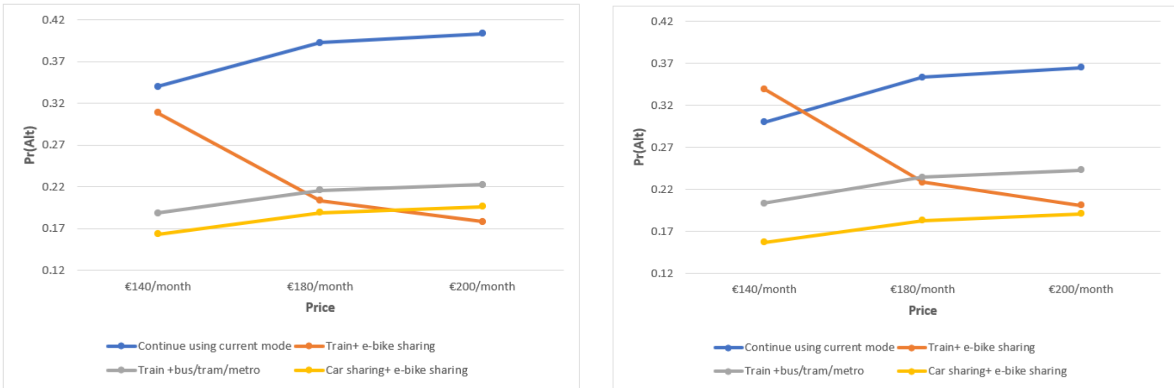
*Note: the models are estimated with Stata's cmxtmixlogit command. The models converged in 6 (N) and 6 (N) iterations. * Significant at 90% CI.*

To obtain a better view of the model estimations, it is necessary to predict the marginal effects of the mobility package elements on choice probably, known as predictive probability. This refers to the probability of an alternative selected by individuals, and sum up to one across all alternatives. For this purpose, margins command is used which calculates the choice probability based on the previously fitted models. Table 4.8 presents the average predicted probabilities of alternatives at 95% CI. As can be seen in the table, 38.3% of employees would continue using their current transport modes. While the probabilities of choosing other packages are 22.3% (train+e-bike sharing), 21.1% (train+bus/tram/metro), and 18.3% (car sharing+e-bike sharing). The choice probability slightly differs in the weighted estimation, where 24.7%, 23.1%, and 17.7% would choose train+e-bike sharing, train+bus/tram/metro, and car sharing+e-bike sharing, respectively. And 34.5% of employees would continue using their current modes. In section 4.2.3, the paper will elaborate more on what the current modes are and how they affect mode choice.

Table 4.8: Choice probabilities at 95% CI

Alternatives	Unweighted		Weighted	
	Prob.	Std. Err.	Prob.	Std. Err.
Continue using current mode	38.3%	0.030	34.5%	0.044
Train+E-bike sharing	22.3%	0.020	24.7%	0.031
Train+Bus/tram/metro	21.1%	0.020	23.1%	0.029
Car sharing+E-bike sharing	18.3%	0.020	17.7%	0.029

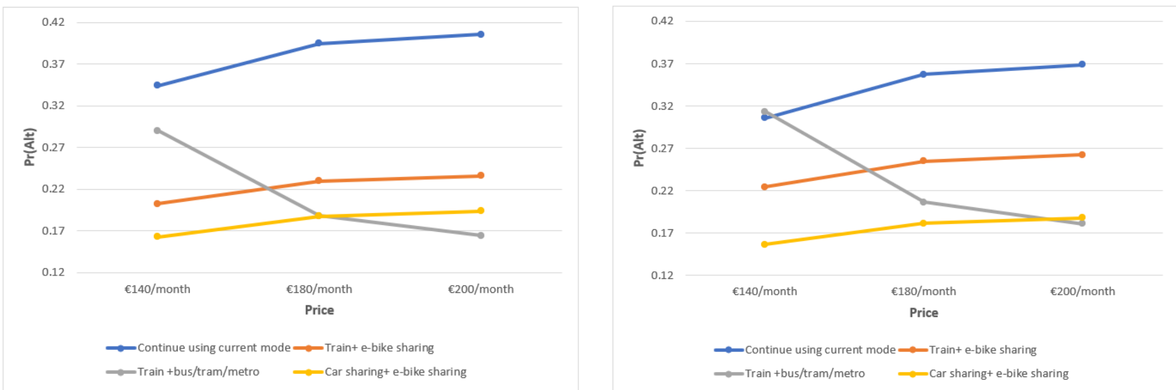
A better way to measure the effect of attributes on choice probability is to calculate their marginal effects for each attribute individually. Figure 4.5-a shows the effect 'train+e-bike sharing' price based on the unweighted estimation. As can be seen in the figure, when the price is €140/month, the probability that employees would choose 'train+e-bike sharing' and 'continue using current mode' is very close to each other. 31% of respondents would choose train+e-bike sharing for commuting and 33% would continue using their current modes. By increasing its price to €200/month, only 19% would choose this package. The effect of price becomes more dominant in the weighted estimation. Around 34.5% of employees would choose this mobility package when its price is at €140/month.



(a) (b)

Figure 4.5: Marginal effect of train+e-bike sharing price, (a) unweighted; (b) weighted

Figure 4.6-a represents the marginal effect of the price associated with train+bus/tram/metro package. At €140/month, it is expected that around 29% of employees would select this package and 35% would continue using their current transport modes. The probability of choosing this package decreases to 17% when its price is increased to €200/month. However, the probability values slightly differ in the weighted estimation (figure 4.6-b).

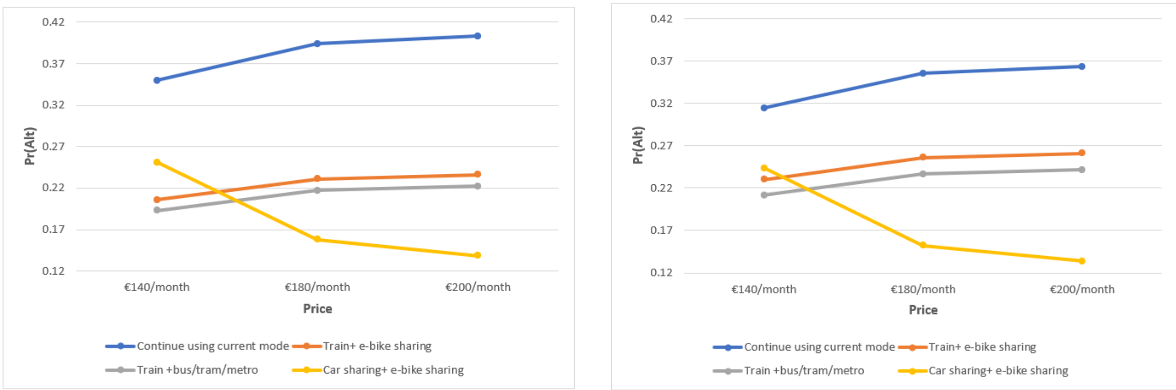


(a) (b)

Figure 4.6: Marginal effect of train+bus/tram/metro price, (a) unweighted; (b) weighted

Figure 4.7 represents the marginal effect of price related to train+bus/tram/metro. At €140/month, it is expected that around 25% of employees select this package and 35% would continue using their current transport modes. The probability of choosing train+bus/metro/tram decreases to

16% when the price increased to €200/month. In the weighted model, these percentages remain similar (figure 4.7-b).



(a) (b)

Figure 4.7: Marginal effect of car sharing+e-bike sharing price, (a) unweighted; (b) weighted

The predicted probabilities as a function of price revealed that the price of mobility packages plays a significant role in commuting mode choice. An explanation might be that travelers, including employees, have a cost-driven mindset, even though it is paid by a third party. Regardless of who pays the costs, people still prefer cheaper transport modes. Another possible explanation would be that around 31.4% of the respondents receive partial travel allowance and 30% do not receive travel allowance at all (see section 4.2.1). This could be the reason why travel cost is still an important factor in employees' mode choice.

Regarding the attribute level of train and e-bike sharing, including 'unlimited rides with trains to working regions' in the mobility package has a noticeable effect on its selection. As it can be seen in figure 4.8, giving unlimited rides with trains to the working region has increased the choice probability of train+e-bike sharing to 27%. This effect increases by about 6% when the model is performed with the weighted sample. Furthermore, the inclusion of unlimited rides with e-bike sharing also increases the choice probability of this package. By giving unlimited rides with e-bike sharing, around 25% of employees would choose the train+e-bike sharing package for commuting (figure 4.8).

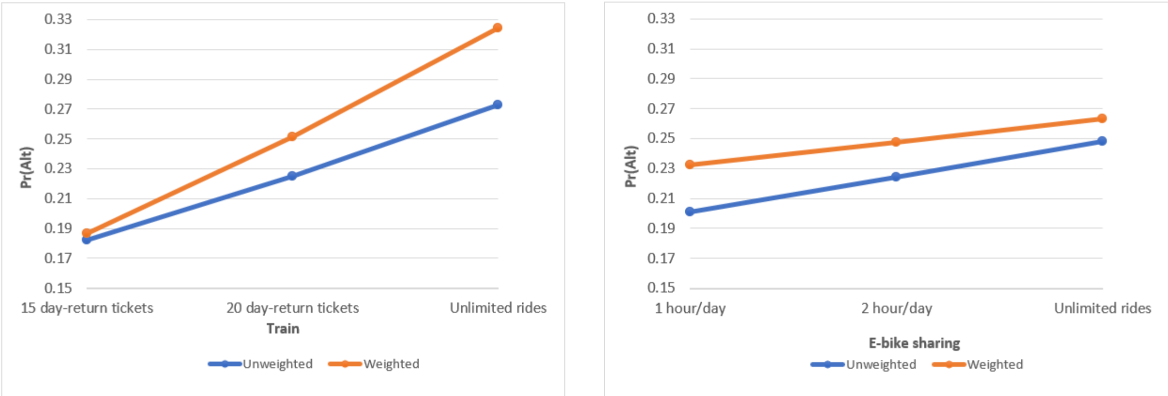


Figure 4.8: Marginal effect of train and e-bike sharing attributes

Similar to the train+e-bike sharing package, the unlimited rides with trains to working regions also have a significant impact on the selection of train+bus/tram/metro. It is expected that 24.5% of employees would choose this mobility package if they are giving unlimited rides to their work regions (figure 4.9). As mentions previously, the coefficient of bus/tram/metro attribute is small and statistically insignificant, hence the choice probability does not vary across its attribute levels. There are small differences between the choice probability of 15-day tickets and unlimited rides to working regions (figure 4.9-b).

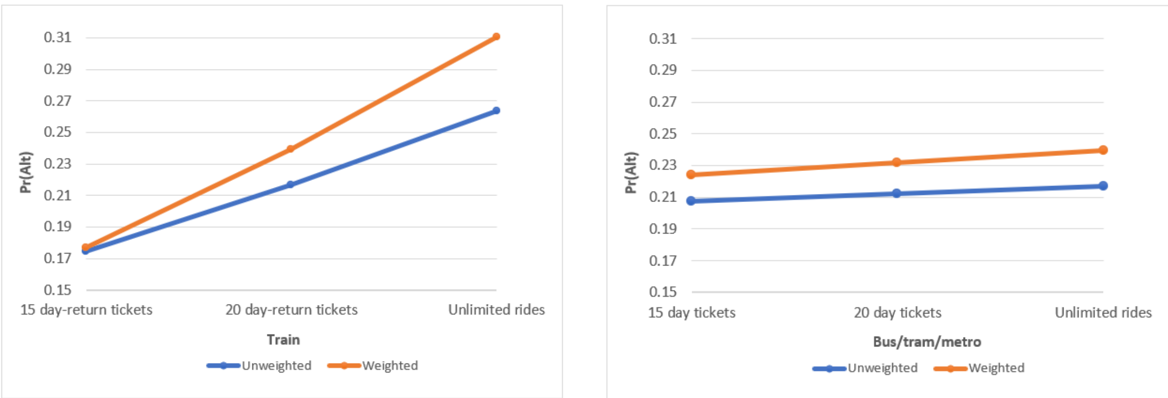


Figure 4.9: Marginal effect of train and bus/tram/metro attributes

Figure 4.10 represents the marginal effects of car-sharing and e-bike sharing attribute levels. By including 40 minutes of driving with car sharing, the probability that employees would choose car sharing+e-bike sharing package is about 16%. Increasing the amount of free driving to 60 minutes increases its choice probability to 21.5%. Likewise, the amount of free rides with e-bike sharing contributes to the choice probability of this package. By including unlimited rides with e-bike sharing, about 27% of employees would choose car sharing+e-bike sharing. However, this effect is weak in the weighted estimation (see figure 4.10).

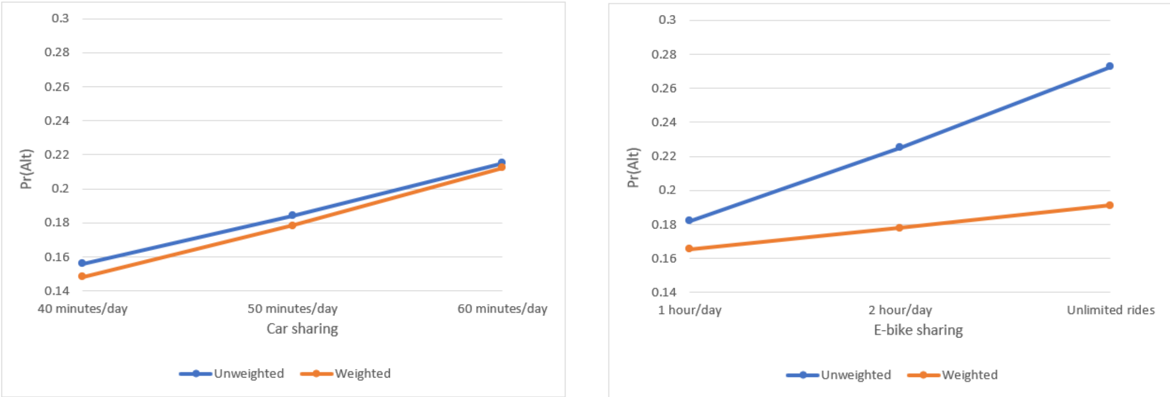


Figure 4.10: Marginal effects of car sharing and e-bike sharing attributes

4.2.2 Impact of socioeconomic characteristics on mode choice

The ML models also incorporate with variables that vary across individuals, known as case-specific variables. These variables are underlying factors that further differentiate employees' mode choice behavior. Basically, the model is the same as the general ML model discussed in the previous subsection, but this time the socioeconomic characteristics of employees are inserted in the model as covariates. These characteristics are gender, age, annual net income, and education level. Table 4.9 shows the coefficient values of socioeconomic characteristics for all mobility packages compared to the based alternative: continue using current mode. Comparing with the general ML model, these models explain the data a little better (smaller AIC & BIC and larger LL). The AIC's of these two models are 2837.03 and 2853.04, which were 2857.85 and 2918.43 in the General ML. As the AIC estimates the relative amount of information lost by the model; the lower AIC, the better. The complete model estimation can be found in appendix F.3 and F.4.

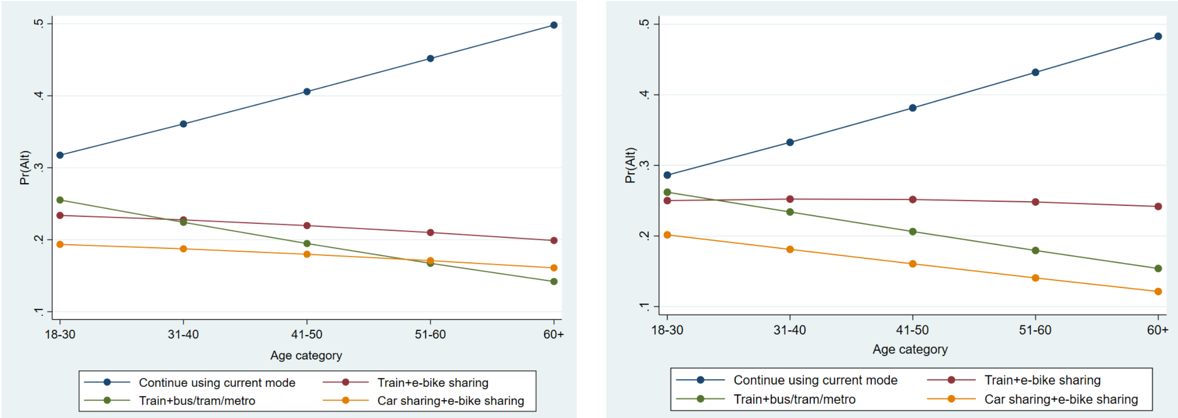
The unweighted model estimations indicate that the effects of gender and education level are statistically insignificant (p-value>0.05). In other words, no indication is found that gender and education level affect the mode choice behavior of respondents. Even with the weighted estimation, the effects of gender and education are still insignificant. On the other hand, age has significant effects (-0.575 to -0.688) on the mode choice behavior of employees. The negative coefficient values indicate that the more employees get older the less likely they are to choose the mobility packages. In other words, older employees are less likely to prefer mobility packages over their current modes. The result is in line with the findings of Karlsson et al. (2017a), where most users of the Smile pilot project were between 20 to 40 years old. With the weighted estimation, the effect of age becomes even more prominent, a 6.5% increase on average. Similar to age, annual net income also has negative coefficient values and are statistically significant for all packages (-0.784 to -0.958). Within the weighted estimation, the influence of income becomes stronger (-0.966 to -1.155). These results imply that employees with higher income are less expected to change their mode choice behavior concerning these mobility packages, or at least with these specifications.

Table 4.9: Coefficients of socioeconomic characteristics

Alternative	Parameter	Unweighted Coef.	Unweighted Sign.	Weighted Coef.	Weighted Sign.
Continue using current mode		base alternative			
Train+ e-bike sharing	Sex(Female)	0.048	0.936	0.018	0.986
	Age	-0.575	**0.024**	-0.590	0.201
	Income	-0.895	**0.011**	-0.966	**0.041**
	Education	0.288	0.538	0.768	0.269
Train +bus/tram/metro	Sex(Female)	0.394	0.511	0.162	0.876
	Age	-0.688	**0.007**	-0.725	0.094*
	Income	-0.958	**0.006**	-1.123	**0.020**
	Education	0.101	0.827	0.311	0.681
Car sharing+ e-bike sharing	Sex(Female)	-0.220	0.711	0.050	0.962
	Age	-0.569	**0.024**	-0.711	**0.056**
	Income	-0.784	**0.025**	-1.155	**0.010**
	Education	-0.145	0.752	-0.260	0.698
	LL	-1397.5		-1405.51	
	Wald chi2(17)	167.06		83.52	
	AIC	2837.01		2853.039	
	BIC	2947.37		2963.406	

Note: The models converged in 6 (N) and 7 (N) iterations.
** Significant at 90% CI.*

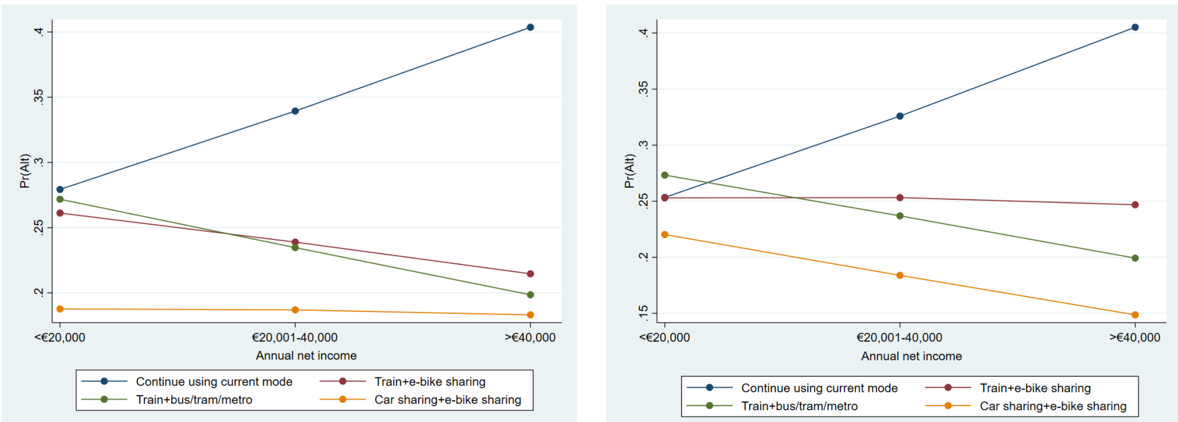
In order to measure the effect of changes in socioeconomic characteristics on choice probabilities, the marginal effects of these variables are calculated. Figure 4.11 presents the effect for different age groups. For instance, the probability that employees under the age of 30 years old would choose train+bus/tram/metro is around 25%, which decreases to less than 15% for employees older than 60 years old. On the other hand, around 31.5% of the youngest group would continue using the current modes, while this percentage rises to 50% for the oldest group. However, the choice probabilities do not change simultaneously for all mobility packages. Train+e-bike sharing and car sharing+e-bike sharing show less variation with age. With the weighted estimation, the effect of age becomes slightly stronger, but not very much (figure 4.11-b). Nearly half of the respondents who are older than 60 years old are still expected to keep their current commuting modes. Again, the choice probability of train+bus/tram/metro reduces as employees get older. A reason could be that work-related trips of older employees might be associated with other activities, e.g. taking/picking up children to daycare or school, which makes them less flexible in their mode choice. Moreover, individuals tend to develop travel habits over time and may no longer consciously choose their travel mode (De Vos et al., 2013). Employees are not exceptions and travel habit of older employees has been formed over several years and hence it is not easy for them to change their habits. While younger employees do not have such strong travel habits yet and are therefore open to change their commuting behavior.



