Shared E-mopeds at NS Railway Stations

The preference of train travelers towards shared e-mopeds in the first and last mile transportation

Master Thesis

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Shared E-mopeds at NS Railway Stations

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by

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Preface

This thesis explored the behavior and perception of train travelers regarding the shared e-moped. Having frequently used shared e-mopeds myself, I was eager to undertake this study. My interest in new technological innovations further fueled my enthusiasm. When I heared about a thesis on shared e-mopeds in the first and last mile at NS, I was excited to start. However, the process was not always enjoyable. I had heard stories from friends about the challenges they faced during the six months of their theses. As I now reach the end of my Master's in Engineering and Policy Analysis, I reflect on what has been an emotional journey. There were many ups and downs, making the experience anything but a smooth train ride. I learned a lot, from mastering a new coding language to following extra lectures at TU Delft to learn more on travel behaviour research. Despite the challenges, I found the experience rewarding overall, and with the knowledge I have gained, I would be willing to undertake it again.

First of all, I would like to thank my NS Supervisors for our weekly meetings and the consistent motivation. Cathelijn, thank you for always providing different perspectives and helping me see the bigger picture. You reminded me of the purpose behind my work and guided me in a practical direction, even though not everything I wanted was possible. Danique, I am grateful for your research expertise and for consistently reminding me of the importance of time management. I also appreciate your support even after moving to another department. Without both of you, this thesis would not be the same.

Secondly, I would like to thank my TU Delft supervisors. Nihit, your meetings were very helpful in adjusting my course and your suggestions were spot on. Maarten, thank you for always being available to answer my questions, which I may have asked more frequently than other students. I enjoyed the meetings because it was always with a smile but serious when needed. Your reassurance, combined with the pressure from Danique, created a balanced environment of support and motivation.

Lastly, I would like to express my gratitude to several people who have supported me throughout these months. I thank my father for staying informed about the entire process, my sister for her help during times of high need, and my mother and Joan for always keeping her door open for me. I also appreciate my roommates for their daily discussions about the thesis. Sharing the same challenges with some of you made it easier to put all the problems we faced into perspective. Lastly, I am very thankful to my girlfriend for her advice on my thesis and for always being there to listen when needed.

Boudewijn Klapwijk
Amsterdam, June 2024

Summary

Urbanization and advancements in transportation have led to increased accessibility. However, public transportation, while essential for fast travel, still faces challenges with the first and last-mile problem due to fixed stations and schedules (Grosshuesch, 2020). Various solutions, including private and public transport, address this issue but have limitations like parking shortages and lack of door-to-door service (Grosshuesch, 2020; Jonkeren & Kager, 2021).

Shared micromobility, such as shared bikes, e-bikes, e-scooters, and e-mopeds, can improve first and last-mile connectivity (Manning & Babb, 2023; Oeschger et al., 2020). Integrating these modes with public transport can enhance accessibility and sustainability by reducing private car usage (Zhang et al., 2023). Since 2017, shared e-mopeds have been introduced in the Netherlands, leading to both satisfied users and some nuisance (Rijksoverheid, 2023). Transport companies aim to improve the door-to-door travel experience. Meanwhile, a gap exists in understanding train travelers' preferences regarding shared e-mopeds during the first and last mile which could aid policy-making on the relatively new mode. To understand people's behavior and preferences regarding them, this thesis addresses the following question:

"How do shared electric mopeds impact the travel behavior of train travelers for first and last-mile transportation?"

This main question is addressed with the help of four subquestions. First, a literature review is conducted on the factors influencing mode choice in the first and last mile. Secondly, a survey is carried out among train travelers, including questions about their current behavior and preferences, followed by a stated preference experiment. Finally, this data is modeled, key influencing factors are analyzed, and the potential modes that are replaced are assessed.

Literature review

The literature review identified various factors influencing the choice of shared e-mopeds and shared mobility for first and last-mile travel. These factors are categorized based on the classifications by Stam et al. (2021), as shown in Figure 1. The font size in the figure represents the frequency of mentions in previous studies; larger fonts indicate factors that were mentioned more frequently. By analyzing the frequency of mentions, the gaps in related research, and considering policy influence, key factors were identified and incorporated into the survey. These key factors are highlighted in bold in the figure.

Survey design

A survey was carried out among train passengers to collect data, with a sample size of 641 respondents. The survey included questions on their current travel behaviour and preferences, followed by a stated preference experiment for last-mile travel scenarios. This experiment specifically targeted last-mile travel, where shared e-mopeds are more frequently used than in the first mile (Van Kuijk et al., 2022). The options considered in the survey included shared e-mopeds, walking, shared bike, and BTM (Bus, Tram, Metro). Two distances, 1.5 km and 3 km, were selected to represent typical last-mile distances. The primary attributes analyzed were travel cost, travel time (which was fixed for each distance), walking distance, and convenience. These attributes are important as they tend to have an impact on the mode choice and can be influenced by policy changes. Walking distance was defined as the time it takes to walk from the station to the transportation mode. Convenience for shared bikes and e-mopeds was measured by the time taken to search for and reserve a vehicle, whereas for BTM, it involved the waiting time for the mode. The levels of these attributes were determined based on existing market data.

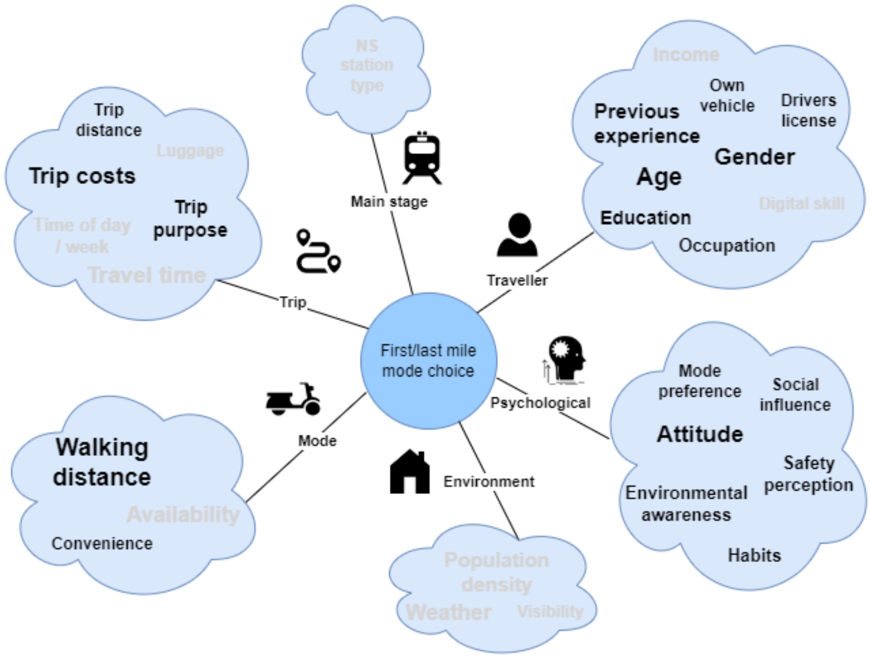

Figure 1: Factors influencing the mode choice in the first and last mile

Modeling

The survey data was collected and transformed. First, an initial exploratory data analysis was conducted to examine behavior and preferences related to the use of shared e-mopeds. Second, a logistic regression analysis was performed on the previous use of shared e-mopeds. Also, a factor analysis needed to be conducted for the psychological factors due to their high correlation, resulting in two factors used in further analysis: emotional satisfaction and perks satisfaction. The stated preference experiment was analyzed using discrete choice modeling, including multinomial logit (MNL) and latent class (LC) models, to capture preference heterogeneity.

Travel choices made

The shared e-moped is not the most popular mode of transport among train travelers. Only 10.9% of the respondents have ever used a shared e-moped. Among those who have never used an e-moped, 72.4% stated they would never use one for the first mile, regardless of the circumstances. For the last mile, this percentage is 64.7%. The shared e-moped use is significantly more in the last mile than in the first mile. Generally, people have a more negative than positive view of shared e-mopeds, with most holding a neutral opinion. Shared e-mopeds are the least used mode of transport, and even among those who have used them, the frequency of use is very low. Users of shared e-mopeds are typically young, educated males who have a favorable view of the service. Those who own motorcycles or mopeds are more likely to have used a shared e-moped before, while car ownership decreases the likelihood of prior use. Additionally, the frequency of car, bike, or walking use impacts the likelihood of having used a shared e-moped. The reasons for using shared e-mopeds are similar for both the first and last mile, primarily due to their fast travel or when no other modes are available. Other transport modes were the most commonly mentioned barrier, preventing people from using shared e-mopeds. Additional barriers included the high price, availability and the lack of a driver's license. The purpose of trips made with shared e-mopeds is consistent across both the first and last mile, with approximately 67% of trips being leisure-related and 33% related to work or school.

Choice experiment

Both the walking distance and trip costs negatively influence the shared e-moped mode choice. The convenience was not found to be significant for the shared e-moped. Analysing the results of the stated preference experiment, latent class modeling revealed distinct attitudes and behaviors towards shared e-mopeds among different groups of train travelers. The 'Conservative Travelers' prefer traditional modes of transport and are hesitant to adopt new technologies. In contrast, 'Mode Adapters' are the most enthusiastic users of shared e-mopeds, reflecting their openness to innovation. Cost-sensitive adapters show potential interest driven by social and economic factors but have not yet embraced shared e-mopeds. Age, education, perception of shared e-mopeds, and previous use of shared e-mopeds influence the classification of individuals into these segments.

Conservative Travelers are the group least likely to choose shared e-mopeds for the last mile of their journey. This group is typically older and has a negative perception of shared e-mopeds, viewing them as less safe and less environmentally friendly. Most members of this group are retired, primarily own cars, and are not frequent train travelers. They are also the least familiar with shared e-mopeds.

Mode Adapters are the group most likely to choose shared e-mopeds for the last mile of their journey. This group is generally younger, more highly educated, and more familiar with shared e-mopeds. They have a more positive perception of shared e-mopeds compared to other groups. Other characteristics of this group include being mostly employed, owning the most bikes, and frequently using OV-bikes. The reservation time for shared e-mopeds (convenience) does not influence mode choice for train travelers.

Cost-Sensitive Adapters prefer transportation methods that do not require physical effort. Most people in this group are young, with the lowest education levels compared to other classes. Regarding shared e-mopeds, this group places significant importance on the social image associated with using them. While they are aware of shared e-mopeds, they have not used them primarily. They have lower education levels, many do not have driver's licenses, and they own fewer personal cars and bikes. Their transportation choices are only influenced by pricing competitiveness.

Mode Choice Model

To predict the likelihood of choosing a shared e-moped for different classes in various situations, a mode choice probability model is developed. This model allows for the creation of snenario's within the stated experiment, considering different costs, walking distances, and levels of convenience. For example, the effect of changing the walking time (or walking distance) is analyzed for both 1.5 km and 3 km trips at The Hague Central. In this scenario, the parking spots were relocated from a 5-minute walking distance to a 2-minute walking distance.

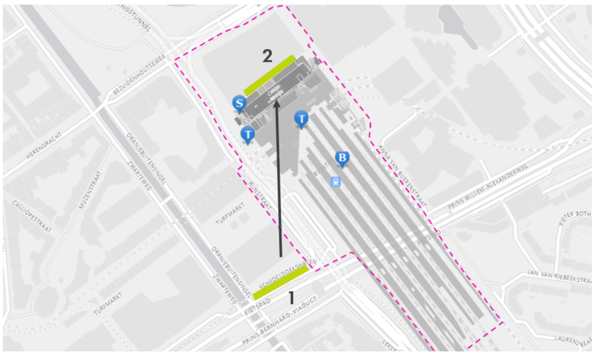

Figure 2: Relocating the shared e-moped parking spot closer to the station

The shared e-moped has a higher probability of being chosen for a 3 km trip than for a 1.5 km trip in the last mile. In the example, the choice of shared e-moped mode increases from 0.9% to 1.6% for the 1.5 km trip. For the 3 km trip, the choice changes from 1.9% to 3.3%. Reducing the walking distance to the shared e-moped increases its likelihood of being chosen for all classes, with the most notable impact on the Mode Adapters. Reducing the travel cost of the shared e-moped also enhances its likelihood of being chosen for all classes. However, the time required to rent the shared e-moped does not significantly affect its choice for train travelers.

Modal shift

To examine the modes that are replaced by the shared e-moped in the first and last mile, three perspectives have been employed to reach a well-considered conclusion.