(a) (b)

Figure 4.11: Marginal effect of age categories; (a) unweighted, (b) weighted

Regarding the income level, respondents who earn less than €20,000 annually show more willingness to choose train+e-bike sharing (24.4%) and train+bus/tram/metro (25.3%). The increase in annual income decreases the chance of choosing these packages. The result is in line with (Dargay, 2001), in which the author found that people with high income are less likely to use public transport. Similar to the unweighted model, in the weighted model, the low-income employees are also prone to choose train+e-bike sharing and train+bus/tram/metro. Only 25% of them want to keep their current transport modes. As the income increases, fewer employees would choose train+e-bike sharing, train+bus/tram/metro, or car sharing+e-bike sharing (figure 4.12-b). Studies show that income is directly correlated with car ownership since it is easily fordable for people with high-income (Dargay, 2001). In this study, around 86% of respondents who earned more than €40,000 per year possessed private/lease cars, while this percentage was only 36% of low-income employees (less than €20,000/year) (see appendix D). So, it makes sense if the high-income employees show less willingness to change their commuting mode choice since they are mostly car-oriented people.



(a) (b)

Figure 4.12: Marginal effect of annual income; (a) unweighted, (b) weighted

As mentioned previously, the coefficient values related to gender and education levels are not statistically significant. So, their marginal effect is presented in appendix G.1 and G.2.

4.2.3 Impact of current commuting patterns on mode choice

Commuting behavior research needs to examine not only current commuting behavior itself but also its impact on the future mode choice. The reason is that commuting behavior is correlated with habits that employees might have developed over time. In that sense, the current commuting patterns of employees are expected to influence their mode choice behavior. To do so, the commuting-specific attributes such as commuting mode, frequency, car ownership, travel time, travel distance, and home distance to the closest railway station are introduced as covariates in the ML models. Table 4.10 presents the coefficient values of commuting-specific attributes for both the unweighted and weighted models. The complete outputs can be found in appendix F.5 and appendix F.6.

Compared to the previous models, these models perform better, where their AIC values are 2671.23 and 2687.241 for unweighted and weighted estimations, respectively. The log simulated likelihoods of these models are -1305.615 and -1313.62, meaning that these models have better goodness of fit compared to the previous ones.

Table 4.10: Coefficients of commuting-specific attributes

Alternative	Parameter	Unweighted		Weighted	
		Coef.	Sign.	Coef.	Sign.
Continue using current mode		base alterantive			
Train+ e-bike sharing	Car users	(base)		(base)	
	Non-car users	2.252	**0.011**	5.765	**0.000**
	Multi-modal	1.832	**0.043**	3.324	**0.014**
	Car ownership: yes	-1.286	0.175	0.312	0.814
	Frequency	0.240	0.377	0.302	0.425
	Travel time	-0.536	0.139	-0.980	**0.038**
	Travel distance	0.212	0.630	1.021	0.125
	Distance to railway station	-0.211	0.647	0.798	0.330
Train+ bus/tram/metro	Car users	(base)		(base)	
	Non-car users	1.650	0.059*	4.818	**0.001**
	Multi-modal	1.882	**0.035**	2.808	**0.029**
	Car ownership: yes	-2.122	**0.025**	-0.595	0.633
	Frequency	0.195	0.469	0.196	0.595
	Travel time	0.017	0.961	-0.441	0.367
	Travel distance	0.091	0.834	0.770	0.265
	Distance to railway station	-0.154	0.739	1.310	0.124
Car sharing+ e-bike sharing	Car users	(base)		(base)	
	Non-car users	0.500	0.567	4.625	**0.002**
	Multi-modal	0.149	0.867	1.724	0.160
	Car ownership: yes	-1.459	0.122	-0.048	0.971
	Frequency	0.147	0.588	0.230	0.519
	Travel time	-0.769	**0.032**	-1.381	**0.008**
	Travel distance	-0.084	0.845	0.625	0.304
	Distance to railway station	-0.021	0.963	1.604	**0.054**
	LL	-1305.615		-1313.62	
	Wald chi2(26)	289.27		142.75	
	AIC	2671.23		2687.241	
	BIC	2828.898		2844.908	

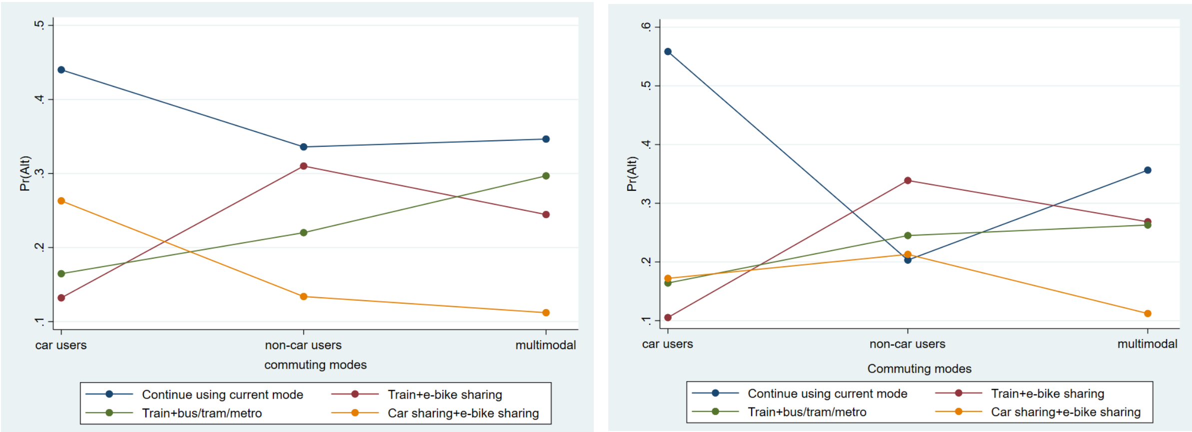
*Note: The models converged in 7 (N) and 8 (N) iteraations. * Significant at 90% CI.*

Commuting mode

Commuting modes have been classified into three categories: car users, non-car users, and multi-modal commuters. Car users group refers to employees who mainly drive private/lease to work. Non-car users refer to the category of employees whose primary commuting mode is other transport modes than cars. It means that they do not use cars for work-related trips. There is a third category of employees who commute by car, meanwhile, ride public transport regularly, e.g. weekly. This category has been named as multi-modal commuters.

The results indicate that current commuting modes explain the mode choice behavior of employees to a large extent. As can be seen in table 4.10, commuting modes have significant effects on the selection of train+e-bike sharing and train+bus/tram/metro packages. Non-car users are 2.25 times more and multi-modal commuters are 1.83 times more likely than car users to choose train+e-bike sharing. Similarly, non-car users and multi-modal commuters are also more likely to choose train+bus/tram/metro. However, commuting modes have statistically insignificant coefficients (p-value>0.05) concerning car sharing+e-bike sharing. When the sample is weighted, the effect of commuting modes becomes stronger. The non-car users are 5.76 times and multi-modal commuters 3.32 times more likely to choose the train+e-bike sharing package. Regarding the train+bus/tram/metro, non-car users are 4.82 times and multi-modal commuters are 2.81 times more likely to choose this package. In the weighted estimation, non-car users are also more likely (4.62 times) to choose the car sharing+e-bike sharing package. This implies that car users are less likely to replace their cars with alternative transport modes. The result is in line with the findings of Knijn (2020), in which car user employees showed less interest in using MaaS. However, the conclusion cannot be made straightforward without considering other factors. Looking at the age and annual income of the respondents, around 72.5% of private/lease car users are over 50 years old and 53.1% earn more than €40,000 per year. As discussed in section 4.2.2, older and higher-income employees showed less interest to change their transport mode. Perhaps, their age makes them car-dependent, and because they can easily afford it, they have no intention to replace their cars with public transport. On the other hand, non-car users are mostly young and low-income employees (see appendix D). This could be the reason they are more open to travel behavior changes.

Figure 4.13-a shows the marginal effects of commuting modes on choice probability based on the unweighted estimation. As can be seen in the figure, around 44% of car users would keep using their private/lease cars, while 34% of non-car users and 35% of multi-modal commuters would keep using their current modes. On the other hand, 26% of car users would choose car sharing+e-bike sharing, whereas only 13% of non-car users and 11% of multi-modal commuters would choose this package. The result also indicates that car users are less likely to choose train+e-bike sharing (13%) and train+bus/tram/metro (16%). While 31% of non-car users would choose train+e-bike sharing and 30.5% choose train+bus/tram/metro. Interestingly, multi-modal commuters behave similarly to non-car users. 25% of this group would choose train+e-bike and 30% train+bus/tram/metro. In the weighted model, the marginal effects of commuting modes become stronger (figure 4.13-b). Nearly 54% of car users would continue using their current mode and drops to 20% for non-car users and 36% for multi-modal commuters. Within this estimation, a large proportion of non-car users (34%) would choose the train+e-bike sharing package.



(a) (b)

Figure 4.13: Marginal effect of commuting modes; (a) unweighted, (b) weighted

This was also found when car users were directly asked if they are willing to substitute part of their car trips with alternative modes when MaaS is available. Table 4.11 presents the distribution of responses. Around 33.1% of car users strongly disagreed with substituting part of their car trips with train, bus/tram/metro, car sharing, or bike sharing. Only 13% of them strongly agreed with changing part of their car trips with train, 8.5% with bus/tram/metro, 7.7% with car-sharing, and 10% with bike sharing. On average, 34% of car users (somewhat to strongly) agreed that they are willing to substitute part of their car trips with the aforementioned alternatives; while 50.6% (somewhat to strongly) disagreed to replace their car trips.

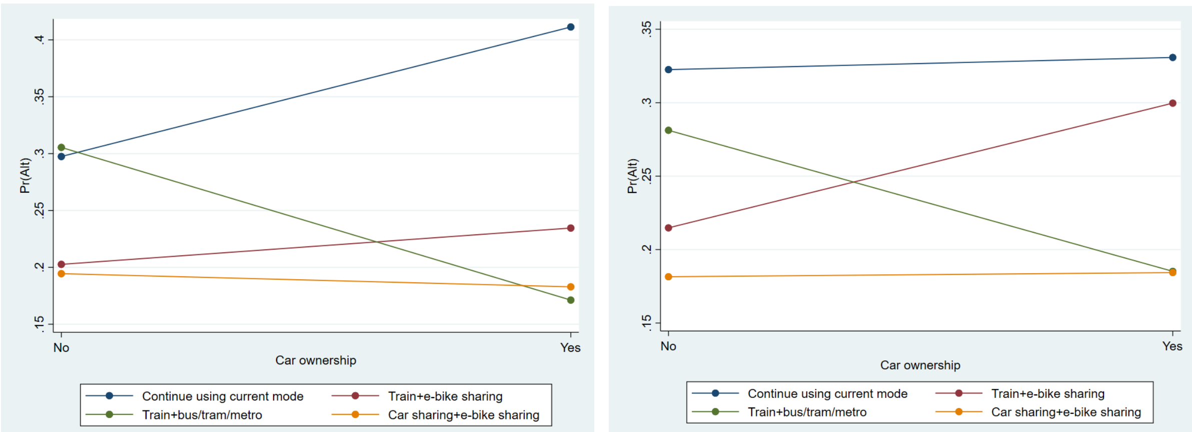
Table 4.11: Willingness to substitute part of car trips with other modes

Alternative	Answer distribution					Total
	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree	
Train	48	20	19	26	17	130
	36.9%	15.4%	14.6%	20.0%	13.1%	100%
Bus/tram/metro	47	23	23	26	11	130
	36.2%	17.7%	17.7%	20.0%	8.5%	100%
Car sharing	31	26	20	43	10	130
	23.9%	20.0%	15.4%	33.1%	7.7%	100
Bike sharing	46	22	18	31	13	130
	35.4%	16.9%	13.9%	23.9%	10.0%	100
Average	33.1%	17.5%	15.4%	24.2%	9.8%	

Car ownership

Regarding the car ownership, the model results show that its effect depends on transport modes included in the package. Based on the unweighted estimation, its coefficient value is statistically significant only regarding the train+bus/tram/metro package. Employees who own cars are 2.12 times less likely to choose this package (table 4.10). This also indicates that even though employees might not drive to work, car ownership itself affects their mode choice for work-related trips.

To obtain a better understanding of how car ownership affects mode choice, its marginal effect is calculated. Figure 4.14-a presents the effect of car ownership based on the unweighted estimation. As can be seen in the figure, around 30% of non-car owners would choose train+bus/tram/metro, 20% train+e-bike sharing, and 22.5% car sharing+e-bike sharing package. Around 28% of these employees would continue using their current modes. On contrary, 42% of car owners would probably keep driving to work. The striking point is that the probability of choosing train+bus/tram/metro rapidly decreases with car ownership. While the respondents showed less sensitivity towards train+e-bike sharing, which is a similar package expect e-bike sharing replaced bus/tram/metro. In the weighted estimation, the effect of car ownership becomes stronger on the selection of train+e-bike sharing. Nearly 31% of car owners are expected to select this package, while none car owners are more interested in train+bus/tram/metro (figure 4.14-b). Notably is that car ownership did not show any effect concerning the car sharing+e-bike sharing package. Moreover, respondents were asked if MaaS can prevent them from buying a private car or getting a lease car. Their answer distribution can be found in appendix H.



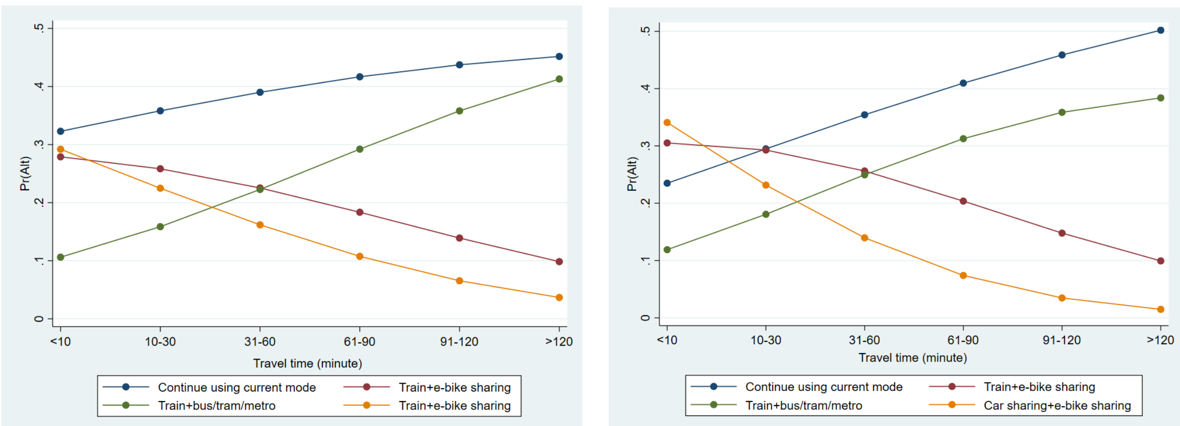
(a) (b)

Figure 4.14: Marginal effect of car ownership; (a) unweighted, (b) weighted

Travel time and distance

Travel time refers to one way travel time between home and workplace on a normal day without any disruption, e.g. traffic accident, train cancellation. Travel distance refers to the distance between home locations and workplaces of employees. These distances have been calculated using ArcGIS (network analyst) based on home postal codes (PC4) and working location. The results of the ML model show that travel time has a statistically significant coefficient regarding the utility of train+e-bike sharing and car sharing+e-bike sharing packages. In the weighted model, the coefficient becomes stronger (table 4.10). The result makes sense because the amount of free ride with car sharing and bike sharing was time-based in the package design. For instance, for travel time longer than 60 minutes, the person had to pay €0.26 for each extra minute of driving with car sharing. Likewise, two of the e-bike sharing attribute levels were 1 and 2 hours per day and then pay €2.0/hour. It was expected that travel distance would have a similar effect on mode choice, but the model results do not prove so. The coefficient values of travel distance are statistically insignificant for all three mobility packages.

To get a clear picture of travel time influence, its marginal effect is calculated. Figure 4.15 presents the choice probabilities of the alternatives as a function of travel time. When travel time increases from less than 10 minutes to more than 120 minutes, the choice probability of ’continue using current modes’ increases from 32% to 45%. The striking point is that for longer travel time, employees preferred train+bus/tram/metro package. As the travel time increases, employees are less likely to choose train+e-bike sharing and car sharing+e-bike sharing. Within the weighted estimation, the effect of travel time becomes stronger (figure 4.15-b). As can be seen in the figure, employees with shorter travel time preferred train+e-bike sharing and car sharing+e-bike sharing. Up to 60 minutes, the choice probabilities are somewhat similar, but afterward, employees would likely continue using their current modes or choose train+bus/tram/metro package. The marginal effect of travel distance can be found in appendix G.3.



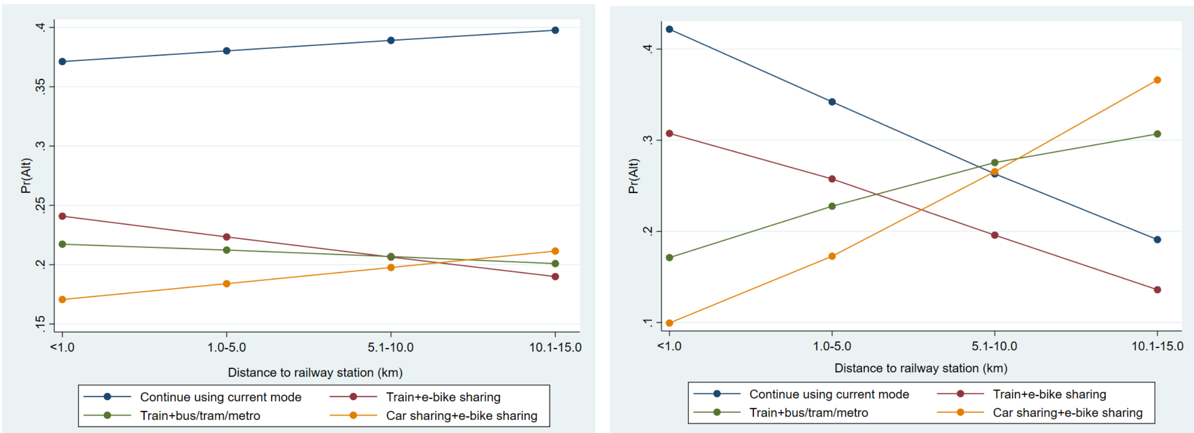
(a) (b)

Figure 4.15: Marginal effect of travel time; (a) unweighted, (b) weighted

Distance to railway station

Residential location is a choice that affects people’s activities and travel patterns in time and space, as well as, the accessibility of possible destinations (De Vos et al., 2013). For some employees, public transport, particularly trains might not be an option since railway stations are located far from their homes. Therefore, distance to the closest railway station is inserted as a covariate in the model estimation. Again, the distance is calculated using ArcGIS (network analyst) based on the home postal code and railway stations.

In the unweighted estimation, distance to the closest railway station has insignificant coefficients for all mobility packages. However, in the weighted estimation, its coefficient value is statistically significant concerning the utility of car sharing+e-bike sharing (coef=1.6). It means employees living far from railway stations are more willing to choose this package. This effect can be clearly seen in figure 4.16. Based on the unweighted estimation, 22% of employees who live far from railway stations (10-15km) would choose car sharing+e-bike sharing. This percentage drops to 14.5% for those who live less a kilometer away from the closest railway station. This effect is more visible with the weighted estimation (figure 4.16-b). This refers to built-environment factors, where residential location constrains people from using public transport, and hence car sharing+e-bike sharing is a preferred package for them. Unexpectedly, employees living far from railway stations are more likely to choose train+bus/tram/metro.



(a) (b)

Figure 4.16: Marginal effect of distance to railway station; (a) unweighted, (b) weighted

Commuting frequency

It was expected that commuting frequency might play an important role in mode choice because it is directly related to commuting costs. However, the result indicates that commuting frequency does not have a significant coefficient values. In both unweighted and weighted estimations, the coefficients of commuting frequency are weak and statistically insignificant. However, its marginal effect shows that employees who commuting more frequently are more likely to choose one of the mobility packages (see appendix G.4). This is in line with the findings of Knijn (2020), in which the author found that employees who use car more often are more willing to use MaaS.

4.2.4 Impact of increasing parking tariffs on mode choice

In this part, the ML model also incorporates with the increase in parking tariffs. As discussed in section 3.2, the choice questions for car users were formulated with an increase in their current parking costs that employees pay at the moment. These increases were €1.0/hour, €1.5/hour, or €2.0/hour. The respondents were asked if they would like to choose one of the mobility packages or 'None'.

For the model estimation, the increase in parking tariffs, and the price of mobility packages are set as random parameters and the remaining elements of mobility packages are set to be fixed parameters. Moreover, parking space and car necessity are assigned as covariates. Table 4.12 presents the coefficient values based on unweighted and weighted estimations. The complete outputs of the models can be found in appendix F.7 and F.8. As can be seen in the table, the increase in parking tariffs is associated with a negative coefficient (-2.25) and is statistically significant (p-value<0.05). This means that increasing the parking tariffs does have a positive contribution to getting employees out of their cars. However, in both models, the standard deviations related to the increase of parking tariffs are very large, which indicates the existence of heterogeneity in the preference of car users over parking costs. Regarding the parking space, the coefficient value related to street/garage parking is statistically significant. This group of employees is 3.14 and 4.02 times more likely to choose train+e-bike sharing and car sharing+e-bike sharing, respectively. However, in the weighted model, these values are statistically insignificant for all mobility packages. Notably, respondents who said that they need their cars due to personal circumstances (e.g. carrying a baby seat) showed less interest in choosing the provided mobility packages. Probably, they might be willing to switch to alternative modes when they do not have such constraints.

Table 4.12: ML model estimations for car users only

Parameter		Unweighted Coef.	Unweighted Sign.	Weighted Coef.	Weighted Sign.
Non-random	train	0.286	**0.007**	0.487	**0.006**
	bus/tram/metro	-0.042	0.747	-0.124	0.450
	e-bike sharing	0.282	**0.010**	0.340	**0.030**
	car sharing	0.189	0.103	0.167	0.505
Random	price	-0.014	**0.000**	-0.023	0.161
	inc. parking tariff	-2.250	**0.008**	-1.421	**0.022**
	sd_{price}	0.009		0.013	
	$sd_{inc.\ parking\ tariff}$	5.114		2.965	
Continue using current mode		(base alternative)			
Train + e-bike sharing	Car necessity	-1.712	0.137	-3.182	**0.043**
	Employer's parking	(base)			
	Street/garage parking	3.143	**0.022**	3.369	0.271
	P+R location	0.407	0.839	1.197	0.564
	ASC	-1.340	0.191	-0.124	0.971
Train + bus/tram/metro	Car necessity	-1.461	0.211	-2.421	0.138
	Employer's parking	(base)			
	Street/garage parking	3.032	0.104	4.590	0.195
	P+R location	1.056	0.612	2.010	0.361
	ASC	-0.939	0.341	0.153	0.961
Car sharing + e-bike sharing	Car necessity	-1.447	0.218	-2.731	0.073*
	Employer's parking	(base)			
	Street/garage parking	4.020	**0.023**	4.611	0.149
	P+R location	-2.323	0.283	0.262	0.908
	ASC	-0.925	0.346	0.370	0.912
	# cases	780		780	
	LL	-692.6131		-531.1886	
	Wald chi2(15)	82.61		105.32	
	AIC	1425.226		1102.377	
	BIC	1518.412		1195.563	

Figure 4.17 shows the marginal effects of the increase in parking tariffs at 95% confidence interval. When the parking tariff is increased by €1.0/hour, it predicted that 48% of car users would continue using their cars and decrease to 40% when the amount of increase is doubled (€2.0/hour). It also increases the choice probability of car sharing+e-bike sharing, but its effect is not ever strong. Based on the weighted estimation, around 55% of employees are expected to keep their cars when the parking tariffs increased by €1.0/hour, which decreases to 45.5% when parking tariffs increase by €2.0/hour.

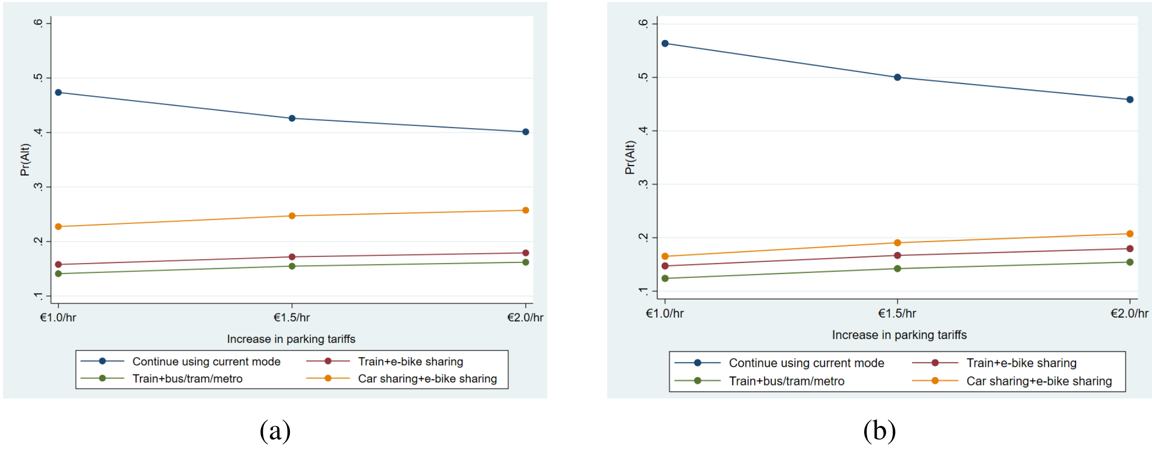
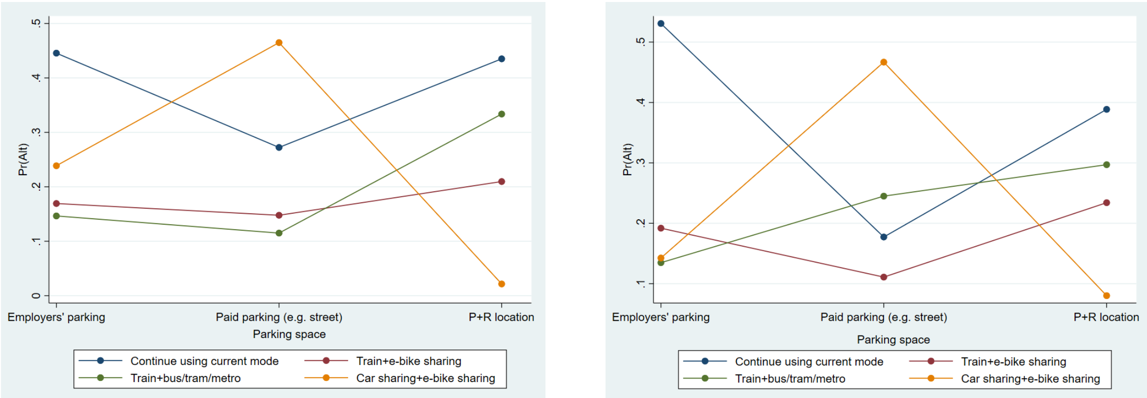


Figure 4.17: Marginal effect of increase in parking tariffs; (a) unweighted, (b) weighted

The marginal effect of parking space indicates that car users who use their employers' parking spaces are less likely to change their commuting mode (figure 4.18-a). For this group of employees, the predicted probability of keeping their cars is around 45%, which drops to 26% and 43% if they use street/garage parking and P+R parking, respectively. The striking point is that the choice probability of car sharing+e-bike sharing fluctuates from 24% (employer's parking) to 47% (street/garage parking) and 2% (P+R location). This indicates that car users who use street/garage parking are very likely to switch to car sharing+e-bike sharing by increasing the parking tariffs. On the other hand, car users who use P+R locations are willing to choose train+bus/tram/metro (figure 4.18-a). Considering the parking discount that car users can get by parking at a P+R location (€1-8/day), it was not unexpected if they prefer train+bus/tram/metro and train+e-bike sharing.

The effect of parking space differs within the weighted estimation (figure 4.18-b). Around 46% of car users who use street/garage parking would choose car sharing+e-bike sharing, while this percentage drops to 15% if they use their employers' parking space and 6% in case of using P+R locations. The results show that a large proportion of street/garage parking users would replace their cars as a consequence of increases in parking tariffs.



(a) (b)

Figure 4.18: Marginal effect of parking place; (a) unweighted, (b) weighted

4.2.5 Conclusion

This section presented the results of the ML model estimations based on the unweighted and weighted estimation. In general, the mobility package elements, age, income, current commuting mode, travel time, distance to railway stations, car ownership, increase in parking tariffs, and parking space are found influential factors in mode choice of employees. Train and car-sharing attributes have larger effects compared to e-bike sharing and bus/tram/metro attributes. Giving unlimited rides with trains towards working regions noticeably increases its choice probability. This is in line with the study of Matyas and Kamargianni (2018a), in which unlimited access to public transport was found the most preferred specification of MaaS bundles among travelers in London. Furthermore, the price has been found as an effective factor in the mode choice behavior of employees. Increasing the price of mobility packages adversely affects their utilities. Because most, if not all, employees in the Netherlands receive reimbursement from employers for work-related trips, it was not expected that price could play a significant role in their mode choice. Perhaps, employees, like every other traveler, have a cost-driven mindset and thereby prefer a cheaper transport mode, even if they do not pay by themselves. Another reason might be that some employees do not receive travel reimbursement or receive partially. That is why the price of mobility packages is still an important parameter for them. The striking point here is that e-bike sharing outperforms bus/tram/metro. Attribute related to bus/tram/metro did not show a significant influence on mode choice. Even giving unlimited access did not affect employees' mode choice behavior.

Regarding the socioeconomic characteristics, only age and annual income are found to have statistically significant effect on mode choice. A substantial difference was found between different age groups. Younger employees (under 30) are more likely to choose one of the mobility packages. On the other hand, employees older than 60 years are less inclined to change their commuting modes. Nearly half of this group is expected to continue using current modes. Perhaps older people have complex activity patterns and time constraints for their work-related trips. Adding the annual income in the model estimation, it was found that high-income employees have low intention in changing their commuting mode. However, a clear cause and effect relationship cannot be drawn here. The reason is that high-income and older employees are mostly car users (see appendix D.2 and D.1), so one cannot conclude whether age and income deprive them to not change their commuting behavior or car dependency. This was more highlighted when the commuting mode was interested in the model estimation, where car-oriented employees seem to be interested in car sharing and e-bike sharing rather than train+e-bike sharing or train+bus/tram/metro. While for non-car users, train+e-bike sharing was the most preferred package. Notably is that multi-modal commuters showed more willingness in switching to public transport and e-bike sharing. Since they do not use cars as their primary commuting mode, they might be less car-dependent. This makes them flexible in choosing their commuting modes. However, car ownership still reduces the probability of choosing public transport as discussed in section 4.2.3.

Travel time and distance to railway stations were other influential factors in the selection of car sharing+e-bike sharing package. Employees with longer travel time are found less likely to choose this package, but if their distance to the closest railway station is long, then this is a preferred package. However, commuting frequency and travel distance had insignificant coefficients concerning all mobility packages. In other words, no indication was found that significant differences exist between employees who commute three times per week and those who commute 5 times per week. It must be noted that the insignificant coefficient value does not mean that the variable does not affect at all. This was demonstrated when the marginal effect of variables was calculated.

Withstanding the fact that most employees use their employers' parking space free of charge or get reimbursement for their parking costs, they are sensitive to increasing parking tariffs. Variation in the parking cost leads to 7% variation in mode choice. However, the effect of increasing parking tariffs is not the same for all employees. Those who use street/garage parking spaces were found more sensitive to parking costs. Obviously, they are the one whose parking cost is a lot, especially if they are working in cities like Amsterdam, where parking price is very high. However, from the TDM perspective, this effect would be limited because they are likely to switch to car sharing rather than public transport (see section 4.2.4).

4.3 Implications

This section sheds light on the implications of the mobility package elements by developing several scenarios and thereby answers research question 3: "what are the possible implications of the investigated measures from the TDM perspective?" These scenarios reflect the effect of mobility package elements on mode choice behavior. To simplify the process, respondents are divided into two groups: car-oriented and non-car oriented. The car-oriented group refers to the group of employees who use private/lease cars for work-related trips. Since the multi-modal commuters are also included in this group, it is labeled as car-oriented to differentiate from car users discussed in the previous section. The non-car oriented group is those who commute mainly by other modes than cars, which is the same as non-car users.

For analyzing the scenarios, the margin command is used. This refers to the choice probability when the predictors or independent variables vary by one unit. In total, eight scenarios have been composed. The first scenario shows the average predicted probabilities, which is specified as the base scenario. The second scenario refers to the situation in which the attribute levels related to train and e-bike sharing are set to their maximum, 'unlimited rides'. The third scenario is similar to the second one except for the price, which is set to its minimum, €140/month. In the fourth scenario, the attribute levels related to train and bus/tram/metro are set to be 'unlimited'. In the fifth scenario, the price of the train+bus/tram/metro is set minimum. The sixth scenario presents the situation in which car-sharing and e-bike sharing attribute levels are specified as '60 free minutes per day then pay per minute (€0.26/minute) and 'unlimited rides', respectively. In the seventh scenario, the price of car sharing+e-bike sharing is set to '€140/month' and the rest is the same as the sixth scenario. The last scenario elaborates on the effect of the increase in parking tariffs for car-oriented employees.

4.3.1 Scenarios

Scenario 1 - base scenario

The first scenario refers to the average marginal effects of all mobility package elements. Figure 4.19 presents the input for the base scenario. For most employees, who commute 4-5 times per week and travel time is less than 60 minutes, the base scenario includes enough free rides at a monthly subscription of €180.

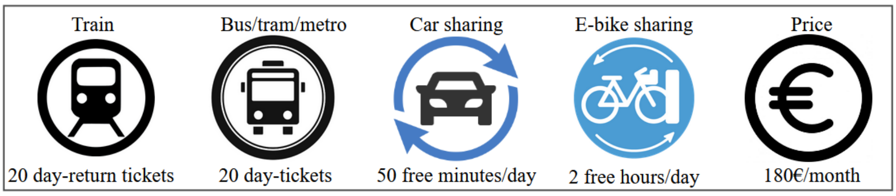


Figure 4.19: Attribute levels for scenario1 - base scenario

As it can be seen in figure 4.20-a, about 30.1% of non-car oriented employees will choose train+e-bike sharing, 29.4% train+bus/tram/metro, and 12.4% car sharing+e-bike sharing. With this configuration, 28% of them would continue using their current modes. 45.9% of car-oriented employees, on the other hand, will not replace their cars with other modes (figure 4.20-b). Comparing the mobility packages, 16.3% of car-oriented employees would choose train+e-bike sharing, 14.7% choose train+bus/tram/metro and 23.1% choose car sharing+e-bike sharing package. Again, car sharing+e-bike sharing is more appealing to this group of employees.

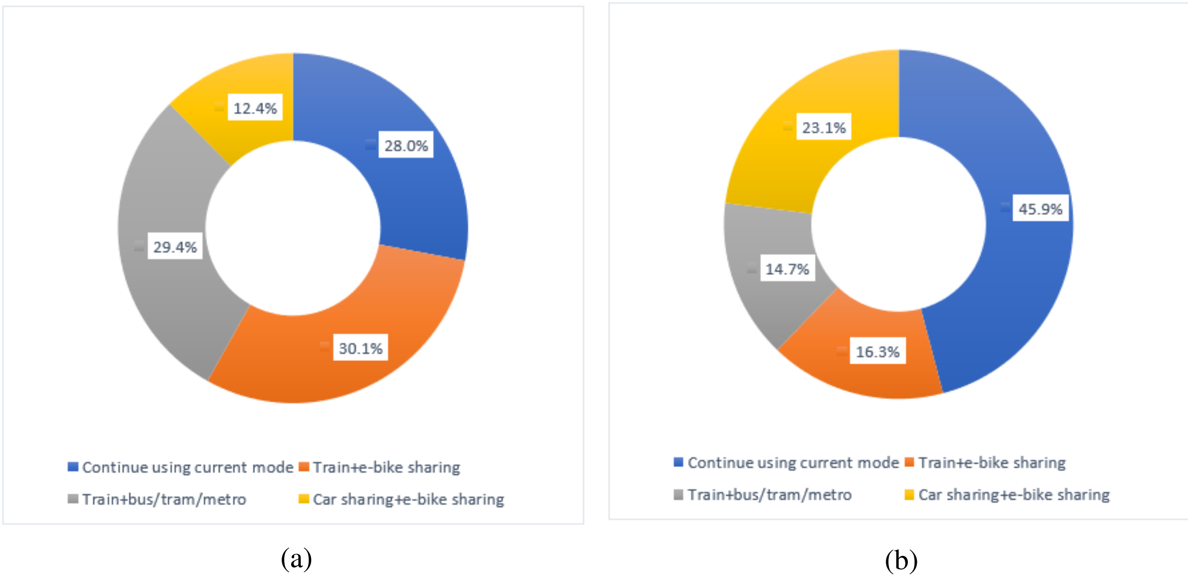


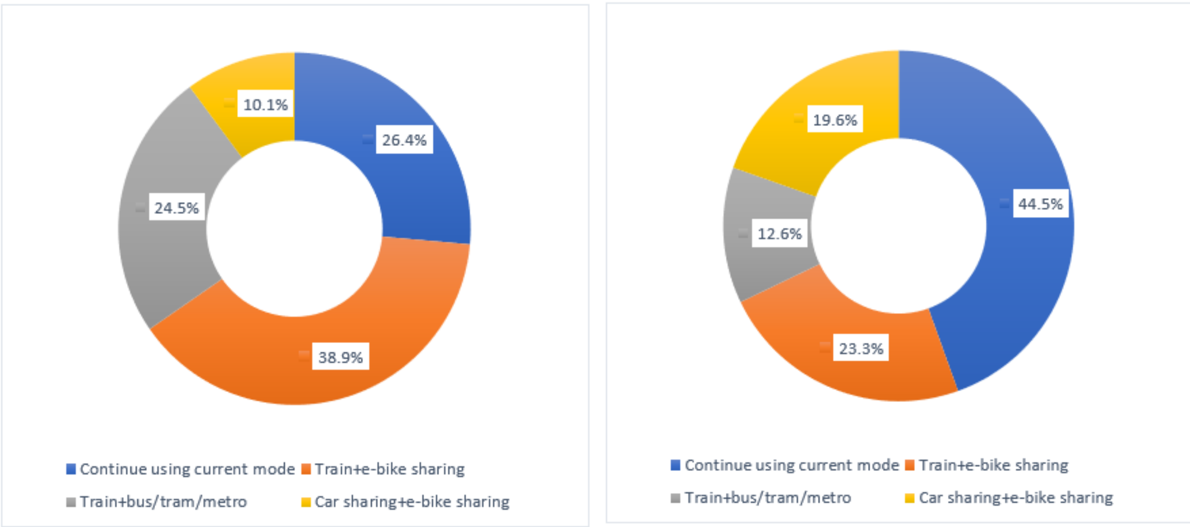
Figure 4.20: Modal split scenario 1; (a) non-car oriented employees, (b) car-oriented employees

Scenario 2 - train and e-bike sharing

In the second scenario, employees are given unlimited rides with trains to working regions and unlimited rides with e-bike sharing for a monthly subscription of €180 (figure 4.21). The rest of the input is the same as the base scenario.

Figure 4.21: Attribute levels for scenario 2

The calculated probabilities are presented in figure 4.22. As can be seen in the figure, the inclusion of unlimited rides with train and e-bike sharing in the package has a strong impact on the choice probability of the train+e-bike sharing package. 38.9% of non-car oriented employees would choose this mobility package for commuting, which was 30.1% in the base scenario. However, the choice probability of 'continue using current mode' is reduced only by 1.6% compared to the base scenario (figure 4.22-a). When car-oriented employees are given unlimited rides with train and e-bike sharing, 25.2% would choose this package (figure 4.22-b), which shows an increase of 7% compared to the base scenario. However, around 44.5% of car-oriented employees would continue using their cars, which does not outperform the base scenario.



(a) (b)

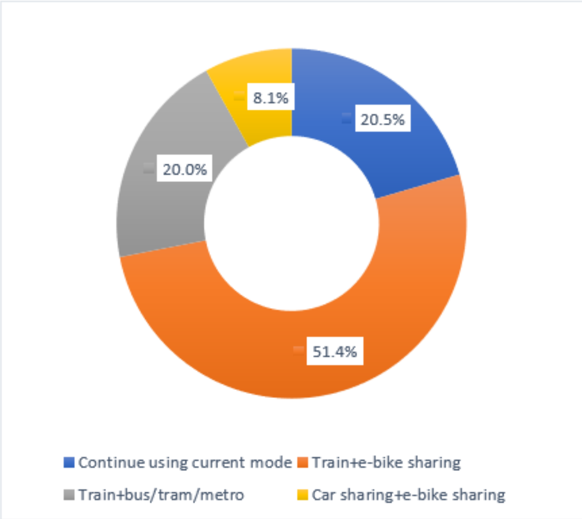
Figure 4.22: Modal split scenario 2; (a) non-car oriented employees, (b) car-oriented employees

Scenario 3 - train+e-bike sharing price reduced

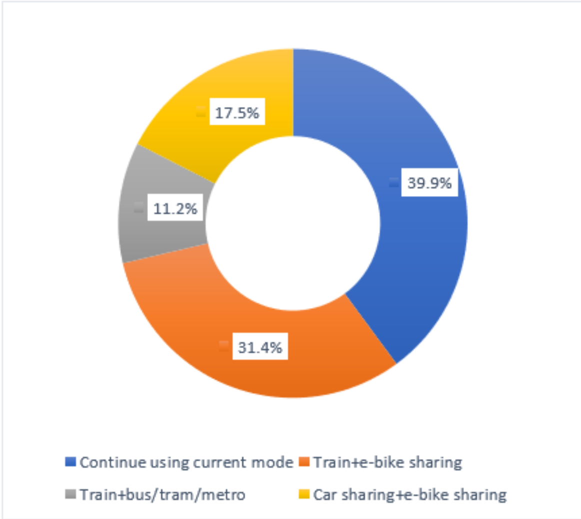
The third scenario is similar to the second scenario except for the price of the train+e-bike sharing, which is set to its minimum (€140/month). Other attributes remain the same as they were in the previous scenario. Figure 4.23 presents the input for this scenario.

Figure 4.23: Attribute levels for scenario 3

As it can be seen in figure 4.24, reducing the price of train+e-bike sharing has noticeably increased the choice probability of this package. It seems that offering unlimited rides towards working regions with train and e-bike sharing at a lower price attracted the interest of both car-oriented employees and non-car car-oriented employees. More than half (51.4%) of them would choose train+e-bike sharing package with this configuration (figure 4.24-a), while this percentage was 38.9% in the previous scenario with the same input except the price. Interestingly, the probability of using current commuting modes reduced from 26.4% to 20.5%. Similarly, this configuration seems interesting for car-oriented employees too. 31.4% of them are expected to choose train+e-bike sharing with the specification provided in this scenario. Comparing with the previous scenario, there is an 8.1% increase in the choice probability of this package. On the other hand, around 39.9% of car-oriented employees would keep using their car (figure 4.24-b), whereas it was 44.5% in the previous scenario. Again, it can be concluded that the price has a substantial effect on employees' mode choice behavior.