- Previous shared e-moped trips
- The modal shift in the mode choice model (last mile)
- Potential users modal shift

The first perspective showed the modes replaced in the previous shared e-moped trips in the first and last mile. Here, people most frequently replaced walking, BTM, and the bike when choosing the shared e-moped. The shared bike also has a significant proportion, but only in the last mile.

The second perspective uses the mode choice probability model made for the last mile. Making the shared e-mopeds more attractive by lowering walking time towards the shared e-moped or reducing costs in the mode choice probability model leads to a noticeable shift that can be measured precisely. Making the shared e-moped more attractive by lowering the walking distance or costs, primarily draws users from shared bikes, and walking for shorter distances.

The third perspective involved analyzing individuals who did not completely reject the use of shared e-mopeds. This includes those who did not state they would never use them or indicated they would only use them if no other options were available. It was found that their shift to shared e-mopeds would occur proportionally from all modes of transport. For the first mile, the biggest shift was from bikes, while for the last mile, it was from walking.

Combining the three perspectives provides a clear overview of the modes replaced in the first and last mile. In both cases, walking, biking, and BTM were the most replaced modes. For the last mile, shared bikes were also replaced.

Discussion

The findings of this study are generally consistent with existing research on shared e-mopeds. Factors such as trip distance, walking distance, trip cost, and various socio-demographic variables align with previous studies. The mode choice probability model appears to be valid when compared with findings from other literature.

Some influencing factors found in the literature were not found to be influencing in this study. These factors include environmental awareness, social influence, occupation, convenience, and the replacement of cars by shared e-mopeds. The differences in findings are mainly due to the scope of the studies. The literature compared focuses on shared e-mopeds in general, while this study specifically examines their use for first and last mile transportation.

The application of Rogers' Diffusion of Innovations Theory suggests that shared e-mopeds could see varied adoption levels among different traveler classes, from the 'early adopters' from rogers model to the class 'conservative travelers' less likely to embrace the shared e-moped. While shared e-mopeds are seen as compatible with the values of train travelers and offer advantages such as trialability and observability, their adoption may be hindered by the current superior integration of shared bikes at train stations.

Methodologically, the survey faced limitations such as a bias toward respondents with higher education levels and possibly outdated socio-demographic data. Furthermore, the design of the stated preference experiment may have introduced biases by the hypothetical way of the experiment.

In terms of generalizability, the findings are specific to Dutch train travelers and may not directly apply to other countries due to differences in travel behaviour, preferences, and transport infrastructure. The mode choice model is primarily applicable to scenarios where only four specific transport modes are considered, and its predictions may require adjustments to fit specific stations with different attributes and traveler behaviors.

Overall, this study enriches our understanding of shared e-mopeds' potential role in combination with railway stations, particularly for train travelers in the Netherlands.

Conclusion

To answer the main question "How do shared electric mopeds impact the travel behavior of train travelers for first and last-mile transportation?", the four subquestions are answered.

The choice of a transportation mode for railway station access and egress is influenced by a combination of traveler characteristics (such as age, gender, and vehicle ownership), trip characteristics (like distance and cost), and mode characteristics (walking distance and convenience). Psychological factors, including attitudes toward sharing and environmental awareness.

Only a small proportion of train travelers have used shared e-mopeds, often preferring other modes due to perceived disadvantages like high costs and limited availability. The perception of shared e-mopeds is generally neutral to negative, especially among those who have never used them.

Key determinants for choosing shared e-mopeds include shorter walking distances to access points and lower travel costs, which each can double the mode choice probability if lowered. The travelers most likely to use shared e-mopeds are the ´Mode adapters´, with a positive emotional satisfaction towards shared mobility.

Shared e-mopeds mainly replace walking and biking, particularly for shorter distances. For longer trips, they are more likely to replace BTM trips. In the last mile, they also tend to replace the shared bike.

Overall, the shared e-mopeds offer a promising addition to the modal split for first and last-mile travel and an addition to the door-to-door experience. They are not yet a dominant mode of transport for these segments, but could gain importance with better spatial integration at stations or when the costs are lowered.

Recommendations

Based on the findings of this thesis, the NS should carefully consider the spatial and digital integration of shared e-mopeds into their transportation options. While there is a segment of train travelers willing to adopt shared e-mopeds, most of this segment prefer shared bikes. By making the shared e-moped more attractive, this could have impact on the OV-fiets use. The shared e-mopeds do not significantly reduce environmental impact or spatial issues compared to other modes like walking, BTM, or shared bikes. Therefore, the recommendation is to prioritize more space and environmentally efficient transportation modes while considering shared e-mopeds as a supplementary option only in strategic locations where it might enhance overall accessibility.

Future research should investigate the spatial impact of incorporating shared e-mopeds compared to private vehicles for the first mile of travel. Additionally, examining whether shared e-mopeds could attract more train users and increase revenue would provide valuable insights. This perspective could offer a different view on the role of shared e-mopeds. Further studies should also focus on long-term trends in user behavior and the role of shared e-mopeds in longer-distance travel.

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1
Introduction

In today's world, urbanization and advancements in transportation have profoundly influenced accessibility and travel behaviors. Although forms of urban planning and transport may change, people are willing to accept a daily travel time of about one hour per day, known as the Marchetti constant (Marchetti, 1994). This means that while transportation is improving every day, individuals can live further away while maintaining a constant and similar travel time over time (Gallotti et al., 2015; Hong, 2018).

Public transportation is essential for facilitating fast and efficient travel. However, due to fixed stations and schedules, it cannot deliver passengers precisely to their desired destinations (Grosshuesch, 2020). Users of public transportation often face challenges with the initial and final segments of their journey, commonly referred to as the first and last-mile problem.

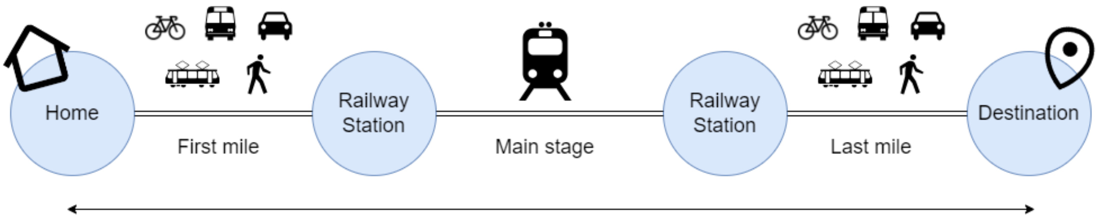


Figure 1.1: The first and last mile

Railway companies prioritize efficiently moving people from station to station. At the same time, railway companies acknowledge the importance of seamless door-to-door experience for travelers (NMBS, 2024; NS, 2022; SBB, 2024; SNCF, 2024). Currently, there are various options for the first and last mile of a train-related journey, including private transport like bikes or cars, as well as public transport such as buses, trams, or metros (Leferink, 2017). Walking is the most space-efficient mode of transport, though it is only practical for those living near a railway station due to its limited range (D'Orso & Migliore, 2018). Private transport enhances the door-to-door experience but is generally limited to the first mile of a journey, as people use their personal vehicles from home (Stam et al., 2021). Also, the widespread use of private transport to access railway stations results in parking shortages due to limited space at railway stations (Jonkeren & Kager, 2021). Meanwhile, public transport does not exactly provide a seamless door-to-door experience, as it typically necessitates walking to and from transit hubs (Grosshuesch, 2020).

One solution that could help improve the door-to-door experience is shared micromobility, which is rising as a potential to address the first and last-mile problem in urban transport systems (Manning & Babb, 2023; Oeschger et al., 2020). Shared micromobility refers to the use of small, lightweight vehicles for short-distance travel within urban areas. These vehicles, such as shared bikes, e-bikes, e-scooters, and e-mopeds are typically available for public use and can be picked up and dropped off at various locations (Gkartzonikas & Dimitriou, 2023; Montes et al., 2023).

Although results differ between studies, there is general agreement that integrating public transportation with shared micromobility can enhance accessibility and improve sustainability (D'Acierno et al., 2022; Manning & Babb, 2023; Oeschger et al., 2020; Zhang et al., 2023). Improving sustainability is mentioned primarily due to the potential for reducing private car usage. Another advantage of shared micro-mobility in the first and last mile is its spatial efficiency, as it can reduce the demand for parking spaces (Manning & Babb, 2023).

The question is whether new solutions such as shared micro-mobility should be available at transport hubs such as railway stations. Understanding how travelers perceive and desire new transportation options to bridge the first and last mile is crucial to answering this question. By filling this knowledge gap, (public) transportation companies like NS can better align their policies with consumer expectations, ultimately improving the overall travel experience.

In the Netherlands, the shared electric moped (e-moped) has gained popularity as a commonly used mode of transportation (Milieudefensie, 2023). The shared electric moped is a two-wheeled vehicle equipped for seated transportation and is called 'shared' because everyone with a driver's license can pick up an e-moped via an app (Fiorini et al., 2022). The NS incorporated e-mopeds as an additional transfer option in their mobile app (NS, 2022). At the same time, the shared e-mopeds seem to be only partly psychically integrated with public transportation, with parking spots being pushed away from some stations, as shown in Appendix A. Research on shared e-mopeds for first and last mile transportation in the Netherlands indicates that 28% of total trips are combined with public transport, with 18.3% specifically linked to train travel (de Wit, 2023; Movares, 2023).

Whether the shared e-moped will be adopted amongst people in the Netherlands is unclear. In 2022, only 5% of the people in the Netherlands has used the shared e-moped (Rijksoverheid, 2022). (Rogers, 1962) developed a diffusion model for the adoption of innovations, illustrated in Figure 1.2, which indicates only a small percentage of the early adopters started to adopt. In his model, he identified five key factors that influence the adoption of innovations: relative advantage, compatibility, complexity, trialability, and observability.

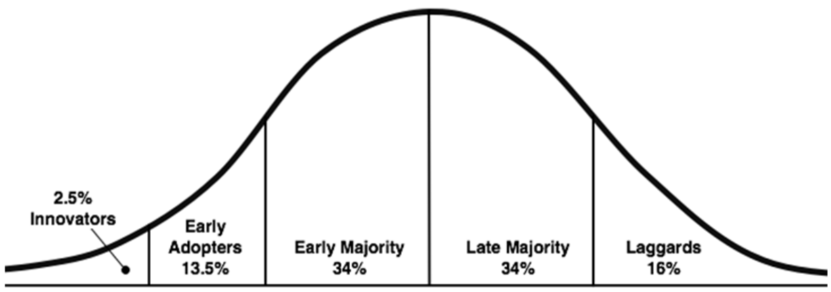


Figure 1.2: Rogers' model of diffusion (Rogers, 1962)

While general studies on shared micromobility and new innovations exist, focused research on e-mopeds in combination with public transport is limited. Garritsen (2022) focused on shared e-mopeds linked to public transport hubs in Rotterdam, analyzing spatio-temporal usage patterns using tripdata. He found that typical e-moped users are young, male, digitally skilled, and own a driver's license (Garritsen, 2022). Montes et al. (2023) also focussed on Rotterdam, studying the combination or competition between the subway and shared micromobility. He showed that the e-moped was the least favorable mode compared to walking and shared bikes for the last mile from the subway station. de Wit (2023) examined factors describing the usage of shared e-mopeds within the first and last mile of train journeys, based on tripdata from an e-moped provider. Van Kuijk et al. (2022) compared all different shared transportation modes by setting up a survey for local public transport users in Utrecht, concluding that most local public transport users do not want to try shared mobility because of their age and current cycling behaviors.

What is still missing in these studies is the perspective of the train user regarding shared e-moped in the first and last mile. What are their preferences regarding shared e-mopeds and how does this perspective influence their travel behavior? Additionally, there is a lack of exploration regarding the transportation modes that e-mopeds may replace in the first and last mile. Understanding a potential modal shift, where travelers transition from their usual mode of transportation to shared modes, is important for evaluating the impact of integrating shared modes at transit hubs (Wang et al., 2023).

Therefore, this thesis aims to explore the preferences and behaviors of train travelers regarding the adoption of shared e-mopeds for the first and last mile of their journeys. This is done by diving into the choice train travelers make regarding the shared e-moped in the first and last mile. By understanding travelers' attitudes and behaviors towards e-mopeds, this research aims to provide insights that can inform policy decisions about integrating shared e-mopeds at railway stations.

1.1. Research questions

This thesis seeks to understand how shared electric mopeds influence the travel choices of train travelers, particularly in the first and last mile. This investigation is structured through three subquestions, each building towards a comprehensive answer to the main research question:

"How do shared electric mopeds impact the travel behavior of train travelers for first and last-mile transportation?"

The following subquestions answer this main question:

- What are the key factors influencing travelers' decisions to choose a mode for railway station access/egress?;
- What is the current travel behaviour and perception of train travelers regarding shared e-moped use?;
- How do key factors contribute to the likelihood of choosing shared e-mopeds for railway station access/egress?;
- Which modes are substituted by the shared e-moped use in first/last mile transportation when integrated at NS stations?;

1.2. Research Approach

To investigate the first subquestion, "What are the key factors influencing travelers' decisions to choose a mode for railway station access/egress?", a literature review was conducted on factors influencing mode choice in the first and last mile, with a focus on shared e-mopeds. This review established a set of factors that will be further analyzed in the other subquestions. A survey was conducted to gather data for addressing the other subquestions.

An exploratory data analysis was conducted to answer the second question. The second question was needed before the third question. A factor analysis was performed, which was essential for further analysis.

For the third subquestion, the survey included a stated preference experiment. The data from this experiment were analyzed using discrete choice modeling. Initially, a multinomial logit (MNL) model was created and specified using a latent class (LC) model, using factors extracted from the second subquestion.

The fourth subquestion, concerning modal shift, was addressed after the second and third subquestions. This subquestion integrates the multiple perspectives from the previous subquestions to provide a comprehensive answer regarding potential modal shifts.

1.3. Research Design

The research design, outlined in Figure 1.3, starts with the study's design described in this chapter. Chapter 1 introduces the topic, formulates the research questions, outlines the research strategy, and justifies its relevance. Chapter 2 focuses on methodology, detailing the comprehensive approach to the study.

Next, a theoretical framework is established, including a literature review to explore the first subquestion. This subquestion seeks to identify the factors that influence travelers' decisions when choosing a transportation mode for accessing or leaving railway stations. The literature review provides an overview of factors that could influence the use of shared e-mopeds for the first and last mile. The key factors identified are then used in a survey, the design of which is elaborated in Chapter 4.

Chapter 5 analyzes the survey data on train travelers' current behavior and preferences, addressing the second subquestion. The third subquestion aims to understand how the identified factors specifically influence the decision to use shared e-mopeds for station access and egress. This is partly answered in Chapter 5, but mostly in Chapter 6, where the Stated Preference Experiment is analyzed and developed into a practical model. Here, the extent to which the key factors make shared e-mopeds an attractive or unattractive option is shown.

In Chapter 7, the fourth subquestion is addressed, examining whether shared e-mopeds substitute other modes of transport in first/last mile connectivity.

Chapter 8 discusses the results of the data analysis. This includes a detailed discussion, ultimately answering the main research question in Chapter 9. Here, the study ends with a conclusion and recommendations based on the insights gathered.

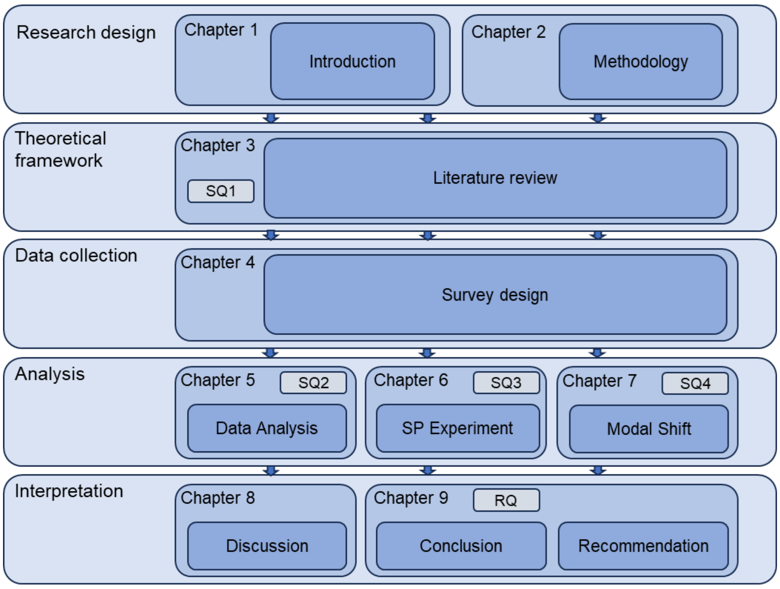


Figure 1.3: Research approach

1.4. Scientific relevance

This thesis explores the behavior and preferences of train travelers regarding the use of e-mopeds for the first and last mile of their journeys. Existing literature on shared micromobility mainly focuses on general usage patterns of shared e-mopeds, and a handful on shared e-mopeds in the first and last mile. Studies by de Wit (2023), Garritsen (2022), and Montes et al. (2023) examine shared e-mopeds in urban settings like Rotterdam, highlighting user demographics. While valuable, these studies do not deeply explore train travelers' perspectives on shared e-mopeds for the first and last mile. A significant gap exists in the focus on train users' preferences and their influence on travel behavior regarding shared e-mopeds.

Firstly, finding factors that influence mode choice in the first and last mile through a literature review does not significantly add to the existing literature. (de Wit, 2023) also searched for factors in the literature that could influence mode choice in the first and last mile. However, these factors are then incorporated into a survey, which provides an overview of the preferences and behavior of shared e-moped use for train travelers. Although the behavior has been researched before, examining how people perceive shared e-mopeds is novel in this field of study.

Secondly, the factors found will be analysed through questions on behaviour, but also a stated preference experiment is conducted. Understanding the impact of these factors can provide insights into how spatial integration of shared e-mopeds with railway stations might affect train travelers. Adding to the current literature, this analysis considers the impact on latent classes, which accounts for individual preferences and other personal characteristics. This novel perspective in the field of shared e-mopeds in the first and last mile will present a methodology designed to study preferences for new transportation technologies amongst train travelers, particularly in the first and last mile.

Using discrete choice modeling and latent class analysis, this thesis captures the heterogeneity among travelers while examining the impact of spatial integration on these classes. This will be used for the development of a mode choice probability model, offering insights into potential modal shifts and the impact of the mode choice when shared e-mopeds are spatially integrated at railway stations. This information is useful for policy decisions tailored to specific train travelers.

Overall, this study contributes to understanding the train traveler´s perceptions on shared e-mopeds in transportation systems. It brings a combined methodology where the impact of factors are analysed while keeping peoples different preferences into consideration. A methodology designed to study preferences for new transportation technologies amongst train travelers, particularly in the first and last mile.

1.5. Societal Relevance

This thesis is relevant to society for several reasons.

First, the study offers insights into the current travel behavior and preferences of train travelers regarding shared e-mopeds. This information is valuable for policymakers to understand travel patterns and how people perceive new modes of transportation.

Second, by identifying different groups with similar characteristics (latent classes), policies can be tailored to these specific groups. This helps in understanding the diversity among train travelers and their varying perspectives.

Third, evaluating the impact of factors on the mode choice that could be influenced by policymakers is useful. It helps in designing effective transportation policies.

Fourth, the mode choice probability model developed from the stated preference experiment can be used at different stations to predict changes in mode choice probability. This is particularly relevant if new modes are introduced or if policies are implemented where these modes already exist. However, assumptions will need to be made for each station, as each one is unique.

Fifth, examining the transportation modes the shared e-mopeds might replace is of great value for the NS. This could have environmental and spatial consequences. Investigating the modes that might be replaced can reveal the potential spatial and environmental impacts.

2
Methodology

This chapter outlines the methodology used in this thesis, detailing the research approach and explaining the methods employed to answer the sub-questions. The chapter will follow a chronological order, aligning with the sequence of the preceding chapters.

2.1. Selection of methods

The literature review analyses the factors influencing the mode choice in the first and last mile regarding shared e-mopeds that have been investigated in previous studies. These factors have to be found first, before they can be further analysed through the other subquestions. The literature is chosen as approach because it provides a variety of perspectives and results (Snyder, 2019), which was useful in considering all factors before identifying which key factors are taken into this research.

The survey is selected as a method to collect data because it effectively captures the preferences of many people from various geographic locations and demographics. This is particularly useful to understand preferences that might vary widely among different groups (Stantcheva, 2023). For this study, it applies to attitudes towards e-moped users as well, since opinions on their use can vary; some people use them, while others view them as a nuisance (Rijksoverheid, 2023).

Within the survey, a stated preference experiment was chosen to conduct. This is done to help explore the influence of some factors, which helps answer the second sub-question: "How do the factors contribute to the likelihood of choosing shared e-mopeds for railway station access/egress?". The stated preference experiment is particularly useful because it allows for the examination of choices in hypothetical contexts, unlike a revealed preference survey, which is limited to existing alternatives (Tabasi et al., 2023). For this study, this is beneficial as the concept of shared e-mopeds is not widely familiar, and their availability is limited in many areas. Consequently, this survey can be conducted nationwide, as the scenarios are hypothetical and do not depend on the current use or availability of the shared e-moped.

The stated preference experiment involves a series of hypothetical scenarios in which respondents are presented with various transportation options. In this experiment, train travelers are asked to choose their preferred mode of transport from the options provided. The analysis of this stated preference experiment is explained later on in this chapter.

2.2. Method Literature review

The search strategy for relevant literature is carried out in stages using Google Scholar and Scopus. Initially, the focus lies on finding research that specifically addresses how different factors influence the use of e-mopeds in first and last mile transport. Given the scarcity of research in this area, the search was expanded to include studies on factors influencing the general use of e-mopeds and on shared transportation modes in the first/last mile. The search areas are shown in figure 2.1, and the keywords and terms for the search are shown in table 2.1.

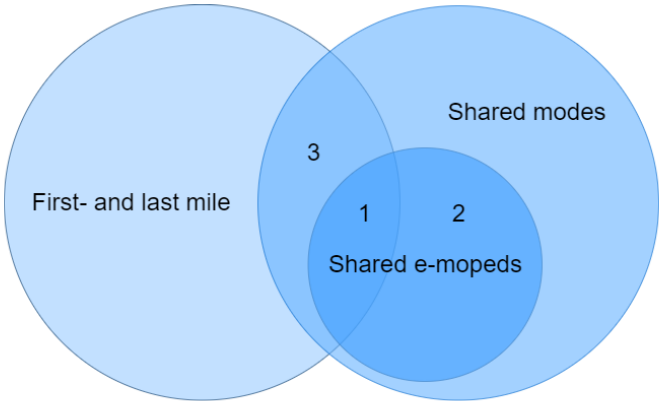


Figure 2.1: Venn Diagram of the Research Areas

Table 2.1: Keywords and Terms for Literature Search

Research Area	Kewords
1. Shared E-Mopeds in the First/Last Mile	”factors influencing” AND ”shared e-mopeds” OR ”shared electric mopeds” AND ”first mile” OR ”last mile” AND ”railway station”
2. Shared E-Mopeds in General	”factors influencing” AND ”shared e-mopeds” OR ”shared electric mopeds”
3. Shared Modes in the First/Last Mile	”factors influencing” AND ”shared mobility” OR ”shared micromobility” OR ”mobility as a service” (MaaS)” AND ”first mile” OR ”last mile” AND ”railway station”

The factors found are used to be selected from for the research. The key factors selected will be analysed.

2.3. Survey Design

The survey design will be shortly explained in this section, but will be explained more in detail in chapter 4.

2.3.1. Sample composition

A survey will be conducted among train travelers who are part of the NS panel, which consists of 80,000 email addresses of individuals who have agreed to participate in surveys. From this panel, a sample was requested to ensure a balanced representation across different genders and age groups. The total requested sample size consists of 600 train travelers, divided equally by gender, and categorized into three distinct age groups (figure 2.2).

To obtain a comprehensive sample overview, understand the impact of age on e-moped usage, and achieve a representative sample compared to train travelers, it is necessary to focus on younger age groups. This approach is based on the observation that e-moped users tend to be younger (Garritsen, 2022). The age groups were skewed towards a younger sample composition because more people tend to use shared e-mopeds when they are young, and because train travelers are typically younger.

- **Young Adults:** Ages 18-25
- **Middle-aged Adults:** Ages 26-45
- **Older Adults:** Ages 45+

The gender factor is also picked for the composition of the sample. Therefore, it will consist of six groups, with each gender represented across three age groups. Each group will contain 100 respondents. This number exceeds the minimum requirement of 30 individuals per age group for significance.

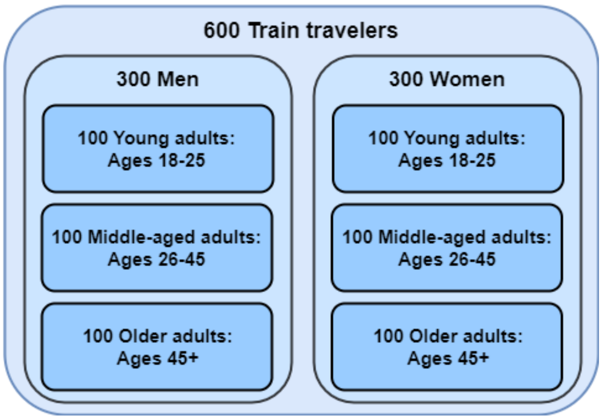


Figure 2.2: Sample composition overview

The extra respondents facilitate the examination of other factors, and helps achieving statistical significance when clustering in the latent class model.