(a)



(b)

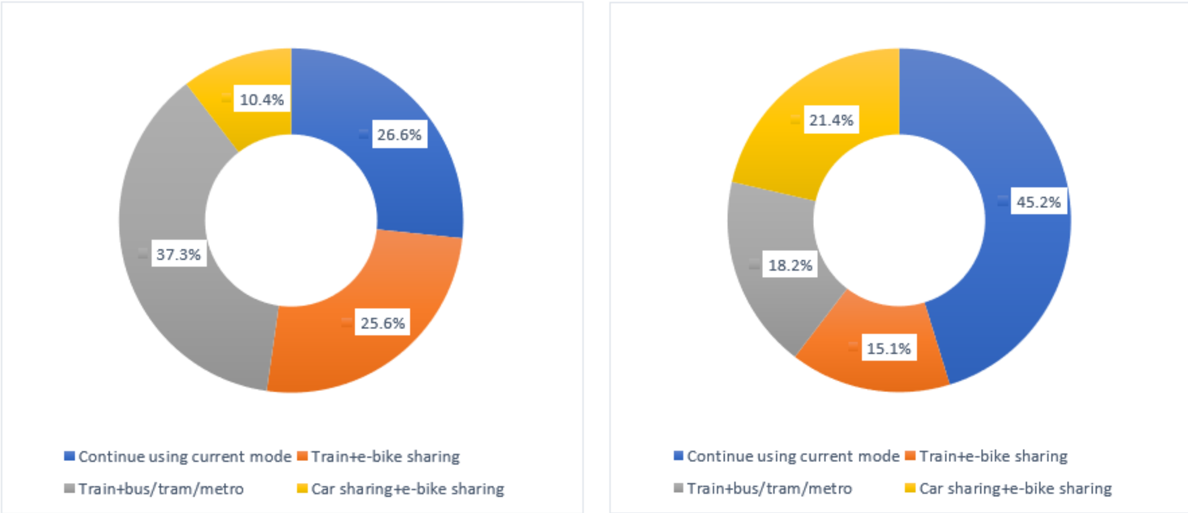
Figure 4.24: Modal split scenario 3; (a) non-car oriented employees, (b) car-oriented employees

Scenario 4 - train+bus/tram/metro

Figure 4.25 shows the input for this scenario. This time, the attribute levels related to train and bus/tram/metro are set to their maximum and the rest of the input is still the same as the base scenario.

Figure 4.25: Attribute levels for scenario 4

The choice probabilities for this scenario are presented in figure 4.26. Comparing to the base scenario, offering unlimited rides with train and bus/tram/metro to working regions increases the choice probability of this package, but not very much. Around 37.3% of non-car oriented employees would choose train+bus/tram/metro with this configuration. On the other hand, only 18.2% of car-oriented employees would choose this package by including unlimited rides with train and bus/tram/metro, which was 14.7% in the base scenario. Moreover, there is a small decrease (0.7%) regarding the selection of 'continue using current mode' (figure 4.26-b).



(a) (b)

Figure 4.26: Modal split scenario 4; (a) non-car oriented employees, (b) car-oriented employees

Scenario 5 - train+bus/tram/metro

Scenario 5 is an extension to scenario 4, in which the price of unlimited rides with train and bus/tram/metro to working region is set to its minimum, €140/month. The complete input for this scenario is presented in figure 4.27.

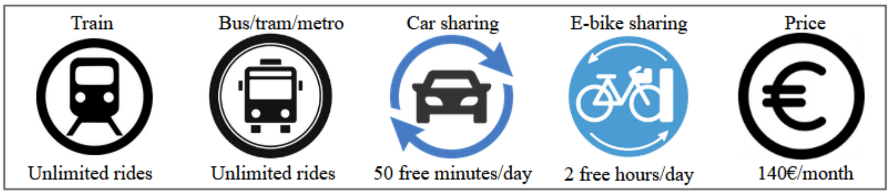
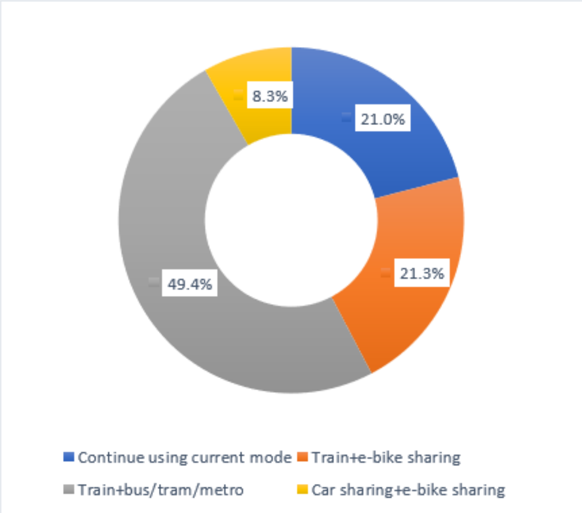
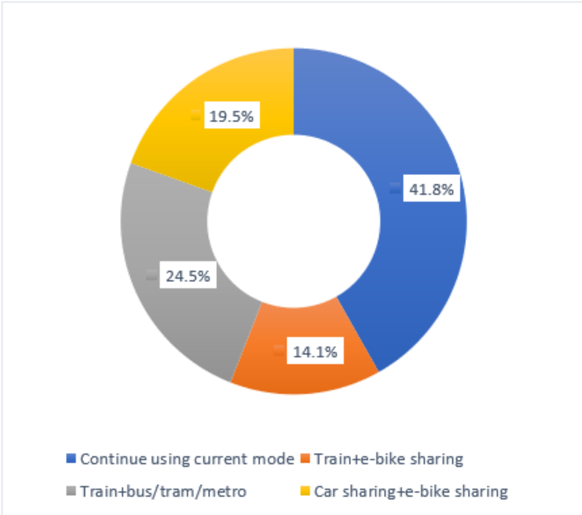


Figure 4.27: Attribute levels for scenario 5

As can be seen in figure 4.28-a, almost half of the non-car oriented employees would choose the train+ bus/tram/metro package. Again, the price has a strong contribution to the choice probability of this package. Though, for non-car oriented employees, this might not be a major modal shift when choosing public transport though MaaS, the effect of the package price is striking. The result corresponds to the findings of (Matyas and Kamargianni, 2018b), where travelers in London preferred to have unlimited access to public transport with MaaS. However, the effect of price on car-oriented employees is not as strong as it was on non-car user employees. Comparing with scenario 4, 24.5% of car-oriented employees would choose this package, which was 18.2% in the previous scenario. Still, 41.8% of car-oriented employees would keep driving to work (figure 4.28-b), which was 45.2% in the previous scenario.



(a)



(b)

Figure 4.28: Modal split scenario 5; (a) non-car oriented employees, (b) car-oriented employees

Scenario 6 - car sharing+e-bike sharing

Figure 4.29 presents the input for this scenario, in which the amount of free ride with car-sharing and e-bike sharing has increased to 60 minutes per day and unlimited rides, respectively. The price for this mobility package is still €180/month. And the attribute levels related to other alternatives are the same as the base scenario.

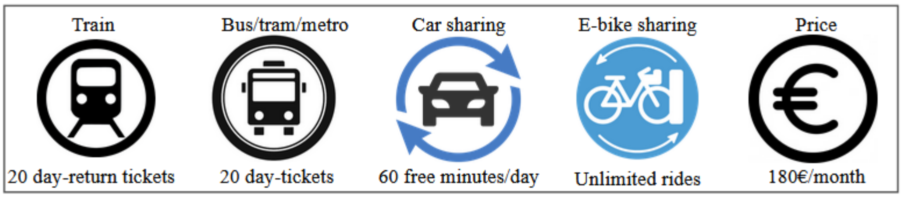
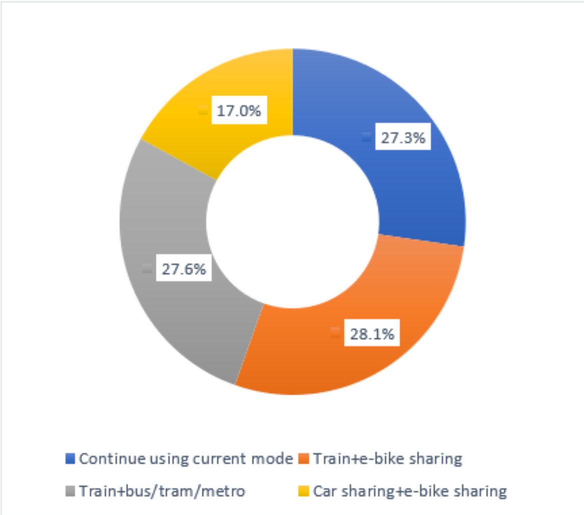
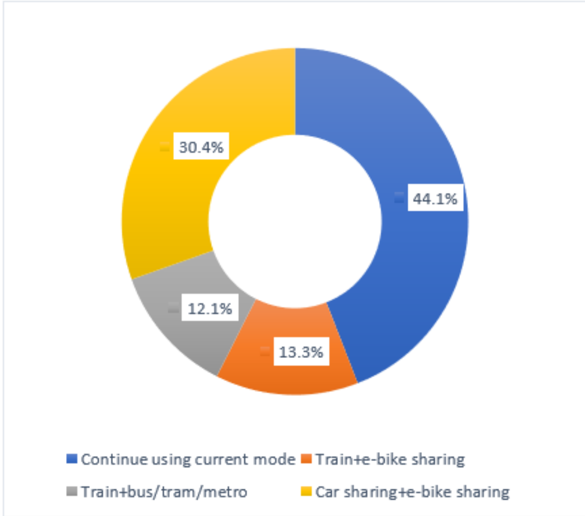


Figure 4.29: Attribute levels for scenario 6

The calculated choice probabilities are presented in figure 4.30. Comparing with the base scenario, increasing 10 minutes of free rides with car-sharing and giving unlimited rides with e-bike sharing leads to an increase of 4.6% in the choice probability of this package by non-car oriented employees. Of these employees, 27.3% would keep using current mode, 17% would choose car sharing+e-bike sharing, 27.6% train+e-bike sharing and 28.1% train+bus/tram/metro (figure 4.30-a). However, a noticeable number of car-oriented employees (30.4%) would select car sharing+e-bike sharing with this configuration. It seems that including 60 free minutes of car-sharing driving per day and unlimited rides with e-bike sharing in the MaaS package works well for car-oriented employees so that a noticeable proportion of them are willing to substitute their cars with this car sharing+e-bike sharing.



(a)



(b)

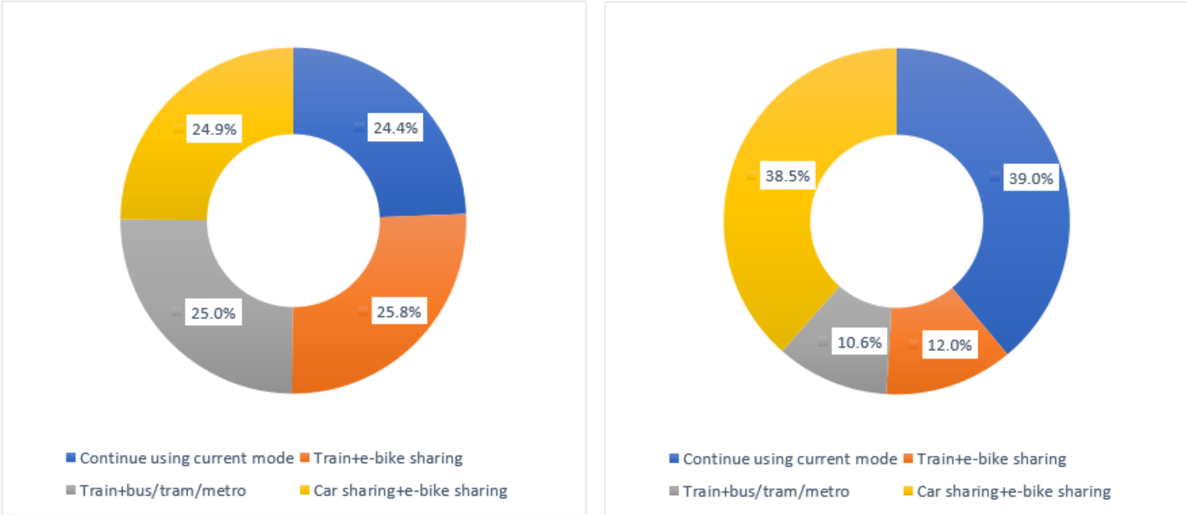
Figure 4.30: Modal split scenario 6; (a) non-car oriented employees, (b) car-oriented employees

Scenario 7 - car sharing+e-bike sharing

This scenario is similar to the sixth scenario except for the price of car sharing+e-bike sharing which is set to €140/month. The inputs for this scenario are still, 60 free minutes of car sharing, unlimited rides with e-bike sharing, 20 day-return tickets with train, and 20 day-tickets with bus/tram/metro (figure 4.31).

Figure 4.31: Attribute levels for scenario 7

As can be seen in figure 4.32, by reducing the price of this package to €140/month, more employees would choose it. Around 24.9% of non-car oriented employees would choose car sharing+e-bike sharing with this configuration. Moreover, 24.4% of non-car user employees would continue using their current modes, while the percentage was 27.3% in the previous scenario. A noticeable change occurs in the mode choice of car-oriented employees. In this scenario, 38.5% of car-oriented employees would choose car sharing+e-bike sharing which shows an increase of 16.6% compared to the base scenario. This indicates that a large proportion of employees might replace their cars if the cost of car-sharing is low enough, as well as, e-bike sharing is provided alongside.



(a) (b)

Figure 4.32: Modal split scenario 7; (a) non-car oriented employees, (b) car-oriented employees

Scenario 8 - increase in parking tariffs

This scenario refers to the increase in parking tariffs for car-oriented employees. As discussed in section 4.2.5, the choice questions for car-oriented employees were formulated with an increase in the parking tariffs on their current parking costs as a discouraging measure. Figure 4.33 presents the input for this scenario which includes an increase of 1.0€/hour, €1.5/hour, and €2.0/hour in parking tariffs. The rest of input is presented in figure 4.33.

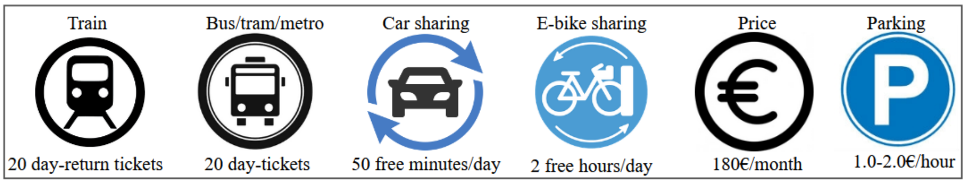


Figure 4.33: Attribute levels for scenario 8

Figure 4.34 shows the choice probabilities for this scenario. With increasing the parking tariffs by €1.0/hr, 47.4% of car-oriented employees would still keep their cars. This percentage reduces to 42.6% and 40.1% when the parking cost is increased by €1.5/hour and €2.0/hour (figure 4.30-b & c). What is striking to note is that by increasing the parking tariffs, more car-oriented employees shift to car sharing+e-bike sharing (25.7%) rather than train+e-bike sharing and train+bus/tram/metro. Again, this result confirms the previous findings where car sharing+e-bike sharing attributes attracted car-oriented employees rather than non-car oriented employees. This is of importance when making a conclusion on the integration of MaaS and increasing parking tariffs. First, variation in the parking tariffs (from €1.0/hour to 2.0/hour) leads to 7% decrease in the choice probability of cars. Second, car-oriented employees are more inclined to switch to car sharing when parking tariff is increased.

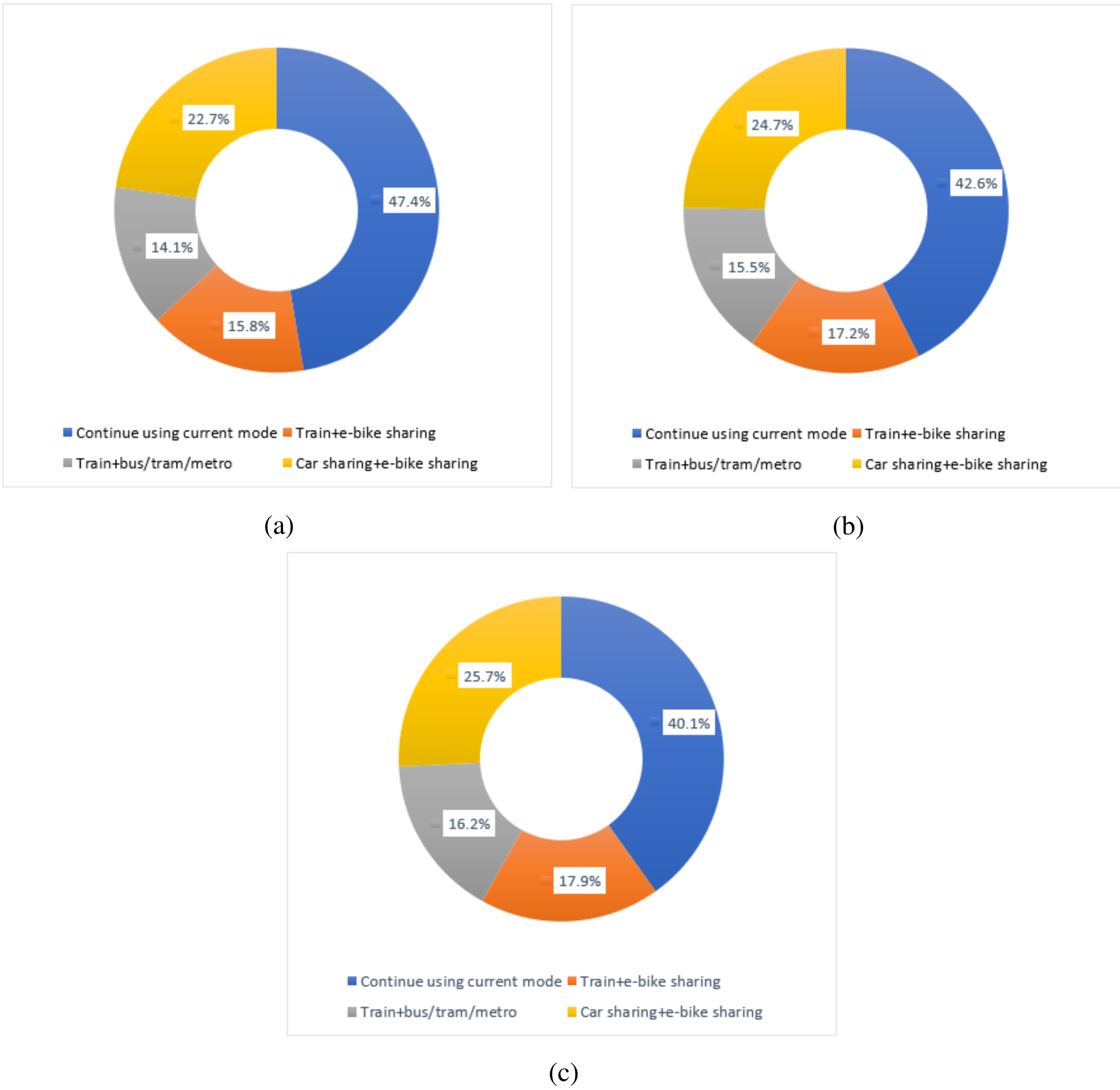


Figure 4.34: Modal split scenario 8; (a) €1.0/hr, (b) €1.5/hr, (c) €2.0/hr

4.3.2 Willingness to Pay (WTP)

The main purpose of WTP assessment is to explore the willingness of customers to pay for a service/product. This allows us to calculate WTP values for services that are not yet in the market (Rischatsch, 2009). Apart from the level of convenience, MaaS packages should be an economically viable option for end-users, including employees.

According to Hole (2007), if the standard deviation of β_p is very low, the variation of denominator (in this case β_p) is negligible. Thereby, the willingness to pay for an improvement in attribute k is:

$$WTP_k = -1 * \frac{\beta_k}{\beta_p} \tag{10}$$

where β_k is the coefficient of the attribute of interest and β_p denotes the coefficient value of the price. For estimating WTP mean, the Krinsky and Robb method is used. In this method, n draws are taken from the distribution of coefficients and then the simulated values of WTP are calculated. In this study, WTP is estimated with 5000 draws at 95% confidence interval. Table 4.13 presents the mean, upper bound, and lower bond of WTP, in which the coefficient of cost is in the denominator and attributes coefficients in numerator based on general ML model estimations (unweighted and weighted). These values indicate WTP in monetary terms for a unit improvement of an attribute.

With the unweighted model, the unlimited rides with trains have the highest WTP value, €21.1. Likewise, when the sample is weighted, employees would like to pay more for this attribute, €31.4. 60 free minutes per day with car-sharing also has the second-highest WTP value, €15.8 in the unweighted model, and €18.3 in weighted mode. Employees would also pay €11.0 for unlimited rides with e-bike sharing, which decreases to €7.2 in the weighted model. When the bus/tram/metro WTP is calculated based on the unweighted ML model, employees are willing to pay only €2.7 for unlimited rides to working regions. This value increases to €4.3 when the sample is weighted. However, the relative coefficient values are statistically insignificant in both models. Table 4.13 presents a complete overview of WTP mean, LL, and UL values for all attributes.