2.3.2. Validity

The obtained sample composition will be compared with the composition of train travelers. This comparison aims to assess the validity and representativeness of the results.

2.3.3. Current travel behaviour and preferences

To further explore key factors and address the third sub-question, ”Which modes are substituted or complemented by e-moped use in first/last mile transportation when integrated at NS stations?”, the survey includes questions about current travel behaviors in the first and last mile. Additionally, questions about preferences regarding shared e-mopeds were implemented which could potentially influence the respondent’s travel choices. For the further design of the survey and the stated preference experiment, the answer on the first subquestion is needed. That is why the further survey design is explained in chapter 4. Here, the key factors are selected obtained from the literature review. Also, the design of the stated preference experiment is elaborated here. Finally, the survey structure is shown.

2.4. Analysis

The survey is analyzed in chapters 5 through 7. This section addresses the remaining sub-questions, providing sufficient information to ultimately answer the main research question in the conclusion.

Data transformation

The raw data collected from the survey is prepared for Exploratory Data Analysis and further analysis using Apollo in R, which requires the data to be in a wide format with each choice on a separate row.

Initially, the raw survey data was imported as a CSV file using the pandas library in Python. To uniquely identify each respondent, an ’ID’ column was added. Where possible, responses were converted into numeric codes using dictionaries. Open answers were analysed and categorized manually. Additionally, the column names were standardized to more accurately reflect their content.

Educational levels, occupation levels, and trip purpose were divided into a smaller number of groups, according to CBS sources (CBS, 2024). The postcodes were merged with a dataset from CBS with 5 measures of population density (CBS, 2022).

Data relevant to specific choice experiments was selectively filtered, reshaped to the wide format, and merged again with the initial dataset. Final adjustments involved filtering, addressing missing values, and refining the dataset. The processed data was then exported to a new CSV file, ready for further analysis. The data transformation code is shown in Appendix D.

2.4.1. Perceptions and behaviour

To address the second subquestion about the current behaviour and perceptions regarding shared e-mopeds, an exploratory data analysis was conducted. All questions related to current behavior and preferences were analyzed.

Factor Analysis

To further analyze train travelers' perceptions of shared e-mopeds, a factor analysis was conducted. This method combines related perceptions into a few underlying factors, simplifying later models by removing correlations among the original variables. Factor analysis was chosen over principal component analysis (PCA) because PCA focuses on data summarization without assuming an underlying structure, whereas factor analysis assumes an underlying structure in the e-moped perceptions. The maximum likelihood method was used for factor extraction, and varimax rotation was applied to improve interpretability by ensuring no correlation between the factors.

Logistic Regression

To understand the variables associated with previous use of shared e-mopeds, a logistic regression model was developed. This method was chosen because it is appropriate for binary classification problems, such as determining whether an individual has previously used a shared e-moped or not.

2.4.2. Stated Preference Experiment

Discrete choice modeling

For insights into the factors from the stated preference experiment, Discrete Choice Modeling is conducted. Discrete choice modeling is used to understand how individuals make a choice when presented with alternatives. As noted by Ben-Akiva and Bierlaire (1999), the model takes into account the attributes of the decision-maker, the options available, and the decision-making process.

Discrete choice modeling often relies on the Random Utility Maximization (RUM) decision rule (Tran & Mai, 2023). This is used to explain the decision-making process of an individual when choosing between different alternatives. Each alternative is evaluated based on its attributes, and the one with the highest utility is chosen (Aguiar et al., 2023). The utility of each alternative has a deterministic component which is observable, and a stochastic (random) component, capturing unobserved factors affecting the utility (Chorus, 2024).

Consider an individual n who faces a choice among a number of alternatives. The utility that the individual derives from alternative i can be represented as: further modeled as a linear combination of attributes of the alternatives, weighted by coefficients:

$$U_{in} = V_i + \varepsilon_{in} = \sum_m \beta_m \cdot x_{im} + \varepsilon_{in} \tag{2.1}$$

where:

- U_{in} is the overall utility of alternative i for individual n.
- V_i is the deterministic component of the utility.
- β_m is the weight or coefficient reflecting the importance of attribute m in the utility of the alternatives.
- x_{im} represents the value of attribute m for alternative i.
- ε_{in} is the stochastic component of the utility, capturing unobserved factors affecting the utility.

MNL model

The Stated Preference Experiment is initially analyzed using the Multinomial Logit (MNL) model, which is known for its simplicity and ease of use. This is the most well-known application using the framework of Random Utility Maximization is the Multinomial Logit (MNL) model (McFadden, 1986).

To derive the MNL model, it is assumed that the stochastic component of utility, ε_{ni}, is independently and identically distributed (i.i.d.) across the alternatives with an extreme value distribution (Cranenburgh, 2024). This implies that the random utility components of different alternatives are not correlated and follow the same probability distribution.

Given this i.i.d. assumption and the choice of the extreme value distribution for the stochastic component, the probability P that alternative i is chosen from a set J is given by the well-known multinomial logit formula:

$$P(Y=i)=\frac{e^{V_i}}{\sum_{j\in J}e^{V_j}} \tag{2.2}$$

where V_i is the deterministic component of the utility for alternative i.

The MNL model is often used for modeling choice behavior because of its straightforward methodology. This simplicity facilitates quick computations and assists in estimating preferences such as willingness-to-pay (Cranenburgh, 2024). The clarity of the results makes it interesting for making policy-making decisions. However, the analysis of the MNL model reveals several insignificant variables and some notable limitations. One major limitation is the Independence of Irrelevant Alternatives (IIA) property, which assumes that the relative odds of choosing between two alternatives are unaffected by other options. Additionally, the MNL model fails to account for unobserved heterogeneity, assuming homogeneous preferences across individuals

LC model

To address the issues of the MNL model, the latent class model (LCM) is employed. The LCM allows for different preference structures within distinct classes, thus relaxing the strict IIA limitation and capturing unobserved heterogeneity. LC models group people into different classes based on their behavior patterns. This allows the models to show how different groups of people have different preferences and decision-making processes (Hess, 2014).

In the LC model, we assume there are K latent classes in the population. The utility U_{ni}^k that individual n derives from choosing alternative i in class k is given by:

$$U_{ni}^k=\beta_k' x_{ni}+\epsilon_{ni}$$

where β_k are the parameters specific to class k, and ϵ_{ni} is the i.i.d. error term.

The probability that individual n belongs to class k is given by:

$$P_{nk}=\frac{e^{\gamma_k' z_n}}{\sum_{l=1}^{K}e^{\gamma_l' z_n}}$$

where γ_k are the parameters for class k and z_n are the covariates influencing class membership.

Within each class, the probability that individual n chooses alternative i is modeled using the MNL model:

$$P_{ni|k}=\frac{e^{\beta_k' x_{ni}}}{\sum_j e^{\beta_k' x_{nj}}}$$

The overall probability that individual n chooses alternative i is a weighted sum of the class-specific probabilities:

$$P_{ni}=\sum_{k=1}^{K}P_{nk}P_{ni|k}=\sum_{k=1}^{K}\left(\frac{e^{\gamma_k' z_n}}{\sum_{l=1}^{K}e^{\gamma_l' z_n}}\right)\left(\frac{e^{\beta_k' x_{ni}}}{\sum_j e^{\beta_k' x_{nj}}}\right)$$

The LC model thus captures the heterogeneity within the population by assigning a probability to each individual belonging to a latent class. This allows the model to account for varying preferences and decision-making processes across different segments of the population, leading to better-informed transport policies that effectively address the diverse needs and preferences of various groups (Hess, 2014).

A challenge within the LCM is determining the optimal number of latent classes. Overfitting can occur if too many classes are specified, while underfitting can occur with too few. Model selection criteria are used, but they are not foolproof (Watson et al., 2022).

This is why some transport studies use the Mixed Logit model (M. Ye et al., 2020). The Mixed Logit model allows for a continuous distribution of preferences across individuals. It can capture more complex substitution patterns and account for random taste variations. It provides greater flexibility by allowing parameters to vary randomly across individuals, potentially offering a more accurate representation of individual preferences (Greene & Hensher, 2003). Both models provide rich insights into behavior. However, the LCM can identify distinct subgroups within the population, offering more insights into heterogeneous preferences, which was preferred in this study (Hess, 2014).

The latent class model is suitable for this thesis because it enables seeing how different factors influence different groups of train travelers. This may improve the insight into the choices people make when considering the use of shared e-mopeds in the first and last mile. The data is analysed in R using the Apollo package. Apollo in R was chosen because it supports hybrid choice models (Hess & Palma, 2019), and because of the goal to gain proficiency in R.

2.4.3. Model selection criteria

In evaluating and comparing different statistical models, it is crucial to assess how well each model fits the observed data. This chapter focuses on several key metrics and criteria used to determine model fit, each with its own methodology and application. The principles and measures discussed here provide a comprehensive framework for model evaluation, ensuring that the selected model not only fits the data well but also maintains a balance between complexity and explanatory power.

Maximum Likelihood-principle

Parameter estimation based on the Maximum Likelihood-principle. Find the set of parameters that make the data the most likely. Outcome of process which estimates β by means of maximizing the LogLik-function $LL(\beta)$ presented beneath.

$$LL(\beta) = \ln\left(\prod_n \prod_i p_{ni}(\beta)^{y_{ni}}\right) = \sum_n \sum_i y_{ni} \cdot \ln\left(p_{ni}(\beta)\right) \tag{2.3}$$

Where:

- β is the vector of parameters to be estimated.
- ln denotes the natural logarithm, converting the product of probabilities into a sum for computational feasibility.
- The double product, $\prod_n \prod_i$, iterates over all groups n and within those, over all individual observations i.
- $p_{ni}(\beta)$ is the probability of observing the ith outcome in the nth group, given the parameters β.
- y_{ni} represents the observed outcome for the same index.
- The double summation, $\sum_n \sum_i$, accumulates the weighted logarithm of the probabilities across all observations, providing the log-likelihood.

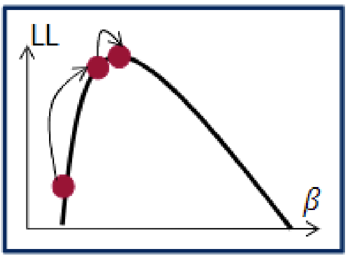


Figure 2.3: Estimation process

The final Log-likelihood can be used for the model fit.

McFadden's Rho-Squared

McFadden's rho-squared (ρ^2) is adapted for models estimated by maximum likelihood. It quantifies the proportionate reduction in uncertainty of the dependent variable afforded by the model in comparison to a baseline null model with no predictive variables.

The formula for McFadden's rho-squared is given by:

$$\rho^2 = 1 - \frac{\log(L_b)}{\log(L_0)} \tag{2.4}$$

where:

- L_b is the likelihood of the estimated model with all predictors included.
- L_0 is the likelihood of the null model, which includes no predictors apart from a constant; this corresponds to setting all regression coefficients β, except the intercept, to zero.

The ρ^2 statistic ranges from 0 to 1, where:

- A ρ^2 of 0 indicates that the model has no explanatory power, akin to making predictions by mere chance.
- A ρ^2 of 1, although not practically attainable, would signify a model with perfect predictive accuracy.

Importantly, McFadden's rho-squared does not have an established benchmark for what constitutes a 'good' fit. It must be interpreted in a relative sense, by comparing the fit of various models to the same dataset rather than against an absolute standard. McFadden's rho-squared indicates the percentage of initial uncertainty that is explained by the model.

Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is a widely used measure for model comparison, based on the concept of information entropy. It assesses the trade-off between the goodness of fit of the model and its complexity, penalizing the number of estimated parameters to avoid overfitting.

The formula for AIC is given by:

$$AIC = 2k - 2\log(L_b) \tag{2.5}$$

where:

- k is the number of parameters in the model.
- L_b is the likelihood of the estimated model.

Key points about AIC:

- A lower AIC value indicates a better model, as it suggests a good balance between model fit and complexity.
- AIC is most useful for comparing multiple models fitted to the same dataset; the model with the lowest AIC is preferred.
- It does not provide an absolute measure of fit quality but rather a relative measure, useful for model selection.

AIC helps in identifying the model that best explains the data without overfitting, ensuring a balance between precision and simplicity.

Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) is another criterion for model selection that, like AIC, considers both the goodness of fit and the model complexity. However, BIC incorporates a stronger penalty for the number of parameters, especially when the sample size is large.

The formula for BIC is given by:

$$BIC = k\ln(N) - 2\log(L_b) \tag{2.6}$$

where:

- k is the number of parameters in the model.
- N is the sample size.
- L_b is the likelihood of the estimated model.

Key points about BIC:

- A lower BIC value indicates a better model, similar to AIC.
- BIC penalizes model complexity more strongly than AIC, which can lead to the selection of simpler models, especially with large datasets.
- It is also a relative measure, used for comparing models fitted to the same dataset.

BIC is particularly useful when the goal is to find a model that generalizes well to new data, favoring simpler models to avoid overfitting.

By evaluating models using these criteria, a model is identified that not only fits the data well but also avoids overfitting, maintaining a balance between precision and simplicity. The model with the highest log-likelihood, a satisfactory McFadden's rho-squared value, and the lowest AIC and BIC values is typically considered the best model. This ensures robust model selection, catering to different aspects of model performance and generalizability.

3

Factors influencing mode choice

The main goal of this chapter is to provide an overview of factors that could influence the choice of transportation mode for the first and last mile of a journey, with a particular focus on shared e-moped usage. This is done with a literature review, with multiple searches to get a complete overview. After this chapter, key factors are identified that may influence the decision-making process in choosing a mode for the first and last-mile transportation. The key factors will be used as input for the survey, which is distributed amongst train travelers.

3.1. Mode choice factors

Stam et al., 2021 concluded that there are 6 different categories of factors influencing the mode choice in the first and last mile to railway stations (Figure 3.1).

- Traveller Characteristics
- Trip Characteristics
- Mode Characteristics
- Environment Characteristics
- Psychological factors
- Main stage factors

These six categories also serve as the subsections of this literature review. Within each section, all factors identified within that category are described, and their influence is explained. In each section, factors are examined that are documented in the literature concerning the use of shared e-mopeds in the first and last mile. Additionally, a broader search will be conducted to identify factors influencing the use of shared e-mopeds in general. Furthermore, factors will be examined based on studies regarding shared modes of transportation in the first and last mile. This approach aims to identify the factors that could influence mode choice in the first and last mile when shared e-mopeds are an option.

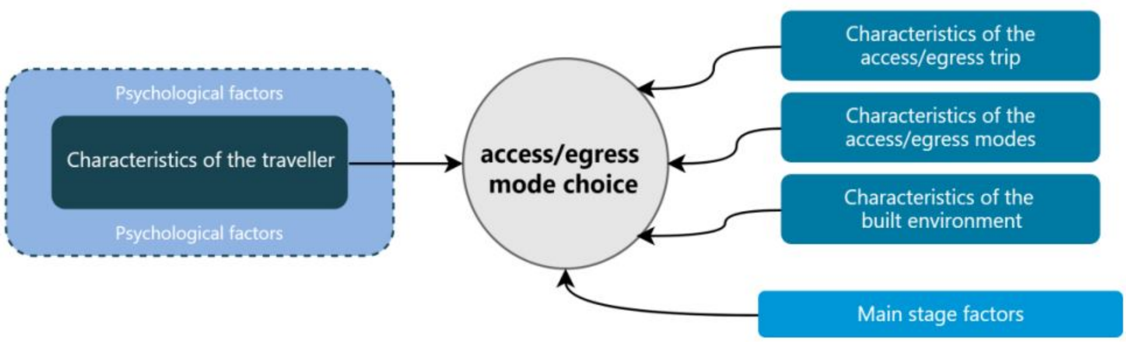


Figure 3.1: Mode choice framework (Stam et al., 2021)

3.1.1. Characteristics of the traveller

The characteristics of the traveler shape the individuals' personal and household situation (Stam et al., 2021). These factors may include socio-demographic elements as well as other distinctive individual factors.

Socio-demographic factors play a significant role in people's decisions to utilize shared e-mopeds for their first and last-mile transportation needs, as highlighted by de Wit (2023), Garritsen (2022), and Van Kuijk et al. (2022). These studies suggest that **age** is a key factor, negatively influencing the choice towards the shared e-moped in the first and last mile. Van Kuijk et al. (2022) concludes that people up to the age of 26 are more willing to use the shared moped than older people. Garritsen (2022) further explores the influence of **gender** and **education**, concluding that younger, highly educated males are more likely to utilize e-mopeds for their first and last miles.

In addition to socio-demographic factors, Garritsen (2022) found that individual characteristics such as possessing a **driver's license**, **digital skills**, and **previous experience** with e-mopeds play crucial roles. The requirement of a driver's license for e-moped use limits the potential user base, while digital skills are necessary for navigating the app of the e-moped sharing provider (Garritsen, 2022). Previous experience with e-mopeds also emerges as a significant factor, as familiarity may reduce perceived barriers to usage (Arendsen, 2019; Garritsen, 2022; Horjus et al., 2022; Loudon et al., 2023).

Expanding the perspective, recent studies by Eccarius et al. (2023) and Hoobroeckx et al. (2023) have investigated factors influencing shared e-moped usage more broadly. They found that **owning a personal vehicle** tends to discourage the use of shared e-mopeds, but following the study of (Stam et al., 2021) this is only a factor influencing the first mile. Other research on e-moped use in general looked at the impact of more socio-demographic factors like **occupation** and **income**. Income is stated as a positive impact the use of these vehicles (Aguilera-García et al., 2021; Eccarius et al., 2023; Hoobroeckx et al., 2023; Vega-Gonzalo et al., 2024). Looking at occupation, Aguilera-García et al. (2021) found that a lower interest in adopting moped sharing is found among employed, housework, unemployed, or retired people, compared to students.

Existing literature suggests that various traveler-related factors influence the decision to use shared e-mopeds for first and last-mile transportation.

Socio-demographic factors play a significant role in the use of shared e-mopeds. Research shows that the typical user of shared e-mopeds is often a young, highly educated male. Understanding how factors like age affect preferences across different age groups is essential for this study. Additionally, there is a notable gap in research regarding why male users are more prevalent in shared e-moped usage. Furthermore, aspects such as occupation or income have generally been examined in the broader context of e-moped usage, rather than specifically for first and last-mile transportation. Thus, focusing on these factors could provide valuable insights for this study.

Individual characteristics, such as having a driver's license and prior experience, are also relevant. Owning a vehicle may only impact the first mile, as not many people have a vehicle for the last mile. The absence of a driver's license can prevent individuals from using shared e-mopeds. Conversely, prior experience suggests that users do not face barriers like a lack of digital skills when using these services.

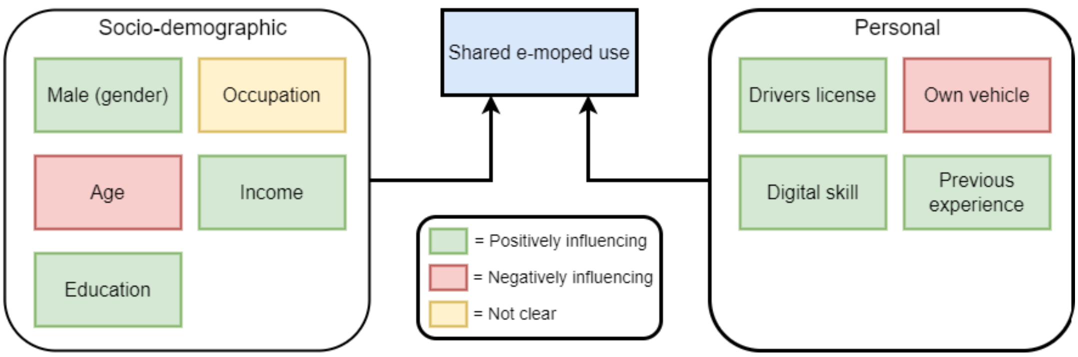


Figure 3.2: Traveler characteristics influencing

3.1.2. Trip Characteristics

Trip characteristics refer to the specific attributes or features of a journey. In essence, trip characteristics include all trip-specific determinants (Stam et al., 2021).

In exploring research on e-moped usage for first and last-mile travel, limited attention has been given to trip characteristics. However, a crucial factor influencing e-moped utilization is the **timing of the trip**, as highlighted by de Wit (2023) and Van Kuijk et al. (2022). This encompasses both the time of day and the day of the week. The influence of the day of the week remains unclear. Van Kuijk et al. (2022) discovered a preference for shared vehicles in the suburban first and last mile on weekends, contrasting with a lesser preference in urban areas. Conversely, de Wit (2023) determined that the average trip count is notably higher during weekdays compared to weekends, yet also noted varying results in existing studies.

Literature on e-mopeds in general and shared modes in the first and last mile acknowledge the time and cost factors (Chen et al., 2023; Hector, 2022; Torabi K et al., 2022; Tzouras et al., 2023; Yan et al., 2021). Hoobroeckx et al. (2023) showed a dislike for longer rides and higher ride fees, resulting in lower e-moped usage. Other studies examining factors affecting e-moped use more broadly provide greater insight into trip characteristics. Hoobroeckx et al. (2023) showed the **trip distance** and the **trip purpose** as influential factors on e-moped use. The contribution to the utility of an increasing trip distance peaks at five kilometers and then starts to drop. This, while the e-moped trip in the first and last mile is around 3 km on average (de Wit, 2023). For the trip purpose, Hoobroeckx et al. (2023) concluded that there is an increased preference for using shared e-mopeds when related to leisure rather than for commutings.

Additionally, the study by Loudon et al. (2023) highlighted that the requirement to transport **luggage** during a trip could affect the valuation of various other attributes. This observation has been corroborated in several other studies concerning shared modes of transportation in the first and last mile (Stam et al., 2021; Torabi K et al., 2022).

Previous research on shared e-mopeds for first and last-mile travel has highlighted the importance of trip distance, trip purpose, and the time of day or week. Additionally, other studies frequently use travel time and travel cost as key comparative factors due to their impact, measurability (in minutes and euros, respectively), and ease of comparison. Luggage is mentioned less in the literature.

3.1.3. Mode characteristics

Mode characteristics refer to the distinct factors that are related to the means of transport (Stam et al., 2021).

In the studies conducted by Garritsen (2022) and de Wit (2023) on shared e-mopeds in the first and last mile, the most important mode characteristic identified is the **walking distance** towards a mode. This walking distance refers to the distance required to walk to access a mode, such as a shared e-moped. In these studies, the walking distance towards the mode came up as negatively influencing the e-moped usage in the first and last mile. Garritsen (2022) also highlighted the user-friendliness of the e-moped as a factor influencing modal choice, which other studies refer to as **convenience** (Hector, 2022; Loudon et al., 2023). Convenience refers to the ease of accessing and using a transport mode. de Wit (2023) added the importance of e-moped **availability**, which significantly affects the usage of shared e-mopeds in the last mile positively with 4.8 trips per day per extra vehicle available at an NS station (de Wit, 2023).

Understanding the characteristics of transportation modes is essential for mode choice in first and last-mile connectivity. The walking distance towards a mode seems to influence the first and last mile. And since the shared e-moped use at railway station often involves some walking, this is a significant factor in the mode choice regarding shared e-mopeds. Convenience and availability also play important roles. Convenient and easily accessible e-mopeds promote usage, and a higher number of e-mopeds at stations increases the number of trips.

3.1.4. Environment characteristics

The environment characteristics refer to the features and conditions of the surrounding built environment (Stam et al., 2021).

From the literature on e-mopeds in the first and last mile, de Wit (2023) came with 2 factors influencing the mode choice. **Population density**, which measures the number of people living per unit of area, is found to have a negative influence on e-moped use in the first and last mile. This is explained by the fact that in highly density areas people live closer to their destination, which means people do not need a shared e-moped (de Wit, 2023). The other factor is **visibility**, which shows whether shared e-mopeds are directly visible from the station, also positively influencing the e-moped use (de Wit, 2023).

Research on shared e-moped in general stated that external factors such as **weather** conditions influence the valuation of other attributes (Loudon et al., 2023). Rain, as a condition of the surrounding environment, is negatively influencing the e-moped use.

Investigating the impact of population density on shared e-moped usage could provide valuable insights for the NS, particularly in understanding in what cities to implement policy measures. The visibility has not been sufficiently explored in research. Also, examining the role of visibility in influencing shared e-moped usage could be of great value, as it is a factor that NS can directly affect.

3.1.5. Psychological factors

Psychological factors refer to the individual cognitive, emotional, and perceptual elements that affect how people select a particular mode of transportation for their travel needs.