Table 4.13: Estimation of WTP values

Alternative	Attribute	Unweighted			Unweighted		
		Mean	LL	UL	Mean	LL	UL
Train	20 day-return tickets	9.3	4.1	15.7	13.4*	4.3	26.1
	Unlimited rides to working region	21.1	14.6	29.0	31.4	18.9	48.8
Bus/tram/metro	20 day tickets	0.9*	-4.4	7.4	8.4*	-0.4	20.7
	Unlimited rides to working region	2.7*	-2.2	8.6	4.3*	-3.0	14.4
E-bike sharing	2 free hours/day	3.0*	-1.0	7.9	-3.4*	-9.0	4.4
	Unlimited rides	11.0	5.8	17.2	7.2*	0.3	16.8
Car sharing	50 free minutes/day	2.7*	-2.5	9.0	13.8*	2.5	29.4
	60 free minutes/day	15.8	8.8	24.3	18.3	7.2	33.8

*WTP is calculated at 95% CI. LL: lower level; UL: uper level. * statistically insignificant*

4.3.3 Conclusion

The scenarios discussed in this section provided a better picture of how different configurations of mobility packages affect employees' mode choice. Figure 4.35 shows the implications of scenarios for non-car oriented employees. Overall, this group of employees prefers train+e-bike sharing and train+bus/tram/metro packages. For this group, train+e-bike sharing is the most preferred option to commute with. Including unlimited rides with train and e-bike sharing towards working regions with a low price could encourage them to choose packages with this configuration (scenario 3). It must be noted that some non-car oriented would switch to car sharing, especially when the price is low (scenario 7). From the transport management point of view, this should not happen. Switching from public transport to car-sharing increases car traffic on roads, which is in conflict with the sustainability goal of MaaS.

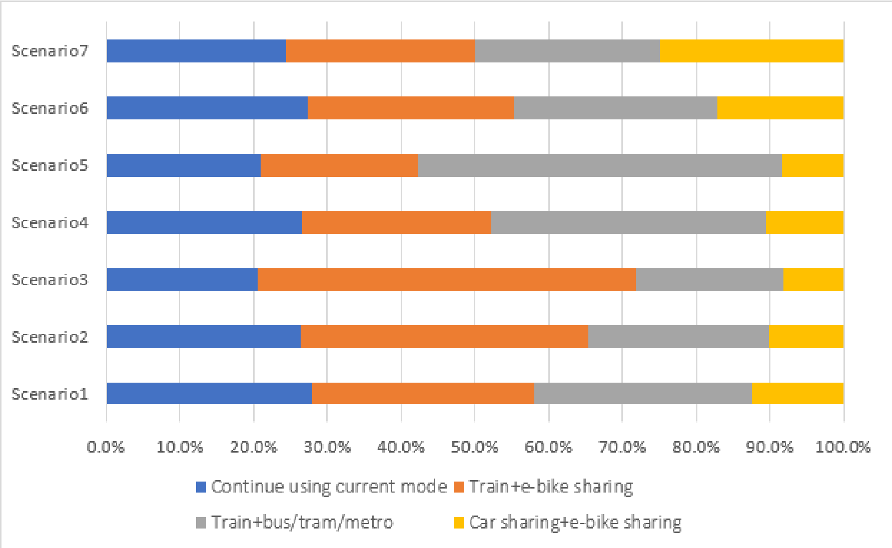


Figure 4.35: Overview of scenarios for non-car oriented employees

Figure 4.36 presents an overview of scenarios for car-oriented employees. For this group of employees, private/lease cars are still the most preferred transport mode. However, several attributes of the mobility packages were found influential in their mode choice behavior. For instance, unlimited rides with train and e-bike sharing and 60 free minutes of driving with car-sharing are their preferred attributes in the MaaS packages (scenario 2 and 5). Furthermore, increasing parking tariffs was also found an effective measure to get them out of their cars, particularly those who use street/garage parking spaces (scenario 8). However, conclusions must be made carefully because a large proportion of them would shift to car-sharing instead of public transport.

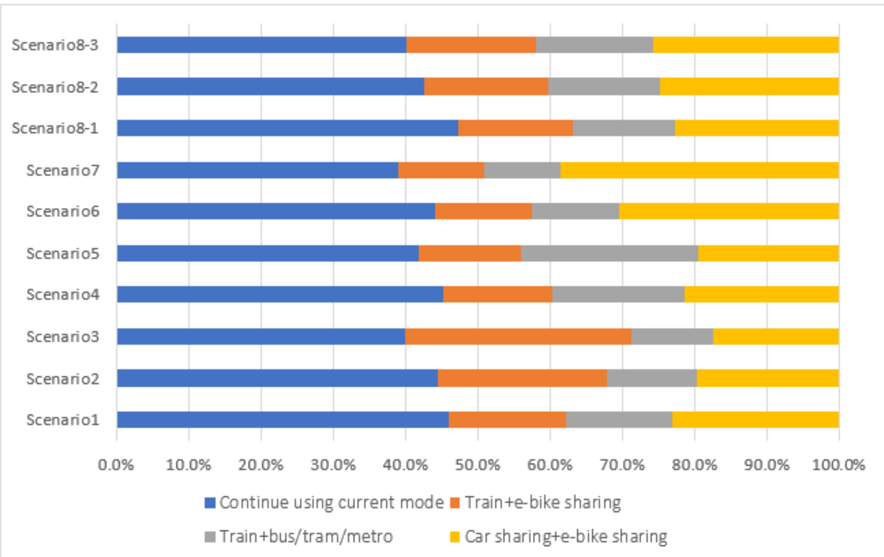


Figure 4.36: Overview of scenarios for car-oriented employees

4.4 Willingness to commute during off-peak hours

This section elaborates on the willingness of employees to commute during off-peak hours. At the end of this section, research question 4 is answered: "To what extent employees are willing to commute during off-peak hours?". Answering this question reflects the willingness of employees to change their commuting time. During the survey questionnaire, each choice question was followed by another question which asked respondents were asked for their willingness to commute during off-peak hours, from 9:00 to 16:00 & 18:30 to 6:30. These questions were associated with up to 40% discount on their preferred mobility packaged.

Table 4.14 reflects the distribution of respondents' answers per category of commuting modes. The multi-modal commuters by far have the highest willingness to shift away from rush hours. On average, around 52% of them have a strong willingness to commute during off-peak hours. The second place goes to car users who expressed willingness in off-peak commuting - 37% on average. This is of interest because car users showed less interest in changing commuting mode, while they are willing to change the commuting time. This might enhance the TDM potential of MaaS in terms of reducing car traffic during rush hours. Non-car users, on the other hand, expressed a lower intention in commuting during off-peak hours, but not very different from car users. This was unexpected since non-car users, mainly public transport users, are already familiar with off-peak traveling.

On average, 41.2% of respondents who selected one of the mobility packages are willing to travel during off-peak if they are given up to 40% discount on their preferred packages. Since most employees commute during peak hours (see figure 4.3), a high percentage of employees could be shifted to off-peak commuting through MaaS. This will have a considerable impact on the distribution of transport demand across the time of day, consequently, reducing pressures on transport infrastructure. 32% of employees are hesitant in changing the time of commuting and said 'maybe' to this question. If MaaS offers are more appealing to this group, the possibility exists to shift them away from peak hours. However, there is still 26.8% of employees who have no willingness to change their commuting time.

Table 4.14: Employees' willingness to commute during off-peak hours

Categories	Discount	Answer distribution Yes	Maybe	No	Total
Car users	20%	30.8%	26.4%	42.9%	100%
non-car users		27.0%	39.0%	34.0%	100%
multi-modal commuters		47.5%	30.0%	22.5%	100%
Car users	30%	39.0%	32.0%	29.0%	100%
Non-car users		33.8%	31.7%	34.5%	100%
multi-modal commuters		52.3%	34.1%	13.6%	100%
Car users	40%	41.2%	33.0%	25.8%	100%
non-car users		42.8%	31.0%	26.2%	100%
multi-modal commuters		56.4%	30.8%	12.8%	100%
Average		41.2%	32.0%	26.8%	100%

4.4.1 Conclusion

Shifting commuting demand from rush time to off-peak hours reduces pressure on transport infrastructures. In this study, it was found the multi-modal commuters were the most flexible group of employees who would to change the time of their commuting. More than half of them showed strong willingness to commute during off-peak hours if they get discounts on their preferred mobility packages. However, because only 15% of the respondents were multi-modal commuters, the final impact on reducing car-based trips will be limited. 1/3 of car users who wanted to replace their cars with one of the mobility packages also expressed their intention in off-peak commuting. Similarly, around 34% of non-car users were willing to commute during off-peak hours by receiving discounts on their preferred mobility package. This itself is a large proportion if generalized to the working population.

4.5 Attitude of employees towards MaaS characteristics and features

This section elaborates on the attitudes of employees towards MaaS characteristics and features and thereby answers the fifth research question of this study: "What is the attitude of employees towards MaaS characteristics and features?" First, the attitude of employees towards additional features of MaaS discussed, and then the importance of MaaS characteristics, from the employees' perspective, is illustrated.

4.5.1 Attitude towards additional features

Throughout several MaaS pilots around the globe, many MaaS apps/websites have been developed, where each one has its exclusive features. Almost all MaaS services provide basic functionalities such as travel information, travel planning, booking, ticketing, invoicing, and payment option. However, some MaaS apps have gone beyond basic functions and added some other features, e.g. parking information and payment, synchronization with google calendar, etc. These features enhance the user experience with MaaS. However, there is a wide variety of these features that could be added to the service.

In this study, seven of these additional features were included in the questionnaire to understand the thoughts of employees about them. They were asked to choose the three most preferred features that they would like to have in a MaaS service when it is available. Table 4.15 presents the percentage and frequency of selected features.

Table 4.15: Employees' attitude towards MaaS additional features

Additional functionalities	Preferred		Not preferred	
	Frequency	Percentage	Frequency	Percentage
Using subscription through the whole Netherlands	171	72.5%	65	27.5%
Real-time information (e.g. congestion, disruption, delay, etc)	147	62.3%	89	37.7%
Parking information and payment (e.g. free spots)	102	43.2%	134	56.8%
Using subscription for other purposes, e.g. shopping	94	39.8%	148	63.0%
Sharing subscription with friends/family members/colleagues	88	37.3%	148	62.7%
Using my subscription through the whole city where I work	54	22.9%	182	77.0%
App synchronization with personal agenda	44	18.6%	192	81.4%

As can be seen in the table, most employees favored using a single MaaS service throughout the whole country rather than a specific region. Of relevance to current practice of MaaS, pilot projects usually cover only specific regions where relevant projects are implemented. This hinders the uptake of MaaS since people will not use multiple apps and buy several packages if the service is not applicable outside a single region. Despite employees usually commute to specific working locations, 'using subscription though the whole Netherlands' was the most desired feature of MaaS services. The second preferred feature that could be attached to the MaaS service is 'real-time information'. Several mobile apps and websites exist in the Netherlands, e.g. TomTom and Waze, that provide real-time traffic information such as congestion, road works, incidents, etc. The integration of this functionality with the MaaS services is one of the top three preferred features for employees. Similar to real-time information, parking information and payment are also preferred by employees. These three features were the most preferred additional features that employees want to have in their MaaS packages.

Furthermore, employees do not like to limit their subscriptions specifically for work-related trips. 39% of respondents preferred the possibility of using their MaaS packages for other purposes, e.g. shopping. Sharing subscription with family members/friends/colleagues is another preferred feature. Furthermore, around 37% of respondents wanted to have an option to shared their subscription with their friends, colleagues, and family members. The last two features, 'using a single subscription through the whole working city' and 'app synchronization with personal agenda' are the least preferred features of MaaS services. It must be mentioned that providing these features might be associated with additional costs, which was not investigated in this study.

4.5.2 Attitude towards MaaS characteristics

In addition to the aforementioned features, MaaS services have some primary characteristics that users might be of interest to end-users. In this study, respondents were asked about the importance of five core characteristics of MaaS services: reliability, privacy, flexibility, user-friendliness, and cost. The questions ware asked on a five-point scale from 'not important at all=1' to 'extremely important=5'. Table 4.16 presents the means and standard deviations of responses.

Table 4.16: Mean and standard deviation of responses

Attribute	Mean	Std. Dev.
Cost	3.814	1.174
Reliability	4.432	0.726
Privacy	4.042	1.043
Flexibility	4.004	0.983
App user-friendliness	3.924	0.837

The most extreme mean belongs to reliability (4.43) with the lowest standard deviation. This indicates that employees give the highest importance to reliability as an essential prerequisite of MaaS services. The second important characteristics of MaaS is privacy assurance. This is understandable since user-privacy has turned out to be a sensitive issue in recent years. Considering the issues with the privacy of mobile apps and social media, it makes sense why employees worry about it. Similar to privacy, flexibility is also a highly important prerequisite. Most often people want to have an option 'just in case'. In that sense, flexibility could be an important factor for the uptake of MaaS. Therefore, the design of the MaaS service can potentially enable or hinder its uptake.

From the users' perspective, MaaS is accessible via smartphone apps and having sufficient ICT skills is crucial (Strömberg et al., 2016). Thus, app user-friendliness is of high importance to make the system easy enough to use. One of the factors that made the Ubigo trial successful in attracting new customers was its simplicity (Karlsson et al., 2016). However, the result shows that employees are less concerned about the simplicity of the service. Perhaps their high education level helps them to easily cope with a new digital service. Though the price was previously found to be an influential factor in employees' mode choice, they give the lowest importance to cost compared to the other aforementioned characteristics. Notably is that this should be differentiated from the impact of price on mode choice and its importance compared to other characteristics. Figure 4.37 presents the distribution of responses concerning cost, reliability, privacy, flexibility, and app user-friendliness.

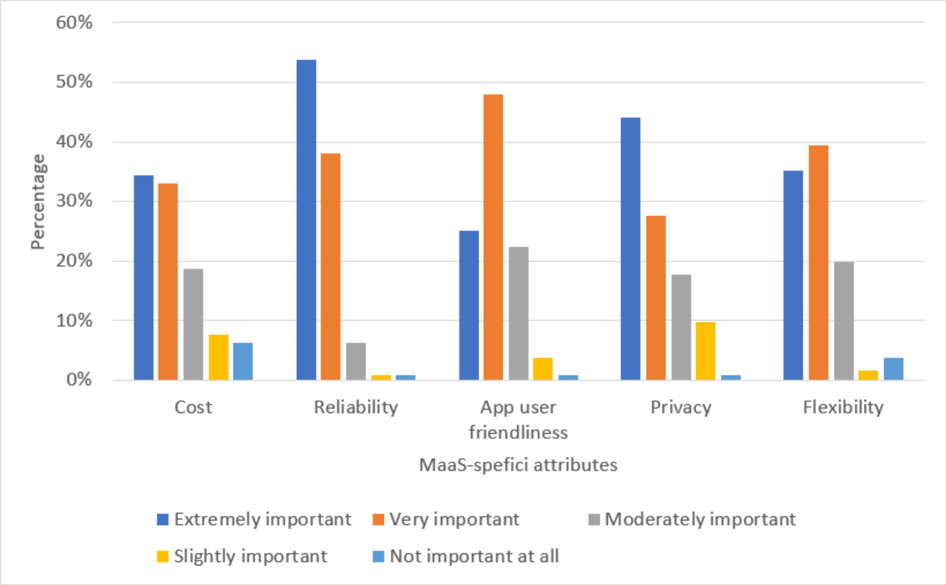


Figure 4.37: Employees' attitude toward MaaS characteristics

4.5.3 Conclusion

This section illustrated the attitudes of employees about MaaS characteristics and additional features. In general, employees are more interested in using MaaS services outside of their working region, as well as, for other purposes than work-related trips. They also like to receive real-time information about traffic situations, disruptions, and parking spots through MaaS services. Sharing subscriptions with friends/family members/colleagues and synchronizing the app with personal agendas are other important features of a MaaS service.

Regarding the characteristics of MaaS, reliability is of high importance to employees. Since the whole concept of MaaS is new and people do not know much about it, building trust is the first step that its providers/operators should take. Secondly, employees value their privacy when using a new mobility service. It is not unexpected since privacy is an important concern of people nowadays. Despite many regulations, people are still carious about installing a new app on their smartphones and inserting their personal information. Moreover, employees also value their freedom in subscribing to MaaS packages. This was also found out by Sochor et al. (2016) that flexibility increases the attractiveness of MaaS. After meeting these characteristics, employees value app user-friendliness and the cost of the packages. Since there is hardly any study based on implemented MaaS projects, it is difficult to compare the attitude of employees with other travelers.

4.6 Conclusion

This chapter elaborated on the results of data analyses and answered the research questions. The descriptive statistics showed that the sample is somewhat over and/or under presents the working population in terms of gender, age, and education. Therefore, the sample was balanced to OViN 2017 and Wave 2016 data using the raking weights technique.

The general ML model revealed that employees have an intrinsic interest in having unlimited access to train and e-bike sharing. The result also showed that employees are cost-sensitive despite receiving reimbursement for their work-related trips. Regardless of mobility packages, reducing the price to €140/month showed a significant influence on mode choice behavior. Two conclusions could be made from this result: (1) employees are cost-sensitive, even if it is paid by a third party (employer), and (2) including unlimited rides with train and e-bike sharing in the mobility package has a strong impact on mode choice. Moreover, it was also found that increasing the parking tariffs up to €2.0/hour has a positive contribution to get employees out of their cars and shift them to alternative modes. In short, the combination of both carrot (unlimited rides) and stick (increasing parking tariffs) measures was found influential for changing commuting behavior. However, there are two unwanted outcomes accompanying this result. First, car sharing is found the most appealing mode to replace private/lease cars. This implies that the nature of car-based trips will not change if car-oriented employees still drive cars. Second, a proportion of public transport users, even small, will switch to car sharing. This will end up in more shared cars on roads and will hinder the TDM potential of MaaS.

Notably is that commuting mode choice behavior depends on many other underlying factors. Regarding the socioeconomic characteristics, young employees (<30 years old) were found to be more likely to change their commuting modes. This was expected because MaaS will be more interesting for the younger generation who has a different view on car ownership, as least according to some scholars (Caiati et al., 2020; Mulley et al., 2018). Conversely, older employees (>50 years old) are resistant to change their commuting mode and thereby are less likely to subscribe to MaaS. The argument is that commuting behavior is related to habit. Older employees have been practicing their commuting patterns for years and therefore it has turned out to habits, and changing habits is difficult. This corresponds to the study of (Caiati et al., 2020; Ho et al., 2018; Mulley et al., 2018), who found that young travelers will be the early adopters of MaaS services. Moreover, older employees might have multiple activities during the day alongside traveling to work, which makes them less flexible in their mode choice. Regarding the income, respondents who belong to the low-income category (less than €20,000) were more likely to change their commuting modes through MaaS. Since MaaS is supposed to provide cheaper transport compared to existing services, at least at the beginning, low-income employees might see it as a way to save money. However, this is contrary to the finding of (Caiati et al., 2020), in which low-income travelers are found to be less interested in MaaS.

It was also expected that women would be more likely to change their commuting mode, especially car users since they have greater pro-environmental mindsets and less preference for driving. But no indication was found that gender plays a role in commuting mode choice. Likewise, education level also has no statically significant effect on commuting choice behavior, which is also in contrast with the findings of (Caiati et al., 2020). Probably, differences exist in the mode choice behavior of people concerning work-related trips and other trips.

Regarding the effect of current commuting mode on mode choice, it was found that non-car users are more inclined to choose one of the mobility packages. For them, using MaaS is not a huge modal shift because they still commute with similar modes, if not the same. In contrast, car users were found less likely to switch to alternative modes. Even owning a car itself mitigated the probability of modal shifts. However, car-sharing was found a favored substitute for private/lease cars, especially when the cost of parking is increased. The result is in line with the study of Alavi (2008) who found that increasing parking tariffs is an influential factor in mode choice of commuters. However, this effect is not the same when controlled by parking spaces. Car users who use street/garage parking spaces are more likely to choose car sharing+e-bike sharing, while they would choose public transport if they park at P+R locations. Furthermore, car users who need their car during the day due to personal reasons (e.g. carrying baby seats) are less likely to replace their cars with other modes. In fact, it is not possible to replace their cars until they have their constraints.

Considering all explanatory factors, the conclusion can be drawn that targeting young and low-income employees who commute by other modes than cars and giving them unlimited rides with train and e-bike sharing at a low price would result in an optimal modal shift. On the other hand, MaaS adoption would increase among car user employees when shared modes are integrated with increases in parking tariffs. This way, the cooperation of MaaS providers and governmental authorities might result in a reduction of private car trips. Here, the role of employers should not be ignored who provide travel allowance and, in most cases, free parking spots. They might also contribute to commuting behavior changes by introducing new policies on their parking.

With respect to off-peak commuting, multi-modal commuters expressed a strong willingness to shift away from rush hours. They are willing to commute during off-peak hours if they are given discounts on their preferred MaaS packages.

Limiting MaaS services to a single region is not favored by employees. The majority of the respondents wanted to use a single MaaS package throughout the whole country, not only their working regions. Furthermore, they would like to have real-time information about the traffic situation via the MaaS platform. Perhaps, this would help them to change their commuting mode, time, or route, which as also highlighted in the study of Gokasar and Bakioglu (2018). Such information could be combined with parking information and payment through the MaaS app. Perhaps this could replace multiple apps that people are using at the moment. In this case, car users might become MaaS customers, but with a different definition. They probably buy its services whenever traveling by car gets difficult due to congestion, incidents, or unavailability of parking spots.

Finally, it was found that employees value the reliability and privacy of their information as primary prerequisites in the MaaS services. This is an important step to build trust among end-users, at least in the initial stage. Once people trust the service, flexibility, cost, and app user-friendliness are secondary characteristics.

5 | Conclusions, discussion and recommendations

The previous chapter discussed the results and answered the research questions. This chapter elaborates on the conclusions, discussion, and recommendations for MaaS practice, policy, and further research.

5.1 Conclusion

The research mainly focused on work-related trips of employees in the Netherlands, who account for about 28% of the total travel demand, of which 77% commute by car, mostly as drivers (72%) (CBS, 2016). Moreover, the majority of car drivers travel during rush hours, which puts more pressure on transport infrastructures. To reduce these pressures, work-related trips need to be distributed over alternative modes than cars, as well as, shift commuters away from the rush hours as much as possible.

To deal with the rise of mobility demand, MaaS is expected to be a promising approach that contributes to sustainability goals. However, there is hardly any information on the TDM aspects of MaaS. In this research, it was tried to study MaaS from a management perspective and obtain insights into the potential role of MaaS as a TDM tool for work-related trips. Since MaaS is in the market yet, the SC choice experiment was designed to collect necessary information on employees' mode choice behavior.

The result of ML model estimations revealed that the amount of ride with train, e-bike sharing, and car-sharing, as well as, price and increase in parking tariffs are influential factors in the mode choice behavior of employees. Including unlimited rides with train and e-bike sharing in the mobility packages had a noticeable impact on changing their commuting modes. Furthermore, the choice behavior of employees was largely influenced by the price, where the most preferred configurations were packages with the minimum price, €140/month. Similar to price, increasing parking tariffs were also found influential on the mode choice behavior of car drivers. This indicates that price can still be used as an encouraging measure for employees, even though most of them receive reimbursement from their employers.

However, different categories of employees had different preferences and mode choice behaviors. The results showed that substantial differences exist between different age groups, where younger employees are more flexible in their commuting mode choice, corresponding to the findings of Raijmakers (2019); Ratilainen (2017). Perhaps, they have not established very strong commuting habits yet like older employees have, and hence changing their commuting mode is easier for them. Similar to age, substantial differences exist in employees' mode choice behavior depending on their income level. Low-income employees are more willing to change their commuting modes compared to high-income ones. The reason could be that they see MaaS as a way to save some money. However, education level and gender were found insignificant factors concerning the selection of these mobility packages.

The study also found that current commuting patterns also differentiate employees' mode choice behavior. Respondents who mainly drive private/lease cars to work were found less likely to replace their cars with other modes, especially with public transport. However, the reason might be beyond this. Looking at the age and annual income of respondents, it became clear that car users were mostly older employees with high income. Since old and high-income respondents were less willing to choose one of the mobility packages, it is difficult to make a direct relationship between car usage and mode choice behavior. Car ownership itself discouraged employees to not choose public transport. Even though they might not use their cars for commuting, having private itself decreased the probability of the modal shift. However, a couple of attributes were found effective to get them out of their cars. For instance, the car sharing+e-bike sharing package was a favored substitute for private/lease cars. This was highlighted in the results of model estimations, as well as when they were directly asked about their willingness to substitute part of their car trips with alternative modes. Non-car users, on the other hand, showed a lot more interest in choosing train+e-bike sharing and train+bus/tram/metro. For them, using MaaS is not a major modal shift because they use more or less the same transport modes. The interesting point was that e-bike sharing outweighed the bus/tram/metro. Perhaps cycling is a favored transport mode for the last-mile travel in the Netherlands and providing e-bikes is even more appealing. The third category of employees (multimodal commuters) showed a similar mode choice behavior to non-car users rather than car users. Though they are not completely public transport users, neither car users, but they showed a strong willingness to choose train+e-bike sharing and train+bus/tram/metro packages. The two later groups of employees have less interest in car sharing. But still, about 13% of non-car users and 11% of multi-modal respondents wanted to switch to car sharing+e-bike sharing. Though the percentage is small, generalizing this to the working population will lead to a huge increase in the number of shared cars on roads.

It was also found that employees who travel longer (on a normal day) are more inclined towards public transport than car-sharing or e-bike sharing. When their travel time is long, the train+bus/tram/metro package was found the favorite mobility option. Notably is that respondents who lived far from railway stations showed a high willingness to commute by car sharing. This is of relevance to the accessibility and availability of transport services. Usually, car-sharing and e-bike sharing facilities are located near railway stations instead of remote areas that have a higher demand for these modes. However, transport demand in remote areas is dispersed, and providing car-sharing facilities is costly.

Regarding the increase in parking tariffs, employees could be differentiated according to their current parking spaces. Car users who used street/garage parking spaces were more likely to substitute their cars by increasing parking tariffs. The interesting point was that they would switch to car sharing+e-bike sharing rather than train+e-bike sharing and train+bus/tram/metro. Car users who used at P+R locations on the other hand preferred train+e-bike sharing and train+bus/tram packages. While those who used employers' free parking were found less likely to be affected by the increase in parking tariffs. The result makes sense because they currently do not pay for parking costs. Moreover, increasing parking tariffs had a low effect on those who have to use cars due to their personal reasons, e.g. carrying a baby seat. In fact, they have no other option until they have such constraints.

The scenario analysis revealed that variation in the package configuration will lead to an increase/decrease in the choice probability of MaaS packages. Unlimited rides with train and e-bike sharing with the lowest price (€140/month) were found the best configuration for non-car oriented employees. On the other hand, 60 minutes/day of car-sharing driving plus unlimited rides with e-bike sharing at the lowest price was the best configuration for car-users. It is concluded that substantial differences exist concerning the commuting choice behavior of car-users and non-car users.

However, the modal shift is not the only approach that reduces pressure on transport systems and infrastructures. Since the majority of respondents make their work-related trips during rush hours, shifting them to off-peak hours will also contribute to the TDM potential of MaaS. On average, 41.2% of respondents who selected one of the mobility packages expressed a strong willingness to commute during off-peak hours. However, this depended on the current commuting mode. Multi-modal commuters were found highly flexible concerning their time of commuting.

Finally, reliability and privacy were found the most important prerequisites for MaaS services. Since the whole concept of MaaS is new and people have no experience with it, building trust would be the first business order of its providers. Once, people trusted the service, other characteristics such as flexibility, price, and user-friendliness of apps come on the table. Moreover, the majority of the respondents preferred to use their packages throughout the whole Netherlands, not only in a specific region. As well as, they favored the integration of real-time traffic and parking information in the MaaS services.

5.2 Discussion

This section discusses the performed research from the TDM perspective. Afterward, the limitations of the research are mentioned.

5.2.1 MaaS and TDM measures

The whole spectrum around the MaaS topic is complex and mostly unexplored. Currently, most researchers focus on the uptake of MaaS among end-users. This study explored a small part of the MaaS spectrum, where it is integrated with the TDM measures. Despite this research found MaaS as a promising TDM tool, but for specific categories of employees. For instance, young, low income, multi-modal commuters, and car users who use street/garage parking spaces are most likely to change their commuting behavior when MaaS is integrated with TDM measures. On the other hand, MaaS might not be an effective TDM tool to change the commuting behavior of those employees who are old, high-income, and car-dependent. However, there are two unwanted consequences of using MaaS as a TDM tool. First, car users are very likely to favor car sharing rather than public transport. It means that the nature of car-based traveling will not change by shifting to car sharing. Second, some employees who commute only by public transport would want to switch to shared modes. This might cross out its impact on car users.

However, a lot of information is needed before the whole potential of MaaS is clear. Not only increasing parking tariffs, but several other TDM measures could also be introduced alongside MaaS. For instance, prioritizing parking spots for car sharers in specific areas where car demand is very high could be a discouraging measure to reduce private car trips. Furthermore, providing an option that MaaS customers could book parking spots beforehand might optimize the usage of existing parking spaces. This way, the service could help car users to decide whether to drive a car or use a mobility option proposed by the MaaS service. Moreover, the role of employers should not be ignored here for two reasons. First, they usually reimburse the costs of work-related trips. Second, most of them have their own parking spaces that employees use free of charge. Therefore, employers can take initiatives by introducing new policies concerning their employees' mobility, e.g. shifting from lease car to car sharing or limiting parking spots. To conclude, the cooperation of MaaS providers, public authorities, and employers would boost the TDM potential of MaaS by introducing different stick and carrot measures simultaneously.

5.2.2 Limitation of the research

There are some limitations to this research that affect the way its results should be interpreted. Since MaaS is not yet a popular concept, different travelers might have different perceptions of its prepositions. During the survey, the MaaS concept was explained to respondents through text and a short video to prevent them from making their own assumptions, but it is still possible that respondents did not fully grasp the concept. The video linked was provided in case respondents needed more explanation, but experience shows that respondents usually do not open survey videos, and the respondents of this survey cannot be an exception.

Furthermore, the survey was conducted during the Covid-19 pandemic, when almost everyone was working from home. Despite it was clarified in the questionnaire introduction to consider a normal situation (without lock-down measures), there is a chance that some respondents did not carefully read or missed the introduction part and thereby answered the questions considering the lock-down situation. Furthermore, the lock-down measures impeded the data collection process, and therefore social media platforms were the main promoting tools. A big disadvantage here is that people participate in the survey that they find interesting. Therefore, the data cannot be a perfect representative of the population.

Regarding the representativeness of the sample, highly educated and high-income employees were over-presented in the sample. Because the survey was long and somewhat complex for some employees, the risk exists that only people who thought they understand the MaaS concept (highly educated) have completed the questionnaire. This issue was solved using raking weights, but the technique has its own pros and cons.

Moreover, in the SC experiment, respondents had to choose one preferred option between several packages, which does not necessarily mean they would actually subscribe to the package or change their travel behavior like that. Such hypothetical bais always exists in stated choice experiments. It is therefore disputable to what extent the modal shift would actually occur, which can only be examined with revealed preference data from pilot projects.

Another limitation of the research is not considering the role of employers on employees' commuting behavior. Since employers finance work-related trips in the Netherlands, they could stimulate their mode choice to a large extent.

Regarding the data analysis, the mixed logit model was used, in which the random parameter was set to be normally distributed. While other distributions such as log-normal or triangular could also be used. Using different distributions of parameters could give different results (Hensher and Greene, 2003). It is therefore desirable to estimate multiple ML models with different distributions and select the superior one that has better goodness of fit.

5.3 Recommendations

5.3.1 Recommendations for practice

This research emphasized the fact the different types of employees have different mode choice behavior. Employees who currently commute by public transport or in a multi-modal way could be the early adopters of MaaS, especially when unlimited rides with train and e-bike sharing are included in the packages. So, it is advised to differentiate end-users based on their mode choice behavior and target them by their interests. Furthermore, it is also advised to include car-sharing in the MaaS packages to catch the interest of car users, especially those who are using street/garage parking. Last but not least, it is recommended to customize MaaS packages concerning different groups of end-users and then target particular customers based on their interests. Providing a predefined and non-customized package, which is a common practice of current MaaS projects, will not end up with appealing success.

5.3.2 Recommendations for policy

To contribute to societal and environmental goals expected from MaaS, people need to change their travel behavior, particularly car users. If policy-makers want to steer MaaS more desirably and make use of MaaS as a TDM tool, better alignment between the MaaS services and public policy goals is viable. An option could be introducing new measures, e.g. increasing parking tariffs or charging per kilometer, with MaaS, that might demotivate car use and consequently contribute to the societal and environmental goals. Furthermore, public authorities should be aware of the negative consequences. Some public transport users might switch to car sharing, which is not in line with sustainability goals. Thus, it is recommended to prevent unwanted consequences of switching from public transport to car sharing. In short, close cooperation between public authorities and MaaS providers, as well as, employers will boost the success of MaaS as a TDM tool. Together, they could apply both stick and carrot measures simultaneously and steer MaaS in favor of sustainable modes.

5.3.3 Recommendations for future research

In this study, the main focus was on work-related trips, not trips for other purposes. Therefore, it is not possible to assess the total potential of MaaS as a TDM tool or generalize the results to other travelers. Perhaps, the TDM potential of MaaS could be more prominent for other travelers because they do not receive travel allowance as employees do. It is recommended to perform research that focuses on the potential of MaaS for other travelers than employees and thereby compare them with employees. Especially, it could be more insightful to study its effectiveness on travel behavior changes with revealed preference data from pilot projects.

In the stated choice experiment developed in this research, everyone was offered a couple of predefined mobility packages, which might not completely cover the travel needs of all individuals. It could be a good idea to pivot the MaaS packages on the current travel patterns of respondents or give them the possibility to design their own desirable packages based on their travel needs. Moreover, it would be helpful to give respondents an indication of their current travel costs so that they can take a more informed decision.

The research classified respondents based on their current travel patterns. A good idea for future research would be to perform latent class analysis. By doing so, respondents are clustered based on their response behavior, where their current travel behavior could act as covariates. This way, travel behavior changes, and the influence of current travel patterns could be reflected more effectively.

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A | Stated choice design matrix

		Train+e-bike sharing			Train+bus/tram/metro			Car sharing+e-bike sharing		
Profile	Choice Set	Train	E-bike sharing	Price	Train	Bus/metro /tram	Price	Car sharing	E-bike sharing	Price
1	1	1	2	2	3	2	2	1	2	2
2	1	1	1	1	1	1	1	1	1	3
3	1	1	1	3	1	2	2	1	1	1
4	1	2	3	2	3	2	3	2	3	3
5	1	2	2	2	3	1	2	1	2	2
6	1	1	1	3	2	1	3	1	3	1
7	1	3	3	2	1	2	1	2	3	3
8	1	1	1	3	1	1	3	2	2	3
9	1	1	1	3	1	3	3	3	1	2
10	2	2	3	3	1	1	3	1	2	2
11	2	2	2	1	1	3	2	3	2	2
12	2	1	2	1	2	3	3	3	2	2
13	2	3	2	3	1	1	3	1	3	1
14	2	2	1	3	2	3	2	3	2	2
15	2	1	3	2	3	2	3	2	2	2
16	2	3	1	3	3	2	1	2	2	2
17	2	3	1	2	3	2	1	3	2	2
18	2	2	2	1	2	1	2	3	3	1
19	3	1	1	2	1	2	3	3	1	3
20	3	1	3	1	1	1	3	2	1	1
21	3	1	1	2	1	3	2	1	3	2
22	3	2	2	1	2	2	1	2	1	2
23	3	1	1	1	1	3	1	1	3	2
24	3	1	1	1	3	3	3	1	1	1
25	3	2	2	1	2	2	1	1	2	3
26	3	1	1	2	1	1	1	1	2	2
27	3	3	2	3	2	1	3	1	1	2
28	4	1	2	3	1	2	3	2	1	1
29	4	1	3	1	2	3	2	2	2	3
30	4	1	2	3	1	3	3	3	3	3
31	4	2	1	2	2	1	3	2	1	2
32	4	3	3	1	3	3	2	2	2	1
33	4	3	1	1	2	3	2	2	1	2
34	4	3	3	1	2	2	3	3	2	1

... continued from previous page

		Train+e-bike sharing			Train+bus/tram/metro			Car sharing+e-bike sharing		
Profile	Choice Set	Train	E-bike sharing	Price	Train	Bus/metro /tram	Price	Car sharing	E-bike sharing	Price
35	4	3	1	1	3	1	3	3	2	2
36	4	3	3	2	2	3	1	3	1	1
37	5	3	2	2	2	3	3	2	3	2
38	5	2	1	3	1	1	1	3	1	1
39	5	1	2	2	2	3	1	2	3	1
40	5	1	1	3	1	1	2	2	3	2
41	5	1	1	3	3	1	2	3	2	1
42	5	1	3	3	2	2	1	1	1	2
43	5	3	3	3	1	3	1	1	1	3
44	5	1	3	1	1	2	2	1	1	2
45	5	3	3	2	2	3	2	2	1	1
46	6	3	2	3	2	1	1	2	2	1
47	6	2	1	1	1	2	3	1	3	1
48	6	3	2	3	3	1	2	3	1	2
49	6	3	2	3	2	1	2	1	1	3
50	6	2	1	2	1	3	3	1	2	1
51	6	3	3	3	3	1	2	1	1	3
52	6	3	3	3	2	1	2	3	2	2
53	6	2	2	3	3	1	1	1	1	3
54	6	2	3	3	3	1	1	3	3	2

B | Questionnaire

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Hello!
Thank you for taking time to participate in this survey. You are a great help!

My name is Skier Farahmand, a master's student at the Technical University ofTwente and I would like to welcome you to my research about mobility services for employees in the Netherlands. In this research, I want to find out the willingness of employees to travel in different ways, considering everyone's personal travel preferences. This survey is composed to get to know your travel behavior and preferences for traveling to your work.

When answering the questions, I would like to ask you to consider your "normal" situation (without 'Corona' measures) as a starting point.

The survey will take approximately 8-10 minutes. As a thank you of filling in the questionnaire, you get a chance at WINNING one of 10 prizes: a hand sanitizer of 500ml! At the end of questionnaire, you have an option to participate in a raffle of prizes. You will be redirect to a separate form, making it impossible to link your responses with your personal information.

As to your privacy concern, your responses will be strictly confidential which fully complies to the GDPR (General Data Protection Regulation). If you have questions at any time about the survey or the results, you may contact Zakir Farahmand at +31 (0) 629904259 or by email at z.h.farahmand@student.utwente.nl.

I want to thank YOU for helping me with this research! Please start the survey by clicking on the continue button below if you agree to participate.

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Part 1: Current travel pattern

The following questions are asked about your current travel behavior to work.

Where do you work?

Please write down the city that you are working in, e.g. Utrecht.

Utrecht

Which company/organization do you work at?

Please write down the name of your company (optional).

How often do you travel to your work?

- ○ 5 times per week
- ◉ **4 times per week**
- ○ 3 times per week
- ○ twice a week
- ○ once a week

Which of the following transport modes do you use for your travel to work?

You can select multiple options.

- [ ] Private car
- [ ] Lease car
- [x] **Train**
- [x] **Bus/metro/tram**
- [ ] Car sharing (or car rental)
- [ ] Bike sharing
- [ ] Normal (electric) bicycle
- [ ] Other, namely

How often do use the following transport mode(s) for your travel to work?

	Daily	Weekly	Monthly	Sometimes	Almost never
Train					
Bus/metro/tram					
Normal (or electric) bike					

Do you own a car?

- Yes
- **No**

What time do you normally leave your home to go to your work?

6:00 - 6:29

What time do you normally leave your work to return home?

18:00 - 18:29

How long does it usually take you to travel from home to work?
This is your travel time on a normal day without unplanned events, e.g. incidents or a missed connection.
In minutes

120

Do you receive travel allowance from your employer?

- Yes, fully
- Yes, partially
- **No**

Do you have an OV-chipkaart?

- **Yes**
- No

What subscription(s) do you have on your OV-chipkaart?

Multiple answers can be selected.

- [ ] NS businesscard
- [ ] Off-peak discount (40%)
- [x] **NS off-peak free**
- [ ] NS always free
- [ ] Bus region discount
- [ ] Bus region free
- [ ] I don't have any subscription
- [ ] Other, namely

Part 2: Mobility choice behavior

As preparation for the upcoming choice questions, the concept of Mobility as a Service is introduced here.
Mobility as a Service is an innovative mobility concept that provides multiple transport modes such as
train, bus/tram/metro, bike sharing, car sharing and taxi through a single app. The app combines functionalities of several mobile apps like travel information, travel planning, booking, ticketing, invoicing and payment for almost all transport modes.

If you would like to know more about the concept, please watch the following video.

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In the upcoming choice questions, you will be given 3 mobility options for your travel to work. The options are: **Train+E bike sharing**; **Train+bus/metro/tram**; and **Car sharing+E-bike sharing**.

Please consider the following points while answering the choice questions:

- The price of each option varies per question as well as between options
- The number of free rides and tickets vary per question as well as between options
- For car users, the amount of increase in the parking tariff also varies per question
- For the car-sharing and E-bike sharing, assume that you can pick up them from spots close to your home/workplace and park them on the same spots. However, you are not obliged to a single car/E-bike during the day. For your next trip, you can pick up another one.
- If you are working in multiple regions, assume that you can use your mobility option for all.

If you are using a mobile, please tilt your mobile phone.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

This is an example choice question, you can skip this question.

Your context	**Travel purpose:** Work **Travel mode:** Train, Bus/metro/tram	**Travel time:** 120 **Travel frequency:** 4 times per week

	Option 1	Option 2	Option 3
	€140 / month	**€200/month**	**€180/month**
Options	Train + E-bike sharing 15 day-return tickets to your working region 2 free hours per day then pay per hour *standard fare: €2/hour*	Train + Bus/metro/tram 20 day-return tickets to your working region Unlimited rides to your working region	Car sharing + E-bike sharing 60 free minutes per day then pay per minute *standard fare: €0.26/minute* 2 free hours per day then pay per hour *standard fare: €2/hour*

	Your choice
Option 1	☐
Option 2	☐
Option 3	☐
None	☐

In the next part, the choice questions will be repeated **6 times**. Note that the questions look similar, but the **prices**, number of **free rides** and **free tickets** and the amount of increase in **parking tariff** (for car users) are different per question.

First choice question: In this question, the **prices**, number of **free rides** and **free tickets** and **parking fares** (for car users) are different from the example question. Please choose the mobility option that you think is the best option for you.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

Your context	**Travel purpose:** Work	**Travel time:** 120
	Travel mode: Train, Bus/metro/tram	**Travel frequency:** 4 times per week

	Option 1	Option 2	Option 3
	€200 / month	€180 / month	€140 / month
Options	Train + E-bike sharing 15 day-return tickets to your working region 1 free hour per day then pay per hour *standard fare: €2/hour*	Train + Bus/metro/tram 15 day-return tickets to your working region 20 day tickets to your working region	Car sharing + E-bike sharing 40 free minutes per day then pay per minute *standard fare: €0.26/minute* 1 free hour per day then pay per hour *standard fare: €2/hour*

	Your choice:
Option 1	☐
Option 2	☑
Option 3	☐
None	☐

Are you willing to travel during off-peak hours if you are given 20% discount on your selected option?