In the literature focusing on shared e-mopeds use in the first and last mile, only **social influence** and **habits** are described as factors (Garritsen, 2022; Van Kuijk et al., 2022). Social influence in this context refers to the extent to which users perceive to be influenced by others, like friends, family, or other authority figures. Garritsen (2022) found that social influence was the most influencing predictor for the shared e-moped use. This factor has not been further explored in the literature. Habits, on the other hand, have been consistently identified as influencing mode choice (Chen et al., 2023; Eccarius et al., 2023; Montes et al., 2023; Van Kuijk et al., 2022). Montes et al. (2023) found that the perception of shared e-mopeds is positively affected by the frequency of use of public transport. Van Kuijk et al. (2022) showed that people who ride their bike in the first mile, are less likely to use suburban non-cycling micro modes in the activity-connected leg. Horjus et al. (2022) concludes that the intention to use the bus or tram is found to be mainly related to habits (current transport usage). The intention for the use of public transport is higher for both people who used public transport more than once a week and people who used cars less than once a week in the past year.

However, when examining the literature on shared e-mopeds in general, additional factors emerge. Chen et al. (2023) highlighted **attitude towards the service** as an important factor. This factor pertains to reflect an individual's evaluation of what the positive and negative outcomes of e-moped sharing might be. Favorable attitudes toward involving present e-moped-sharing schemes and are likely to accept and use the services (Chen et al., 2023). **Environmental awareness** has also been shown to influence mode choice (Aguilera-García et al., 2021), positively influencing the e-moped usage.

When looking at studies on shared modes in the first and last mile **safety perception** also came up as an important factor to take into consideration (Loudon et al., 2023). Kim et al. (2021), who studied other modes in the first and last mile found that the effect of safety perception on the mode choice behavior in time unit was found as same as between 3.17 and 5.06 minutes. In other literature focused on shared modes for the first and last mile, the factor of **mode preference** was identified (Arendsen, 2019). This factor involves the preference for other modes, like cars for example, resulting in a negative influence on e-moped usage. Arendsen (2019) found that costs and in particular time attributes are found to be less important than the intrinsic mode preference.

The exploration of psychological factors play a crucial role in this thesis, aiming to get to know the motivations behind individuals' preferences for shared e-mopeds. By integrating the factors found in the different categories of literature into a survey, the research could gain a deeper insight into what influences people's choices in transportation.

3.1.6. Main stage factors

The main stage factors are the factors of the NS train trip that can influence the mode choice in the first and last mile. Research by de Wit (2023) highlighted that the **Railway station type** plays a role in the e-moped use in the first and last mile. Specifically, he concluded that intercity stations positively impact the e-moped use for the first and last mile of the journey.

Examining how the type of NS station influences shared e-moped usage could offer crucial insights for NS, particularly in identifying which NS station could benefit from targeted policy interventions.

3.2. Summary

The factors that have been found from the literature are logged in Table 3.1. This table displays these identified factors, along with their associated literature references. The factors identified are on the right side, divided in the categories mentioned per subsection in this literature review. The columns across the top list are the studies found, and each cell marked with an 'X' indicates that the corresponding study covered that particular factor. This layout allows for a quick overview of which factors have been frequently examined in the literature and which might still need more research focus.

The scientific literature is divided into three categories, separated by black lines. The first category focuses on research concerning shared e-mopeds in the first and last mile, with case studies from the Netherlands. These studies provide the most relevant factors for this thesis, as the subjects of the studies align closely with its focus. The second category comprises studies that examine factors affecting the use of e-mopeds in general. These factors influence the use of shared e-mopeds, though they may not specifically align with their use in the first and last mile. The third category encompasses research on all shared modes in the first and last mile. It addresses shared modes in general, without specifically focusing on shared e-mopeds.

	Modes in the first/last mile																	*E-mopeds in general*							*E-mopeds in the first/last mile*				
Number of times mentioned	Zhang et al. (2023)	Schwinger et al. (2022)	Kim et al. (2021)	Fan et al. (2019)	Arendsen (2019)	Hector (2022)	Stam et al. (2021)	Yap et al. (2016)	Torabi K et al. (2022)	Edel et al. (2021)	Fearnley et al. (2020)	Javadiansr et al. (2023)	Yan et al. (2022)	Tzouras et al. (2023)	McQueen and Clifton (2022)	Horjus et al. (2022)	Montes et al. (2023)	Hoobroeckx et al. (2023)	Loudon et al. (2023)	Eccarius et al. (2023)	Aguilera-García et al. (2021)	Fiorini et al. (2022)	Vega-Gonzalo et al. (2024)	Chen et al. (2023)	Van Kuijk et al. (2022)	de Wit (2023)	Garritsen (2022)		
8				X			X				X				X			X		X			X				X	Gender	Traveller
11			X		X		X									X	X			X	X		X		X	X	X	Age	
3							X														X						X	Drivers license	
3							X											X		X								Own vehicle	
5					X						X					X						X					X	Education	
2																X											X	Digital skill	
4							X														X	X	X					Occupation	
5																		X		X	X		X	X				Income	
7					X											X	X		X		X		X				X	Previous experience	
3							X											X								X		Trip distance	Trip
6		X					X										X	X			X					X		Trip purpose	
4							X														X				X	X		Time of day / week	
3							X		X										X									Luggage	
9						X			X	X			X	X	X		X		X					X				Travel time	
10					X	X			X				X	X	X		X	X	X					X				Trip costs	
3						X													X								X	Convenience	Mode
8				X		X												X	X			X				X	X	Availability	
10	X			X		X	X											X	X			X		X		X	X	Walking distance	
6												X									X	X	X		X	X		Population density	Env.
2	X																									X		Visibility	
6							X		X			X						X	X							X		Weather	
2					X	X																						Mode preference	Psychological
4			X					X											X		X							Environmental awareness	
1																											X	Social influence	
7								X		X					X		X			X	X			X				Attitude	
4																	X			X				X	X			Habits	
4			X									X		X					X									Safety perception	

Table 3.1: Summary of literature on shared e-moped use and shared modes in first/last mile

Patterns evident in the table primarily highlight the distinctions among various categories of research. Firstly, studies focusing on shared e-mopeds in the first/last mile show a lack of investigation into factors such as ’own vehicle’, ’occupation’, ’income’, ’luggage’, ’travel time’, and ’travel cost’. These factors are thoroughly examined in other research categories. Additionally, there is a noticeable lack of research on psychological factors within this category.

Secondly, there is a high amount of varied factors in the research concerning shared e-mopeds generally, not specific to the first or last mile. This suggests a broader scope of research interests in studies that consider shared e-mopeds in a general context.

The most frequently mentioned factors across studies are ’gender’, ’age’, ’previous experience’, ’travel time’, ’travel cost’, and ’walking distance’. Notably, travel time and travel cost are overlooked in studies focusing on shared e-mopeds for first and last mile travel.

Conversely, factors such as ’digital skill’, ’visibility’, ’mode preference’, and ’social influence’ are mentioned less often in the literature. Thus interesting to take into account in this thesis.

Figure 3.3 categorizes the various factors related to shared e-mopeds in the first/last mile, shared e-mopeds generally, and shared modes in the first and last mile. These factors are presented in different sizes; the larger the font, the more frequently these factors are mentioned in the literature. This presentation aims to provide a clearer overview of the system. While this format helps visualize the prominence of each factor, it does not definitively determine their impact on mode choice.

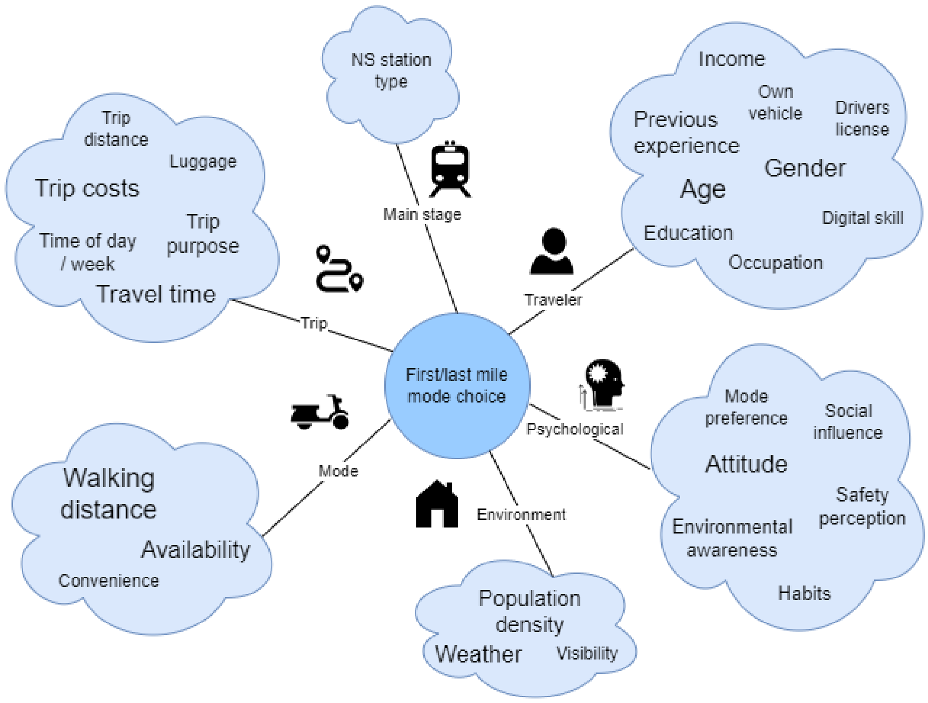


Figure 3.3: Factors influencing the mode choice in the first and last mile

The identified factors come from literature, categorized into three fields. This provides an overview of the possible factors influencing the mode choice of train travelers in the first and last mile. However, it does not confirm that these factors are indeed significant for train travelers. Identifying these factors is crucial for understanding mode choice in the first and last mile for train travelers. This is important for the rest of the study, which involves a comprehensive approach that combines different analyses, examines preferences, and explores substitution patterns. Also, this study will capture the diversity among travelers, showing that the factors may impact some segments of the population differently than others. This is a novel approach in studies on shared e-mopeds, which will be done through a survey conducted among train travelers with various components. The selection of the key factors and the design of this survey is elaborated on in the next chapter, ’Survey design’.

4 Survey Design

To address the second, third and fourth subquesitons, a survey is conducted. The survey includes questions on the current travel behaviour and preferences, combined with a stated preference experiment. The design of the components in this survey are elaborated in this chapter. First, the key factor that influence selecting shared e-mopeds in the first and last mile and that are relevant are selected. Then, the design of the questions are elaborated. Next, the rationale behind the stated preference experiment is discussed. Lastly, the structure of the survey is outlined.

4.1. Key Factor Selection

Not all factors identified in the literature review are examined in this research. A selection of key factors was made based on previous literature, interest, and policy relevance. These key factors were further analyzed for their impact on the likelihood of choosing a shared e-moped. The factors were categorized according to the classifications established by Stam et al. (2021). The selection process for these factors is explained here.

For this study, it is beneficial to consider as many traveler characteristics as possible. This approach can help in forming latent classes and identifying patterns among different groups. However, income is excluded as a characteristic because people are often reluctant to disclose it. This exclusion aims to prevent hesitancy in survey participation and incomplete data.

Environmental factors and main stage factors are not considered key factors in this study. The focus is on the traveler rather than the surrounding environment. While the population density of the traveler's home area is considered, factors like the environment in the last mile are not included.

All psychological factors are included in this study since the perception of shared e-mopeds is a primary focus. The perception of shared e-mopeds has not been extensively researched before.

Travel distance and trip costs have been adequately covered in the literature concerning the first and last mile context or shared e-mopeds in general, but not specifically regarding e-moped usage in the first and last mile. The trip purpose provides valuable information for later calculations on the number of shared e-mopeds needed at a specific railway station.

Additionally, the impact of key factors that can be influenced by policy is studied. Walking distance to a mode and the convenience of a mode can be affected by policymakers. Availability is not researched in this study, as the objective is to understand the behavior of train travelers assuming the shared e-moped is always available.

Category	Factors
Traveler Characteristics	Gender, Age, Education, Occupation, Previous Experience, Driver's License, Own Vehicle
Trip Characteristics	Trip Distance, Trip Purpose, Travel Cost
Mode Characteristics	Walking Distance, Convenience
Psychological Factors	Social Influence, Environmental Awareness, Safety Perception, Attitude Towards the Service, Habits

Table 4.1: Factors Influencing Mode Choice

4.2. Current Behaviour and Preferences

The survey begins by asking respondents about their previous use of shared e-mopeds. If a respondent has used shared e-mopeds before, they will be directed to questions regarding their use of the shared e-moped for the first or last mile of their journey, including inquiries about their reasons for using it and the purpose of their trips. For respondents who have not chosen shared e-mopeds before, the survey will direct them to questions identifying the barriers that prevented them from choosing this mode of transport.