Off-peak hours : 9:00 to 16:00 & 18:30 to 6:30

- (●) **Yes**
- ( ) Maybe
- ( ) No

Second choice question:

In this question, the **prices**, number of **free rides** and **free tickets** and **parking fares** (for car users) are different from the first question. Please choose the mobility option that you think is the best option for you.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

Your context			
	Travel purpose: Work	**Travel time:** 120	**Car Parking:**
	Travel mode: Train, Bus/metro/tram	**Travel frequency:** 4 times per week	

Options	Option 1	Option 2	Option 3
	€200 / month	€140 / month	€180 / month
	Train + E-bike sharing	Train + Bus/metro/tram	Car sharing + E-bike sharing
	Unlimited rides to your working region	Unlimited rides to your working region	50 free minutes per day then pay per minute *standard fare: €0.26/minute*
	1 free hour per day then pay per hour *standard fare: €2/hour*	20 day tickets to your working region	2 free hours per day then pay per hour *standard fare: €2/hour*

	Your choice:
Option 1	☐
Option 2	☑
Option 3	☐
None	☐

Are you willing to travel during off-peak hours if you are given 30% discount on your selected option?

Off-peak hours : 9:00 to 16:00 & 18:30 to 6:30

- (●) **Yes**
- ( ) Maybe
- ( ) No

Third choice question:

In this question, the **prices**, number of **free rides** and **free tickets** and **parking fares** (for car users) are different from the first and second questions. Please choose the mobility option that you think is the best option for you.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

Your context	**Travel purpose:** Work	**Travel time:** 120
	Travel mode: Train, Bus/metro/tram	**Travel frequency:** 4 times per week

Options	Option 1	Option 2	Option 3
	€180 / month	**€140 / month**	**€180 / month**
	Train + E-bike sharing	Train + Bus/metro/tram	Car sharing + E-bike sharing
	15 day-return tickets to your working region	15 day-return tickets to your working region	40 free minutes per day then pay per minute *standard fare: €0.26/minute*
	1 free hour per day then pay per hour *standard fare: €2/hour*	15 day tickets to your working region	2 free hours per day then pay per hour *standard fare: €2/hour*

	Your choice:
Option 1	☐
Option 2	☑
Option 3	☐
None	☐

Are you willing to travel during off-peak hours if you are given 40% discount on your selected option?

Off-peak hours : 9:00 to 16:00 & 18:30 to 6:30

- (●) **Yes**
- ( ) Maybe
- ( ) No

Fourth choice question:

In this question, the **prices**, number of **free rides** and **free tickets** and **parking fares** (for car users) are different from the previous questions. Please choose the mobility option that you think is the best option for you.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

Your context	Travel purpose: Work Travel mode: Train, Bus/metro/tram	Travel time: 120 Travel frequency: 4 times per week

	Option 1 €140 / month	Option 2 €180 / month	Option 3 €180 / month
Options	Train + E-bike sharing Unlimited rides to your working region 1 free hour per day then pay per hour *standard fare: €2/hour*	Train + Bus/metro/tram 20 day-return tickets to your working region Unlimited rides to your working region	Car sharing + E-bike sharing 50 free minutes per day then pay per minute *standard fare: €0.26/minute* 1 free hour per day then pay per hour *standard fare: €2/hour*

	Your choice:
Option 1	☑
Option 2	☐
Option 3	☐
None	☐

Are you willing to travel during off-peak hours if you are given 20% discount on your selected option?

Off-peak hours : 9:00 to 16:00 & 18:30 to 6:30

- ○ Yes
- ◉ **Maybe**
- ○ No

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Fifth choice question:

Again, the **prices**, number of **free rides** and **free tickets** and **parking fares** (for car users) in this question are different from the previous questions. Please choose the mobility option that you think is the best option for you.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

Your context	Travel purpose: Work Travel mode: Train, Bus/metro/tram	Travel time: 120 Travel frequency: 4 times per week

	Option 1	Option 2	Option 3
	€180 / month	**€140 / month**	**€140 / month**
Options	Train + E-bike sharing 15 day-return tickets to your working region 2 free hours per day then pay per hour *standard fare: €2/hour*	Train + Bus/metro/tram 20 day-return tickets to your working region Unlimited rides to your working region	Car sharing + E-bike sharing 50 free minutes per day then pay per minute *standard fare: €0.26/minute* Unlimited rides in your working region

	Your choice:
Option 1	☐
Option 2	☑
Option 3	☐
None	☐

Are you willing to travel during off-peak hours if you are given 30% discount on your selected option?

Off-peak hours : 9:00 to 16:00 & 18:30 to 6:30

- (●) **Yes**
- ( ) Maybe
- ( ) No

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The last choice question:

In this question, the **prices**, number of **free rides** and **free tickets** and **parking fares** (for car users) are also different from the previous questions. Please choose the mobility option that you think is the best option for you.

Suppose, you are offered three mobility options with the following characteristics. Which one would you choose for your travel to work?

Your context	**Travel purpose:** Work **Travel mode:** Train, Bus/metro/tram	**Travel time:** 120 **Travel frequency:** 4 times per week

	Option 1	**Option 2**	**Option 3**
	€140 / month	**€200 / month**	**€140 / month**
Options	Train + E-bike sharing 20 day-return tickets to your working region 1 free hour per day then pay per hour *standard fare: €2/hour*	Train + Bus/metro/tram 15 day-return tickets to your working region 20 day tickets to your working region	Car sharing + E-bike sharing 40 free minutes per day then pay per minute *standard fare: €0.26/minute* Unlimited rides in your working region

	Your choice:
Option 1	☑
Option 2	☐
Option 3	☐
None	☐

Are you willing to travel during off-peak hours if you are given 40% discount on your selected option?

Off-peak hours : 9:00 to 16:00 & 18:30 to 6:30

- (●) **Yes**
- ( ) Maybe
- ( ) No

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You have reached the third part of the questionnaire!

Starting point for the following questions is that the mobility options in the last questions are available as a mobility service. In the following questions you will be asked about your opinion towards the characteristics of such a mobility service.

Suppose, you have a subscription to one of the previous mobility options, what additional functionalities do you want to have?

*You may select **three** most preferred features.*

- [ ] Real-time traffic information (i.e. congestion, disruption, delay, etc)
- [ ] Parking information and payment (i.e. free spots)
- [x] **App synchronization with personal agenda**
- [ ] Sharing my subscription with friends/family members/colleagues
- [x] **Using my subscription in the whole Netherlands**
- [ ] Using my subscription in the whole city where I work
- [x] **Using my subscription for other purposes, e.g. shopping**

To what extent these criteria are important to you to be in the mobility service?

	Extremely important	Very important	Moderately important	Slightly important	Not at all important
Subscription price	●	○	○	○	○
Reliability	○	●	○	○	○
User friendliness of app	○	○	●	○	○
Privacy	○	●	○	○	○
Flexibility	●	○	○	○	○

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To what extent do you agree/disagree with the following statements?

I would not need to buy my own car or get a lease car if the mobility service fulfils my travel needs.

- **Strongly agree**
- Somewhat agree
- Neutral
- Somewhat disagree
- Strongly disagree

You are almost at the end of this questionnaire!
Only a few more questions are asked about your socio-demographic characteristics.

What is your zip code?

Enter only the 4 digits of the zip code.

7512

What is your gender?

- **Male**
- Prefer not to say
- Female
- Other

How old are you?

27

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What is your highest level of education?

- ◯ Primary school/special education
- ◯ Secondary education
- ◯ Vocational education
- ◯ Undergraduate (bachelor)
- ◉ **University Master, PhD or PDEng**
- ◯ Other, namely

How much is your annual net income?

- ◯ Less than €10,000
- ◉ **€10,000 - €20,000**
- ◯ €20,000 - €30,000
- ◯ €30,000 - €40,000
- ◯ more than 40,000
- ◯ I'd rather not say

YES! You have reached to the end of this quationnaire.
I am truely grateful for your participation!
Stay active and healthy during the Coronavirus pandemic!

Do you want to try your chance at winning one of 10 prizes?

- ◯ Yes
- ◉ **No**

C Data cleaning

Of 307 respondents who finished the questionnaire completely, 243 (79.2%) respondents could meet the sample requirements. Employees whose main commuting mode was bicycle/scooter and walking or do not work in the Netherlands are not in the target group of this study. Table C.1 shows the descriptive of in-target and off-target respondents.

Table C.1: Descriptive of in-target and off-target the sample

Questionnaire			Off-target	In-target	Total
Language	EN	Count	29	80	109
		Percentage	26.6%	73.4%	100.0%
	NL	Count	35	163	198
		Percentage	17.7%	82.3%	100.0%
Total		Count	64	243	307
		Percentage	20.8%	79.2%	100.0%

Furthermore, responses have been checked for outliers, strange values and incompleteness. One respondent did not meet the requirements of participating in this research because of working in Barcelona and thereby removed from the data. Four respondents had continued filling the questionnaire in spite of not being in the target group due to commuting only by bicycle. The data does not provide any evidence why the survey was not ended for them; however, they are being removed. The data were also checked for the duration of survey completion. Considering the total number of questions displayed to each respondent, it was estimated that the questionnaire takes approximately 8-10 minutes and any responses completed in less than 4 minutes would be unreliable. Two respondents had completed the questionnaire in less than 3 minutes, which seems impossible if they read the questions properly. Thus, these responses were considered unreliable and excluded from further analyses. On the other hand, 17 people probably paused the survey, as the duration of their survey completion was longer than 30 minutes. However, there was no evidence of wrongly entered values and, therefore, they were obtained. In total, 71 responses were deleted and 236 responses remained for further analyses.

D Descriptive statistics

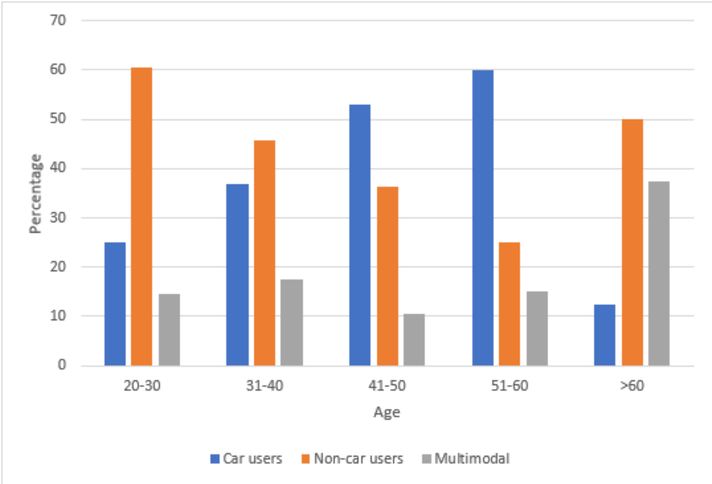

Figure D.1: Commuting mode vs age

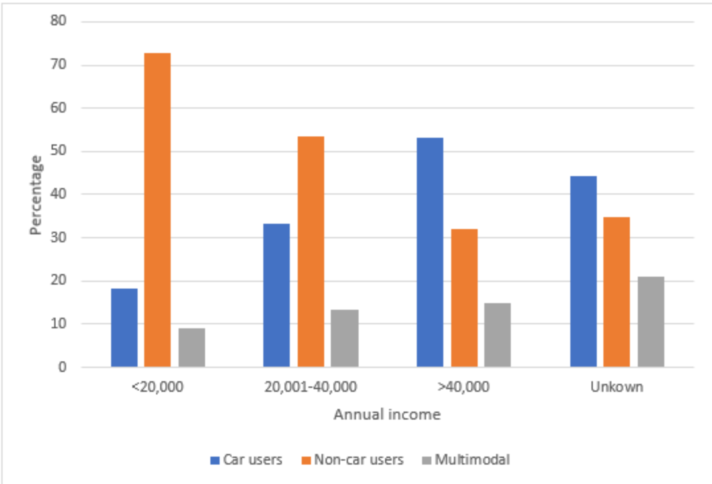

Figure D.2: Commuting vs income

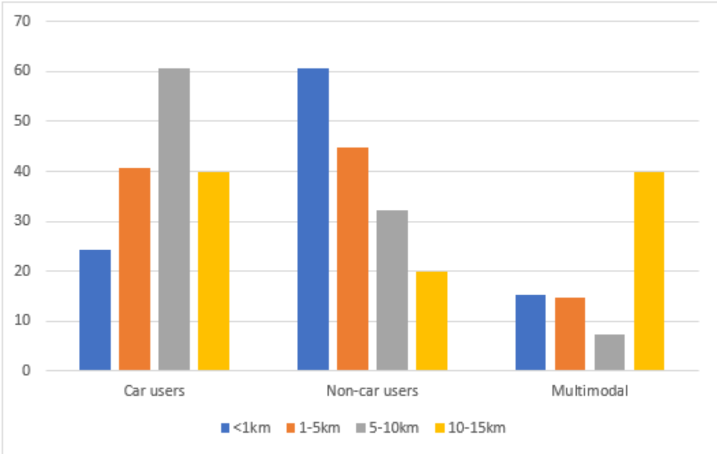

Figure D.3: Distance to railway station

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E|Raking weights syntax

```
library(readxl)
dat <- read_excel("C:/Users/User/Desktop/new weight/weights3.xlsx")
str(dat)

#specifying raking weights variables
library(weights)
#education levels 1:low 2:middle 3:high
wpct(dat$edulevel)

# gender 1:male 2:female
wpct(dat$gen)

# income 1: <10,000 2: 10,000-20,000 3: 20,000-30,000 4: 30,000-40,000 5:
>40,000 6: unknown
wpct(dat$Income)

#specify the population distribution of the selected variables.

#OViN 2017 data
edulevel <- c(.21,.4,.39)
gen <- c(.522, .478)

#Wave 2016 data
Income <- c(.09, .284, .332, .112, .04, .142)

# definitions of target list
targets <- list(gen, edulevel, Income)

# important: to use the same variable names of the dataset
names(targets) <- c("gen", "edulevel", "Income")
# id variable
dat$caseid <- 1:length(dat$edulevel)

dat <- as.data.frame(dat)
class(dat)
#Using the anesrake package to find the differences between sample
distribution and population distribution.
library(anesrake)
anesrakefinder(targets, dat, choosemethod = "total")

#Apply ANES method as follows:

outsave <- anesrake(targets, dat, caseid = dat$caseid,
                    verbose= FALSE, cap = 5, choosemethod = "total",
                    type = "pctlim", pctlim = .05 , nlim = 3,
                    iterate = TRUE , force1 = TRUE)
summary(outsave)

# add weights to the dataset
dat$weightvec  <- unlist(outsave[1])
n  <- length(dat$edulevel)

# weighting loss
((sum(dat$weightvec ^ 2) / (sum(dat$weightvec)) ^ 2) * n) - 1

#export data
library(xlsx)
write.xlsx(dat, "C:/Users/User/Desktop/new weight/weights.xlsx")
```

F Output of ML model estimations

Table F.1: General ML model estimation - unweighted

	Parameter	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Non-random	Train	0.326	0.069	4.730	**0.000**	0.191	0.461
	Bus/tram/metro	0.036	0.086	0.410	0.679	-0.133	0.204
	E-bike sharing	0.170	0.063	2.700	**0.007**	0.047	0.294
	Car sharing	0.235	0.090	2.600	**0.009**	0.058	0.413
Random	Price	-0.031	0.003	-10.160	**0.000**	-0.037	-0.025
	SD	0.031	0.003			0.026	0.036
Continue using current mode		Base alternative					
Train+ e-bike sharing	ASC	4.738	0.455	10.410	**0.000**	3.846	5.630
Train +bus/tram/metro	ASC	4.937	0.459	10.760	**0.000**	4.038	5.837
Car sharing+ e-bike sharing	ASC	4.662	0.472	9.880	**0.000**	3.737	5.587
	Number of cases	1416					
	Log simulated Likelihook	-1419.93					
	Wald chi2(5)	132.84					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	2857.85					
	BIC	2905.15					

Table F.2: General ML model estimation - weighted

	Parameter	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Non-random	Train	0.338	0.098	3.460	**0.001**	0.146	0.529
	Bus/tram/metro	0.149	0.084	1.770	0.077	-0.016	0.315
	E-bike sharing	0.189	0.077	2.470	**0.014**	0.039	0.339
	Car sharing	0.182	0.120	1.520	**0.130**	-0.053	0.417
Random	Price	-0.029	0.004	-8.080	**0.000**	-0.036	-0.022
	SD	0.029	0.003			0.024	0.036
Continue using current mode		Base alternative					
Train+ E-bike sharing	ASC	4.383	0.576	7.610	**0.000**	3.254	5.512
Train +Bus/tram/metro	ASC	4.444	0.606	7.330	**0.000**	3.256	5.631
Car sharing+ E-bike sharing	ASC	4.466	0.631	7.080	**0.000**	3.229	5.702
	Number of cases	1416					
	Log simulated Likelihook	-1435.86					
	Wald chi2(5)	85.33					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	2889.72					
	BIC	2937.02					

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Table F.3: ML model and socioeconomic characteristics - unweighted

	Parameter	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Non-random	Train	0.333	0.070	4.790	0.000	0.197	0.470
	Bus/tram/metro	0.025	0.087	0.290	0.773	-0.145	0.196
	E-bike sharing	0.242	0.092	2.640	0.008	0.062	0.421
	Car sharing	0.171	0.064	2.700	0.007	0.047	0.296
Random	Price	-0.030	0.003	-10.040	0.000	-0.036	-0.024
	SD	0.030	0.002			0.025	0.035
Continue using current mode		Base alternative					
Train+ e-bike sharing	Gender(female)	0.048	0.601	0.080	0.936	-1.130	1.227
	Age	-0.575	0.255	-2.260	0.024	-1.074	-0.204
	Income	-0.895	0.353	-2.540	0.011	-1.587	-0.075
	Education	0.288	0.468	0.620	0.538	-0.629	1.206
	ASC	7.602	1.733	4.390	0.000	4.205	10.998
Train+ bus/tram/metro	Gender(female)	0.394	0.599	0.660	0.511	-0.780	1.567
	Age	-0.688	0.254	-2.710	0.007		
	Income	-0.958	0.351	-2.730	0.006	-1.646	-0.271
	Education	0.101	0.463	0.220	0.827	-0.806	1.009
	ASC	8.523	1.720	4.960	0.000	5.152	11.895
Car sharing+ e-bike sharing	Gender(female)	-0.220	0.593	-0.370	0.711	-1.382	0.942
	Age	-0.569	0.252	-2.260	0.024	-1.063	-0.075
	Income	-0.784	0.349	-2.250	0.025	-1.467	-0.100
	Education	-0.145	0.458	-0.320	0.752	-1.042	0.753
	ASC	8.441	1.711	4.930	0.000	5.087	11.794
	Number of cases	1416					
	Log simulated Likelihook	-1397.5					
	Wald chi2(17)	167.06					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	2837.01					
	BIC	2947.37					

Table F.4: ML model and socioeconomic characteristics - weighted

	Parameter	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Non-random	Train	0.437	0.134	3.260	0.001	0.174	0.699
	Bus/tram/metro	0.044	0.114	0.390	0.695	-0.178	0.267
	E-bike sharing	0.229	0.140	1.630	0.103	-0.046	0.504
	Car sharing	0.082	0.104	0.790	0.430	-0.122	0.286
Random	Price	-0.027	0.005	-5.670	0.000	-0.037	-0.018
	SD	0.029	0.004			0.022	0.037
Continue using current mode		Base alternative					
Train+ e-bike sharing	Gender(female)	0.018	1.030	0.020	0.986	-2.001	2.037
	Age	-0.590	0.462	-1.280	0.201	-1.496	0.315
	Income	-0.966	0.473	-2.040	0.041	-1.894	-0.039
	Education	0.768	0.694	1.110	0.269	-0.593	2.129
	ASC	6.220	2.535	2.450	0.014	1.251	11.189
Train+ bus/tram/metro	Gender(female)	0.162	1.043	0.160	0.876	-1.882	2.207
	Age	-0.725	0.433	-1.670	0.094	-1.573	0.124
	Income	-1.123	0.483	-2.330	0.020	-2.069	-0.177
	Education	0.311	0.756	0.410	0.681	-1.171	1.792
	ASC	7.799	2.558	3.050	0.002	2.785	12.81
Car sharing+ e-bike sharing	Gender(female)	0.050	1.033	0.050	0.962	-1.975	2.074
	Age	-0.711	0.372	-1.910	0.056	-1.440	0.019
	Income	-1.155	0.449	-2.570	0.010	-2.035	-0.275
	Education	-0.260	0.672	-0.390	0.698	-1.577	1.057
	ASC	9.156	2.492	3.670	0.000	4.271	14.04
	Number of cases	1416					
	Log simulated Likelihook	-1405.51					
	Wald chi2(17)	83.52					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	2853.039					
	BIC	2963.406					

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Table F.5: ML model and commuting-specific attributes - unweighted

Attribute		Coef.	Std. Err.	z	P>lzl	[95% Interval]	Conf.
Non-random	Train	0.346	0.072	4.810	0.000	0.205	0.487
	Bus/tram/metro	0.086	0.091	0.940	0.347	-0.093	0.264
	E-bike sharing	0.197	0.067	2.930	0.003	0.065	0.328
	Car sharing	0.255	0.099	2.580	0.010	0.061	0.450
Random	Price	-0.032	0.003	-10.190	0.000	-0.038	-0.026
	sd(price)	0.030	0.003			0.026	0.036
Contineu using current mode		(base alternative)					
Train+ e-bike sharing	Car users	(base)					
	Non-car users	2.309	0.879	2.630	0.009	0.586	4.031
	Multi-modal	1.903	0.909	2.090	0.036	0.122	3.684
	Car ownership	-1.312	0.945	-1.390	0.165	-3.165	0.540
	Frequency	0.221	0.272	0.810	0.416	-0.311	0.753
	Travel time	-0.616	0.366	-1.680	0.093	-1.335	0.102
	Travel distance	0.228	0.287	0.800	0.426	-0.334	0.790
	Distance to railway station						
	ASC	5.206	1.373	3.790	0.000	2.514	7.898
Train+ bus/tram/metro	Car users	(base)					
	Non-car users	1.696	0.871	1.950	0.051	-0.010	3.402
	Multi-modal	1.934	0.896	2.160	0.031	0.177	3.691
	Car ownership	-2.168	0.943	-2.300	0.021	-4.015	-0.320
	Frequency	0.180	0.269	0.670	0.504	-0.347	0.707
	Travel time	-0.093	0.362	-0.260	0.799	-0.803	0.618
	Travel distance	0.086	0.283	0.300	0.761	-0.469	0.641
	Distance to railway station						
	ASC	5.137	1.373	3.740	0.000	2.446	7.827
Car sharing+ e-bike sharing	Car users	(base)					
	Non-car users	0.508	0.869	0.590	0.558	-1.194	2.211
	Multi-modal	0.201	0.890	0.230	0.822	-1.544	1.945
	Car ownership	-1.482	0.939	-1.580	0.115	-3.323	0.359
	Frequency	0.133	0.271	0.490	0.624	-0.399	0.665
	Travel time	-0.847	0.363	-2.340	0.019	-1.558	-0.137
	Travel distance	0.047	0.281	0.170	0.867	-0.505	0.599
	Distance to railway station						
	ASC	7.455	1.368	5.450	0.000	4.773	10.136
Number of cases		1416					
Log simulated Likelihook		-1307.563					
Wald chi2(23)		286.98					
Prob > chi2		0.000					
Number of Halton draws		1000					
AIC		2669.126					
BIC		2811.027					

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Table F.6: ML model and commuting-specific variables - weighted

Attribute		Coef.	Std. Err.	z	P>|z|	[95%	Conf. Interval]
Non-random	Train	0.447	0.140	3.200	0.001	0.173	0.720
	Bus/tram/metro	0.191	0.108	1.780	0.075	-0.020	0.402
	E-bike sharing	0.139	0.112	1.240	0.213	-0.080	0.359
	Car sharing	0.181	0.140	1.280	0.199	-0.095	0.456
Random	Price	-0.028	0.005	-5.370	0.000	-0.038	-0.018
	sd(price)	0.029	0.004			0.022	0.037
Contineu using current mode		(base alternative)					
Train+ e-bike sharing	Car users	(base)					
	Non-car users	5.336	1.504	3.550	0.000	2.388	8.285
	Multi-modal	3.442	1.428	2.410	0.016	0.643	6.242
	Car ownership	0.495	1.336	0.370	0.711	-2.124	3.115
	Frequency	0.265	0.387	0.680	0.493	-0.493	1.023
	Travel time	-0.734	0.483	-1.520	0.128	-1.680	0.212
	Travel distance	0.548	0.444	1.230	0.218	-0.323	1.418
	Distance to railway station						
	ASC	1.363	2.107	0.650	0.518	-2.766	5.492
Train+ bus/tram/metro	Car users	(base)					
	Non-car users	4.187	1.514	2.770	0.006	1.220	7.153
	Multi-modal	2.874	1.445	1.990	0.047	0.042	5.706
	Car ownership	-0.433	1.241	-0.350	0.727	-2.865	2.000
	Frequency	0.193	0.387	0.500	0.617	-0.565	0.952
	Travel time	-0.118	0.512	-0.230	0.818	-1.122	0.886
	Travel distance	0.355	0.463	0.770	0.443	-0.552	1.263
	Distance to railway station						
	ASC	1.283	2.151	0.600	0.551	-2.934	5.499
Car sharing+ e-bike sharing	Car users	(base)					
	Non-car users	3.811	1.504	2.530	0.011	0.862	6.759
	Multi-modal	1.821	1.428	1.280	0.202	-0.977	4.620
	Car ownership	0.069	1.319	0.050	0.958	-2.516	2.655
	Frequency	0.226	0.368	0.610	0.540	-0.496	0.948
	Travel time	-1.088	0.558	-1.950	0.051	-2.181	0.005
	Travel distance	0.369	0.425	0.870	0.386	-0.465	1.203
	Distance to railway station						
	ASC	4.147	2.296	1.810	0.071	-0.353	8.646
	Number of cases	1416					
	Log simulated Likelihook	-1335.218					
	Wald chi2(23)	118.29					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	2724.435					
	BIC	2866.336					

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Table F.7: ML model estimations for car users only - unweighted

	Attribute	Coef.	Std. Err.	z	P>z	[95% Conf. interval]	
Non-random	Train	0.286	0.106	2.690	0.007	0.078	0.495
	Bus/tram/metro	-0.042	0.129	-0.320	0.747	-0.295	0.212
	E-bike sharing	0.282	0.109	2.590	0.010	0.069	0.496
	Car sharing	0.189	0.116	1.630	0.103	-0.038	0.417
Random	Price	-0.014	0.004	-3.590	0.000	-0.022	-0.006
	Parking tariff inc.	-2.250	0.855	-2.630	0.008	-3.925	-0.575
	sd(price)	0.009	0.007			0.002	0.037
	sd(parking tariff inc.)	5.114	1.021			3.458	7.562
Continue using current mode		(base alternative)					
Train + e-bike sharing	Car necessity	-1.712	1.151	-1.490	0.137	-3.968	0.544
	Employer's parking	(base)					
	Paid parking	3.143	1.377	2.280	0.022	0.445	5.841
	P+R location	0.407	2.002	0.200	0.839	-3.517	4.330
	ASC	-1.340	1.024	-1.310	0.191	-3.348	0.668
Train + bus/tram/metro	Car necessity	-1.461	1.168	-1.250	0.211	-3.750	0.827
	Employer's parking	(base)					
	Paid parking	3.032	1.866	1.630	0.104	-0.624	6.689
	P+R location	1.056	2.084	0.510	0.612	-3.028	5.141
	ASC	-0.939	0.987	-0.950	0.341	-2.874	0.996
Car sharing + e-bike sharing	Car necessity	-1.447	1.174	-1.230	0.218	-3.749	0.854
	Employer's parking	(base)					
	Paid parking	4.020	1.765	2.280	0.023	0.561	7.478
	P+R location	-2.323	2.164	-1.070	0.283	-6.564	1.919
	ASC	-0.925	0.981	-0.940	0.346	-2.846	0.997
	Number of cases	780					
	Log simulated Likelihook	-692.6131					
	Wald chi2(15)	82.61					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	1425.226					
	BIC	1518.412					

Table F.8: ML model estimations for car users only - weighted

	Attribute	Coef.	Std. Err.	z	P>z	[95% Conf. interval]	
Non-random	Train	0.487	0.178	2.730	0.006	0.138	0.837
	Bus/tram/metro	-0.124	0.163	-0.760	0.450	-0.444	0.197
	E-bike sharing	0.340	0.157	2.170	0.030	0.033	0.647
	Car sharing	0.167	0.250	0.670	0.505	-0.323	0.656
Random	Price	-0.023	0.016	-1.400	0.161	-0.054	0.009
	Parking tariff inc.	-1.421	0.621	-2.290	0.022	-2.638	-0.204
	sd(price)	0.013	0.015			0.001	0.117
	sd(parking tariff inc.)	2.965	2.305			0.646	13.61
Continue using current mode		(base alternative)					
Train + e-bike sharing	Car necessity	-3.182	1.576	-2.020	0.043	-6.270	-0.094
	Employer's parking	(base)					
	Paid parking	3.369	3.060	1.100	0.271	-2.628	9.365
	P+R location	1.197	2.077	0.580	0.564	-2.874	5.268
	ASC	-0.124	3.392	-0.040	0.971	-6.773	6.525
Train + bus/tram/metro	Car necessity	-2.421	1.633	-1.480	0.138	-5.621	0.779
	Employer's parking	(base)					
	Paid parking	4.590	3.539	1.300	0.195	-2.347	11.527
	P+R location	2.010	2.202	0.910	0.361	-2.306	6.327
	ASC	0.153	3.155	0.050	0.961	-6.031	6.336
Car sharing + e-bike sharing	Car necessity	-2.731	1.525	-1.790	0.073	-5.720	0.259
	Employer's parking	(base)					
	Paid parking	4.611	3.195	1.440	0.149	-1.651	10.783
	P+R location	0.262	2.259	0.120	0.908	-4.165	4.688
	ASC	0.370	3.367	0.110	0.912	-6.228	6.969
	Number of cases	780					
	Log simulated Likelihook	-531.1886					
	Wald chi2(15)	105.32					
	Prob > chi2	0.000					
	Number of Halton draws	1000					
	AIC	1102.377					
	BIC	1195.563					

Effect of working location on mode choice

In this ML model estimation, working location of employees is introduced as covariate. It is expected that differences exist between employees' preferences who work in different regions in the Netherlands. The attribute related to working location (city) has been generalized to the province level. The reason is that not enough observations existed per city to clearly identify their differences in the ML model. Moreover, provinces with less than 10 respondents are excluded because too few data points will hinder the model accuracy.

First, the ML model is performed based on the unweighted sample. Similar to the general ML model attributes related to train, bus/tram/metro, e-bike sharing and car sharing are specified as fixed coefficient and price as random coefficients. Table F.9 shows the coefficient values of working locations based on the unweighted sample, where Utrecht was set as a base category. As can be seen in the table, almost all provinces have negative coefficients concerning the mobility options. For train+e-bike sharing, the coefficient related to Overijssel has significant value, -2.68 (unweighted) and -4.36 (weighted). It means that employees in this province are less likely to choose train+e-bike sharing. Likewise, the coefficient values related to Gelderland, Overijssel and Zuid-Holland are statistically significant concerning the train+bus/tram/metro alternative. For instance, people who work in Gelderland are 5.1 times less likely to choose train+bus/tram/metro. Concerning the car sharing+e-bike sharing, working locations do not have statistically significant coefficients within the unweighted estimation. With the weighted estimations (table F.9), the coefficient values of some provinces differ from the unweighted. Overijssel, for istance, has negative coefficient concerning the car sharing+e-bike sharing option. Employees in this province are 2.85 times less preference toward this option. In short, employees in Utrecht have more inclination towards train, bus/tram/metro and e-bike sharing, which makes sense because of its intense public transport network.

Table F.9: Coeffient values of working location

Alterantive	Parameter	Unweighted		Weighted	
		Coef.	Sign.	Coef.	Sign.
Cont. using current mode	base alternative				
Train+E-bike sharing	Utrecht	(base)		(base)	
	Flevoland	-1.789	0.285	-1.165	0.469
	Gelderland	-3.296	0.121	-3.663	0.095
	Groningen	-3.791	0.065	-2.933	0.150
	Noord Brabant	0.144	0.931	-0.341	0.831
	Noord Holland	-1.599	0.216	-1.285	0.299
	Overijssel	-2.682	**0.048**	-2.577	**0.053**
	Zuid Holland	-1.757	0.188	-1.935	0.118
	ASC	6.597	**0.000**	5.770	**0.000**
Train+Bus/tram/metro	Utrecht	(base)		(base)	
	Flevoland	-1.742	0.312	-1.151	0.510
	Gelderland	-5.109	**0.010**	-5.633	**0.006**
	Groningen	-1.709	0.464	-0.573	0.818
	Noord Brabant	-0.239	0.891	-0.858	0.617
	Noord Holland	-1.329	0.292	-1.037	0.399
	Overijssel	-3.351	**0.014**	-3.246	**0.019**
	Zuid Holland	-2.519	**0.056**	-2.804	**0.027**
	ASC	6.597	**0.000**	5.925	**0.000**
Car sharing + E-bike sharing	Utrecht	(base)		(base)	
	Flevoland	-0.554	0.737	-0.299	0.853
	Gelderland	-1.631	0.423	-2.510	0.222
	Groningen	-3.203	0.203	-2.016	0.445
	Noord Brabant	1.669	0.322	0.746	0.649
	Noord Holland	-0.599	0.628	-0.746	0.531
	Overijssel	-1.607	0.226	-1.791	0.181
	Zuid Holland	-1.303	0.314	-1.862	0.142
	ASC	5.500	**0.000**	5.630	0.000
	Number of cases	1368		1368	
	Log simulated Likelihook	-1317.014		-1312.19	
	Wald chi2(20)	186.67		158.81	
	Prob > chi2	0.000		0.000	
	Number of Halton draws	1000		1000	
	AIC	2694.02		2684.38	
	BIC	2850.661		2841.01	

*Note: the models are estimated with Stata's cmxtmixlogit command. The models converged in 9 (N) and 9 (N) iterations. * Significant at 90% CI.*

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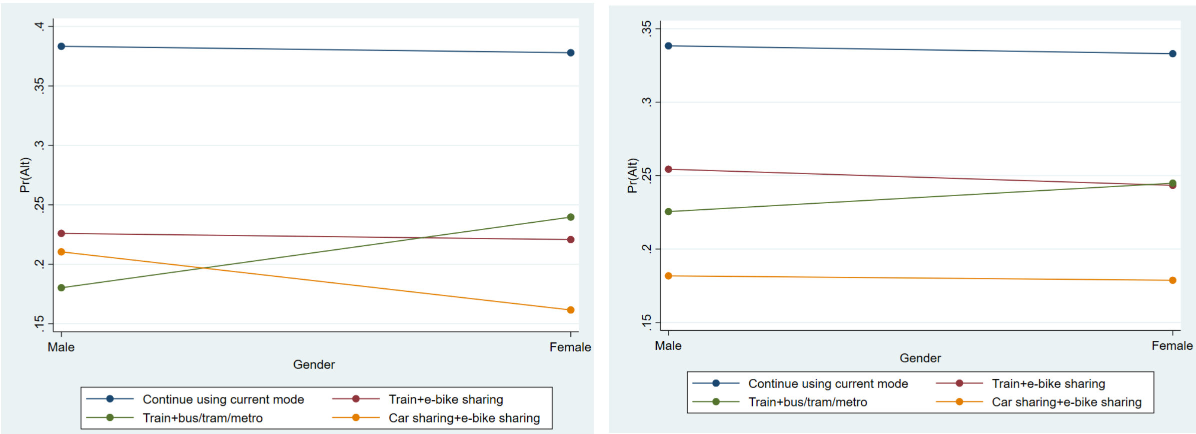
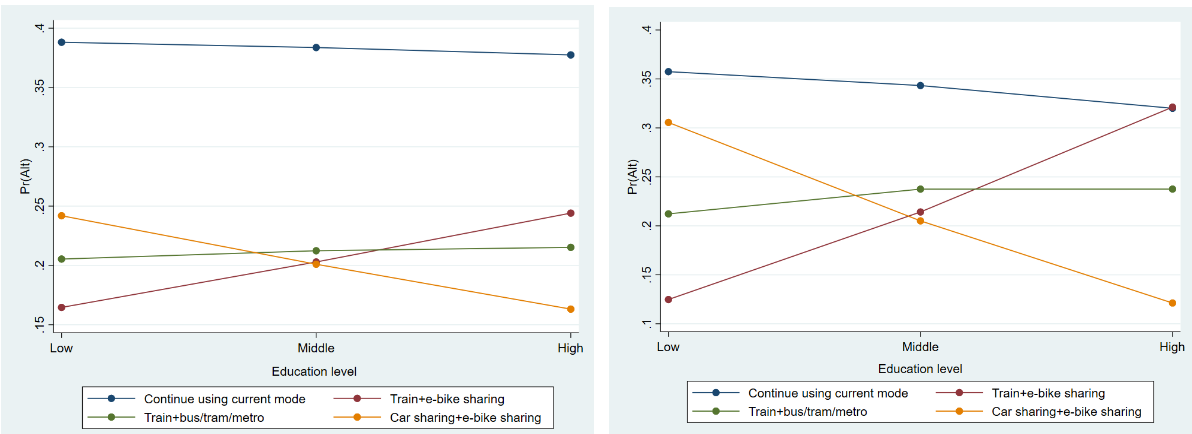
G | Marginal effects



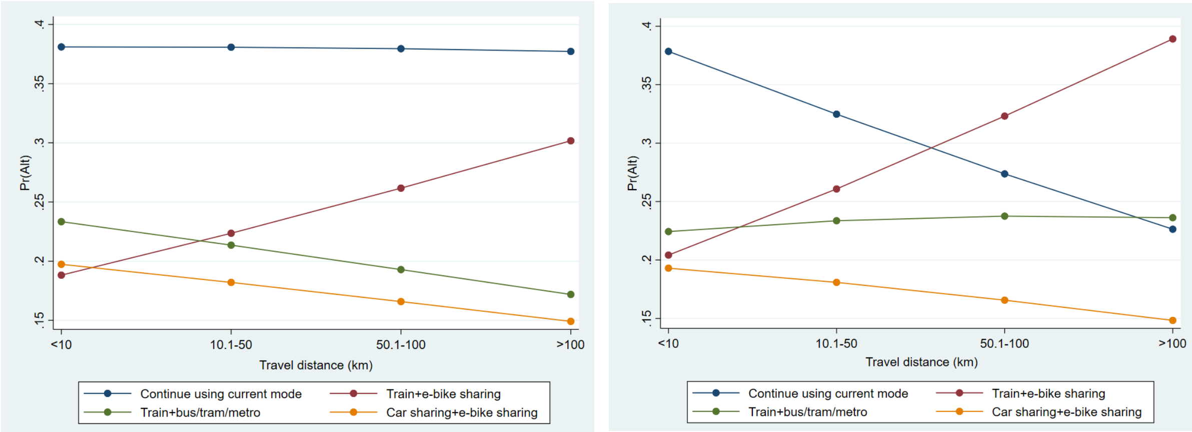
(a) (b)

Figure G.1: Marginal effect of gender; (a) unweighted, (b) weighted



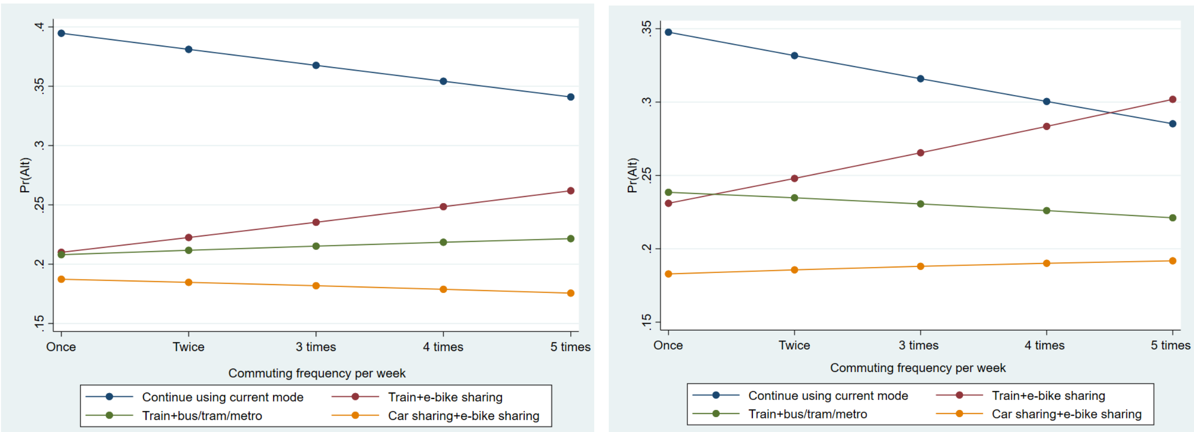
(a) (b)

Figure G.2: Marginal effect of education; (a) unweighted, (b) weighted



(a) (b)

Figure G.3: Marginal effect of travel distance; (a) unweighted, (b) weighted



(a) (b)

Figure G.4: Marginal effect of commuting frequency; (a) unweighted, (b) weighted

H Employees’ attitude towards Car ownership

Car users seem to be less convinced with the fact that the MaaS service reduces car ownership (mean=2.92, sd=1.44). The result corresponds with the results of the ML models where car users showed less interest in switching to alternative transport modes. Only 17.7% of car users strongly agree that by using MaaS, they might not need to have private cars (table H.1). This was also found by Knijn (2020), in which employees in the Netherlands did not believe if MaaS has the potential to reduce car ownership. The situation is a little better for multi-modal commuters whose primary commuting mode is not private/lease car (mean=3.11, sd=1.47). Around 45.8% of them strongly/somewhat agreed that MaaS can fulfill their travel needs to not own private/lease car (table H.1). On the other hand, non-car users believe that MaaS can reduce car ownership (mean=3.53, sd=1.43). 36.2% strongly agree and 21.9% somewhat agree with the statement that asked them if MaaS can fulfill their travel needs and make them to not purchase a private car or get lease car.

Table H.1: Employees attitudes towards car ownership

Commuting mode	Answer distribution					Total
	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree	
Car users	21 21.9%	23 24.0%	12 12.5%	23 24.0%	17 17.7%	96 100%
multi-modal commuters	7 20.0%	6 17.1%	6 17.1%	8 22.9%	8 22.9%	35 100%
non-car users	12 11.4%	20 19.1%	12 11.4%	23 21.9%	38 36.2%	105 100%
Total	40 17.0%	49 20.8%	30 12.7%	54 22.9%	63 26.7%	236 100%