For understanding travel habits, the survey includes questions about the frequency of use of six different modes of transport: Train, Car, Bike, Walking, Bus/Tram/Metro (BTM), and shared e-mopeds. A 7-point scale is used, ranging from 'Never' to '4 or more days per week'. This scale is consistent with the one used in national travel research conducted by CBS.

To assess other psychological factors, the survey employs a 5-point Likert scale. For each factor, one or two questions are asked. The factors examined include 'Social Image', 'Attitude', 'Environmental Awareness', 'Safety', and 'Ease of Use'. This approach allows for a detailed understanding of the respondents' perspectives on these important aspects.

4.3. Stated preference experiment

A stated preference experiment is done with hypothetical scenario's in the last mile. If the experiment would be with both the first and last mile, the choice task would be too long or too many respondents will be needed. The last mile is chosen for this trip, because e-mopeds are more often used in the last mile than in the first mile (Van Kuijk et al., 2022).

4.3.1. Alternatives

For the selection of the alternatives, the most recent NS dataset (2023) of the first and last mile is analyzed. BTM stands for Bus, Tram, and Metro.

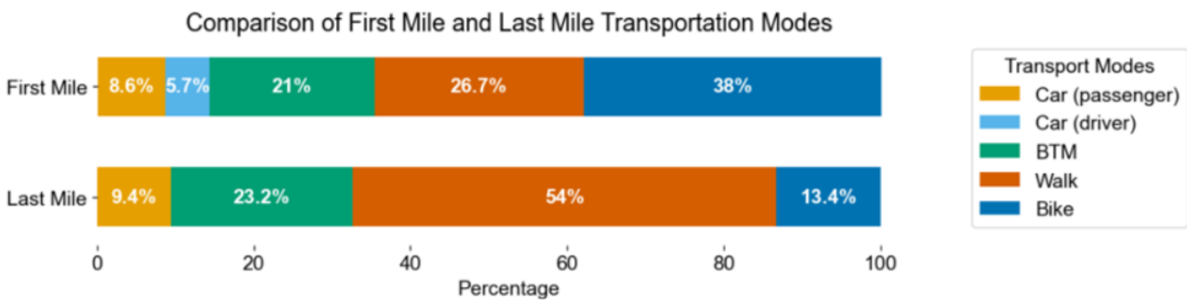


Figure 4.1: Modal split in the first and last mile (NS, 2023)

As shown in Figure 4.1, the primary modes of transportation for the last mile in 2023 were walking, cycling, public transportation, and car usage as passenger (NS, 2023). The choice of transportation varies between the first and last mile due to personal ownership of bicycles or cars, which influences the options available in the first mile (Leferink, 2017). However, bicycle usage remains prevalent in the last mile, including a 1 out of 5 contribution from the use of the (shared) OV-fiets, a bike-sharing service provided by NS (NS, 2023). Next to this OV-fiets, other companies are extending to shared bikes, with some following the same 'free-floating' model as shared e-mopeds. There has also been an increase in walking for last-mile travel, likely due to the shorter distances typically involved. Car use in the last mile predominantly involves traveling as a passenger. Since the stated preference experiment focuses on the last mile, the other alternatives with the largest modal shares will be researched:

Figure 4.2: Mode alternatives in the SP experiment

4.3.2. Context

In the stated preference survey, we examine two specific trip distances to understand people's transportation choices comprehensively. The selected distances are 1.5 km and 3 km. These distances were chosen for several reasons. First, they are ranges where all transportation alternatives have a notable impact, as shown in Figure 4.3. Second, the average last-mile trip distance is 2 km, with more than 80% of last-mile trips falling within 3 km at the stations were the OV-fiets is available, according to NS (2023). Trips shorter than 1.5 km are predominantly taken on foot, and the likelihood of using a shared e-moped for such short distances is assumed to be minimal.

The distance of 3 km represents the average trip length for shared e-moped usage in the context of first and last-mile travel, as documented by de Wit (2023). Additionally, an analysis of shared e-moped provider apps shows that only a few cities offer trips of more than 3 km from a railway station without another station being within reach.

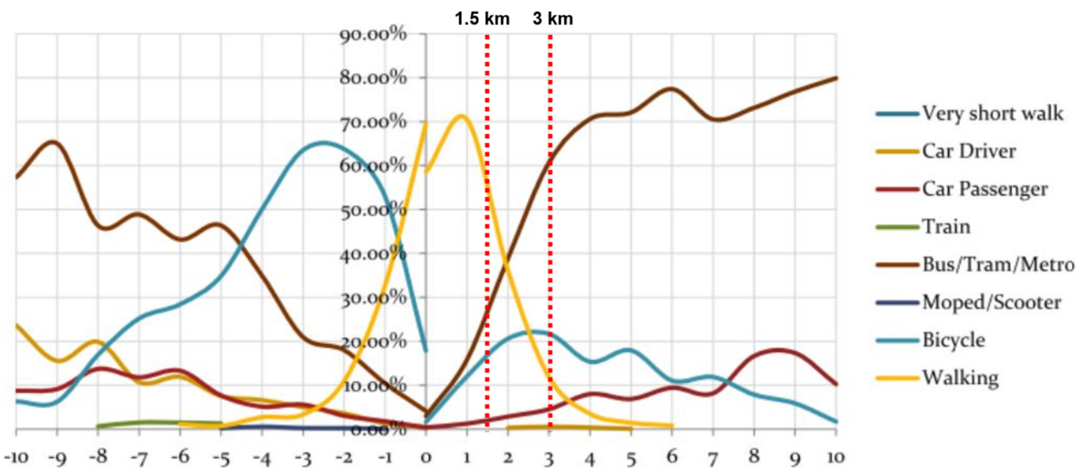


Figure 4.3: Distance-decay graph for the first mile (left) and last mile (right) trip between 2010 and 2015, with distance in kilometers (Source: (Leferink, 2017))

Furthermore, a general context for the trip will be established, placing it in an unfamiliar city to ensure that participants do not have access to their personal vehicles. Factors such as weather, luggage, and time of day will remain undefined, allowing the experiment to be applicable to a wide range of trip scenarios.

4.3.3. Attributes

In the design of the stated preference survey, attributes were selected to measure their impact on the mode choice. Attributes that needed to be included were the travel time and cost as main attributes, given their frequent discussion in transportation research and because they are easily measurable.

Furthermore, it is crucial that the attributes selected can be influenced, either directly or indirectly, by policy interventions. Hence, walking time and convenience are identified as significant attributes. Convenience can be measured by the time spent searching for an e-moped (navigating through the app, selecting the e-moped) or waiting on the BTM, while walking distance can be quantified by the number of minutes it takes to walk to the vehicle. Both allow for comparison across different options.

- In vehicle time (minute)
- Walking time (minute)
- Convenience (search/rent/wait) (minute)
- Total cost (euro)

Range of attribute levels

The range of the attribute levels must include all current and potential future options to guarantee inclusiveness and precision. At the same time, the ranges should be broad to increase the validity and reliability (Sarikhani et al., 2021). To ensure the attributes remain orthogonal, thus simplifying the analysis, equal spacing between levels should be maintained. The middle-level ranges are the realistic average attribute level.

The in-vehicle times were gathered through an exploration on Google Maps. For ten different NS stations (with different types of stations), three points were selected at 1.5 km or 3 km distances. The in-vehicle times were extracted per mode for all points, and the average time per mode was taken to represent the middle-range attribute. The in-vehicle times for shared e-mopeds were gathered by choosing the car option but only considering roads with a speed limit of 50 km/h, as this experiment focuses on 45 km/h shared e-mopeds.

The costs were obtained from different mode provider websites. For the shared e-mopeds, an average was calculated from the costs per minute of Felyx, Check, and Go Sharing found in their app. These costs were determined by multiplying the costs per minute by the travel times found on Google Maps. For shared bikes, an average was also taken from different providers. Some providers charge per minute, like Donkey Republic, while others have a 24-hour tariff (NS OV-Fiets). These 24-hour tariffs were divided by 2, assuming a minimum of two trips (including the return trip). For public transport, an average cost per kilometer was calculated for the bus, tram, and subway from public transport websites (9292, 2024). For all modes, the cheapest and most expensive options currently available on the market were considered.

The walking time for buses, trams, and metros (BTM) is also based on Google Maps data from different NS station types. The same walking distances were used for the shared bike and shared moped. To determine the convenience factors of waiting time for BTM, operations of GVB, a Dutch bus company, were analyzed. The convenience of renting the shared e-moped or shared bike was assessed by consulting multiple users of the OV-fiets and shared e-mopeds.

Attribute	Range, 1.5 km	Range, 3 km
Shared e-moped		
Convenience (search/rent)	1, 2, 3 min	1, 2, 3 min
Walking time	2, 4, 6 min	2, 4, 6 min
In vehicle time	4 min	7 min
Cost	1, 2, 3 euro	3, 4, 5 euro
Shared bike		
Convenience (search/rent)	1, 2, 3 min	1, 2, 3 min
Walking time	2, 4, 6 min	2, 4, 6 min
In vehicle time	6 min	12 min
Cost	1.10, 2.80, 4.5 euro	1.5, 3, 4.5 euro
Public transport		
Convenience (search/wait)	3, 6, 9 min	3, 6, 9 min
Walking time	2, 4, 6 min	2, 4, 6 min
In vehicle time	9 min	16 min
Cost	0.80, 1.40, 2 euro	1, 1.70, 2.40 euro
Walking		
In vehicle time	20 min	40 min

Table 4.2: Range of attribute levels in the last mile

4.3.4. Construction of the choice sets

The choice sets are constructed in the Ngene software (Appendix E). Here, a d-efficient design of 6 rows was created for each experiment. The efficient design helps avoiding dominance, and requires a smaller number of choice sets versus orthogonal designs.

$$\text{min. \# choices sets} = \left(\frac{\text{\# parameters}}{2}\right) + 1 = 4.5 + 1 = 5.5 = 6$$

The design is divided into 2 blocks, so that every respondent has to fill in 3 choice tasks for each experiment (6 per respondent).

To achieve an efficient design, having prior knowledge is important. This involves making the best possible estimates of the values of parameters that will be used in the models. These estimated values are referred to as ”priors.” In this study, the priors are based on research conducted by Hoobroeckx et al. (2023) and Loudon et al. (2023). Loudon et al. (2023) investigated the choice of e-mopeds in a broader context, while Hoobroeckx et al. (2023) estimated explanatory variables and the value of ride fee savings associated with shared e-mopeds.

4.4. Survey structure

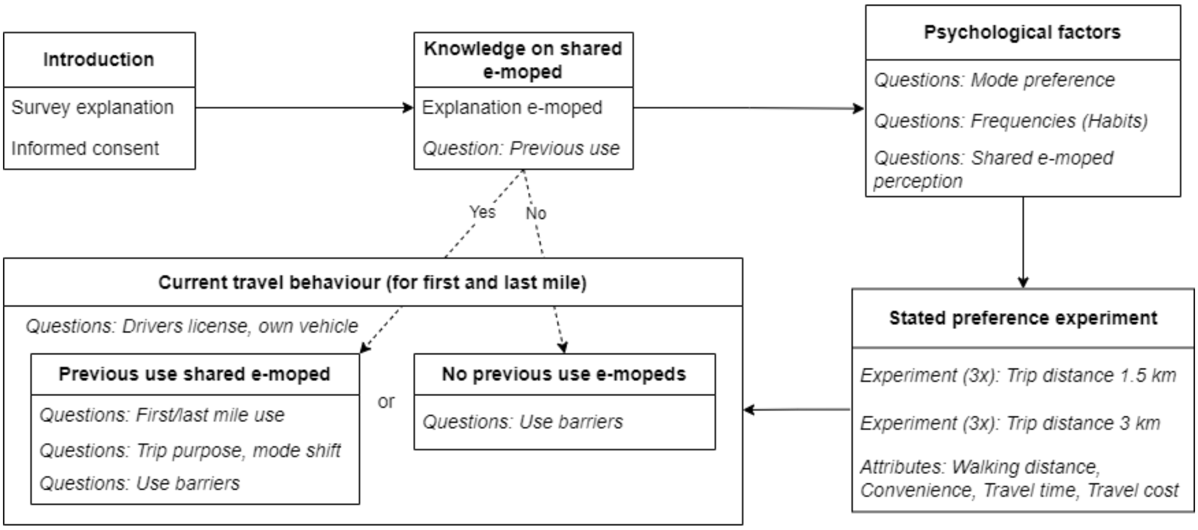


Figure 4.4: Survey structure

The survey is divided into five main sections, the full survey can be viewed in appendix C.

The survey begins with an introduction that explains its objectives and procedures in detail. Participants are also presented with an informed consent form, which they must agree to before continuing.

The next section ensures that all participants have a basic understanding of shared e-mopeds. It starts with an explanation of what shared e-mopeds are and then asks participants if they are familiar with or have ever used a shared e-moped.

Following this, the survey explores the psychological aspects that influence participants' travel choices. This section includes questions about mode preferences, habits, and perceptions of shared e-mopeds.

The subsequent section is a stated preference experiment that simulates different travel scenarios. Participants are presented with six various trip scenarios involving different distances (1.5 km and 3 km). Each scenario includes attributes such as walking distance, convenience, travel time, and travel cost.

In the final section, there are two paths depending on whether participants have used a shared e-moped before. First, everyone is asked about their ownership of personal modes of transport and driver's licenses. For participants who have used a shared e-moped, there are questions about their travel behavior using shared e-mopeds for the first and last mile. For participants who have not used a shared e-moped, the survey explores the reasons why they have not used shared e-mopeds, including questions to identify barriers to using this mode of transport.

5

Current behaviour and perception

5.1. Sample Composition

This chapter presents the composition of the sample. There is a difference between the sample composition that was requested and the sample that was obtained. This discrepancy arises because not all individuals who were asked to complete the survey did so. In the actual sample composition, the gender category includes 'unknown' because the initial survey for joining the NS panel did not require all questions to be answered.

Table 5.1: Sample Composition: Requested vs. Obtained

Category	Requested	%	Obtained	%
Gender	Female	50%	Female	45%
	Male	50%	Male	53%
			Unknown	1.4%
Age	18-25 years	33%	18-25 years	23%
	26-45 years	33%	26-45 years	37%
	45+ years	33%	45+ years	40%

The obtained sample composition differs from the requested one, resulting in a higher proportion of males and older individuals than desired. This discrepancy could lead to a sample composition that deviates further from that of typical rail train travelers.

Other demographic characteristics of the respondents in the sample are shown in Table 5.3 on the left side. Similar to age and gender, information on occupation, education, and postcodes was previously collected from the individuals in the NS panel.

The urbanity was linked to a dataset from the CBS, where postcodes were associated with urbanization levels. The urbanization levels based on average address density per square kilometer are as follows (CBS, 2022):

1. **Not urbanised**: <500 addresses/km².
2. **Hardly urbanised**: 500–1000 addresses/km².
3. **Moderately urbanised**: 1000–1500 addresses/km².
4. **Strongly urbanised**: 1500–2500 addresses/km².
5. **Extremely urbanised**: ≥2500 addresses/km².

The education levels can be explained as follows (CBS, 2024):

1. **Low (Level 1)**: Primary education.
2. **Secondary (Level 2)**: Senior general secondary education (HAVO) or pre-university secondary education (VWO), secondary vocational education (MBO 2, 3, or 4).
3. **High (Level 3)**: Higher vocational education (HBO), university degrees (WO), doctoral studies.

Table 5.2: Demographics Sample Composition of Participants (N = 641)

Category	Subcategory	%	Train traveler[1]	%
Gender	Female	45%		
	Male	53%		
	Unknown	1.4%		
Age	18-25 years	23%	18-25 years	33%
	26-45 years	37%	26-45 years	39%
	45+ years	40%	45+ years	28%
Occupation	Employed	50%	Employed	78%
	Retired	17%	Retired	3%
	Student	19%	Student	11%
	Unemployed	4%	Unemployed	4
	Unknown	11%	Unknown	4%
Education	Level 1	1%	Level 1	15%
	Level 2	33%	Level 2	40%
	Level 3	61%	Level 3	45%
	Unknown	6%		
Urbanity	Not urbanised	7%	Not urbanised	14%
	Hardly urbanised	8%	Hardly urbanised	14%
	Moderately urbanised	13%	Moderately urbanised	16%
	Strongly urbanised	30%	Strongly urbanised	24%
	Extremely urbanised	36%	Extremely urbanised	31%
	Unknown	5%		
Drivers license	Yes	74%	Yes	84%
	No	26%	No	16%

[1] Source: CBS, 2023.

Comparison to train traveler

The sample composition is compared to the general composition of train travelers. Since all respondents are train travelers, this comparison is crucial for drawing conclusions about train travelers in general. Data on the composition of train travelers was obtained from CBS, which provided the number of train trips per day per individual per group (CBS, 2023). These numbers were multiplied by the number of people in each group (also from CBS), resulting in an estimate of the number of people in each group using the train.

The gender distribution in the sample shows 45% female, 53% male, and 1.4% unknown. The gender distribution of train travelers is not known, but it is assumed that it will not differ much from the sample composition, as their participation in traffic changes every year but is mostly around 50-50 (CBS, 2021).

For all other variables (Age, Occupation, Education number, Urbanity, and Drivers license), the Chi-squared test results indicate significant differences between the observed and expected frequencies. This suggests that the distributions of these variables in the sample data do not match the train traveler data.

In terms of age, the sample has an overrepresentation of older participants (45+ years) and an underrepresentation of younger train travelers (18-25 years). This, while skewed sample composition was intentional to get more respondents of a younger age.

Occupation-wise, there is a significant discrepancy, with a much lower representation of employed individuals and higher proportions of retired and unknown participants in the sample.

For education, there is an underrepresentation of participants with lower education levels (level 1) and an overrepresentation of those with higher education levels (level 3) in the sample.

The urbanity of participants reveals an overrepresentation of very strongly urban participants and an underrepresentation of not urban and slightly urban participants in the sample.

Lastly, regarding driver's license ownership, there is a lower proportion of participants with a driver's license in the sample compared to the real train traveler population.

Overall, the sample composition is similar when looking at the relative proportions. However, there are some significant differences in most of the demographic categories compared to the actual train traveler population. These discrepancies, particularly in age, occupation, education, and drivers license suggest that the sample may not fully represent the train traveler population. This could affect the generalizability of the study's conclusions.

First and last mile comparison

In addition to the demographics of the respondents, it is important to examine the proportion of modes used in the first and last mile compared to the actual behavior of train travelers in these segments. Within the NS panel, the respondents were asked on there most chosen mode in the first and last mile. These are shown in table 5.3, and compared to the current first and last mile of the train travelers from recent NS data.

Table 5.3: First and Last Mile Sample Composition of Participants (N = 641)

Category	Subcategory	%	Train traveler[2]	%
First Mile	Bike	46%	Bike	38%
	BTM	17%	BTM	21%
	Car	7%	Car	14%
	Moped	0.5%	Moped	-
	Taxi	0.2%	Taxi	-
	Unknown	5%	Unknown	-
	Walk	24%	Walk	27%
Last Mile	Bike	15%	Bike	13%
	BTM	24%	BTM	23%
	Car	6%	Car	9%
	Taxi	0.2%	Taxi	-
	Unknown	11%	Unknown	-
	Walk	44%	Walk	54%

[2] Source: NS, 2023.

The first and last mile figures are similar to the national averages for these segments when looking at the most recent datasets of the NS (NS, 2023). The percentage of people biking in the first mile of this sample is higher than the national average, although it is slightly lower in the last mile. Additionally, some respondents (5.3% in the first mile and 11% in the last mile) did not specify their mode of transportation for these segments. Nevertheless, the sample generally matches the profile of train travelers, allowing for meaningful conclusions to be drawn.

5.2. Train travelers behaviour and perception

An exploratory data analysis is conducted to gain a better understanding of the data and obtain an initial impression of the travel behaviour and perception regarding shared e-mopeds.

5.2.1. Perception on Shared E-Mopeds

Respondents were asked questions regarding shared e-mopeds to gather insights into the train travelers' perceptions. Figure 5.1 illustrates the distribution of responses.

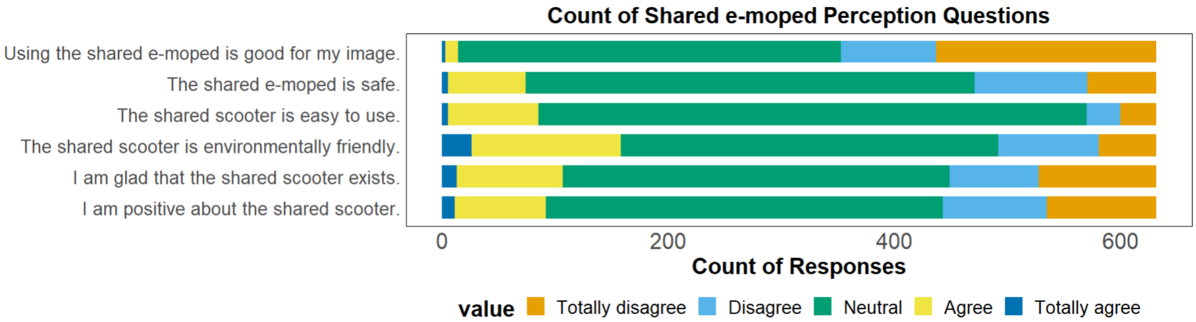


Figure 5.1: Count of Responses Regarding Shared E-Moped Attitudes

Figure 5.1 shows that the majority of respondents chose 'neutral'. This might be due to the high percentage of people unfamiliar with shared e-mopeds, leading them to select the neutral option when uncertain about their answers.

A correlation matrix was computed to explore the relationships among the variables, as shown in Figure 5.2. The correlation matrix revealed moderate to strong positive correlations among the variables, suggesting underlying common factors. Notably, the variables related to attitude (positive and happy) displayed a particularly high correlation (0.743), indicating a significant overlap in the positive perception of shared e-mopeds and the happiness associated with their use. Since these variables are relatively highly correlated, combining these into a few (non-correlating) factors is useful for further analysis.

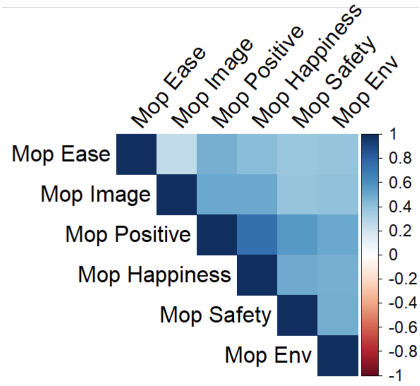


Figure 5.2: Correlation between the questions on shared e-moped perception

Factor analysis

The factor analysis was conducted on the six variables related to user perceptions of shared e-mopeds: environmental impact, ease of use, safety, positivity, happiness, and social image.

Table 5.4: Factor Analysis Loadings for Shared E-Moped Perception

Variable	Factor 1	Factor 2
I am positive about the shared e-moped.	0.734	0.471
I am glad that the shared e-moped is available.	0.769	0.378
Using the shared e-moped is good for my image.	0.458	0.373
The shared e-moped is environmentally friendly.	0.293	0.654
The shared e-moped is easy to use.	0.337	0.436
The shared e-moped is safe.	0.377	0.573

The factor analysis yielded two distinct factors:

- **Emotional satisfaction**: Factor 1 predominantly loaded on 'positive' (0.73) and 'glad' (0.77), suggesting that this factor represents the emotional satisfaction derived from using e-mopeds. This factor also had significant loadings from 'social image' (0.46), implying that the public image of e-mopeds contributes to overall user satisfaction.
- **Perks satisfaction**: Factor 2 was heavily loaded by 'environmentally friendly' (0.654), pointing to the environmental impact as a significant perk of e-moped use. This factor also included moderate contributions from 'ease of use' (0.436) and 'safety' (0.573), indicating the perceived practical benefits of shared e-mopeds.

The proportion of variance explained by the two factors was 50%, with Factor 1 accounting for 29% and Factor 2 for 21%. This suggests a balanced contribution of the two factors in shaping user perceptions of e-mopeds. The model fit was evaluated using several statistics. The Tucker-Lewis Index (0.977) and RMSEA (0.054) indicated a good fit, implying that the model successfully captured the main dimensions of the shared e-moped perception. The two factors derived from the factor analysis will be used in all subsequent analyses. Since they are not correlated, they will not introduce multicollinearity when included in the models.

5.2.2. Previous use Shared e-moped

Shared e-mopeds have been hardly adopted within the sample. Among the respondents, 11.7% have never heard of this shared mode of transportation. 77.4% are aware of the shared e-moped but have never used one. Only 10.9% have prior experience with shared e-mopeds. This group of users does not use shared e-mopeds frequently. Compared to other modes of transportation, shared e-mopeds are used less often, as shown in Figure 5.3. People who have used a shared e-moped before did not do so on a weekly basis.

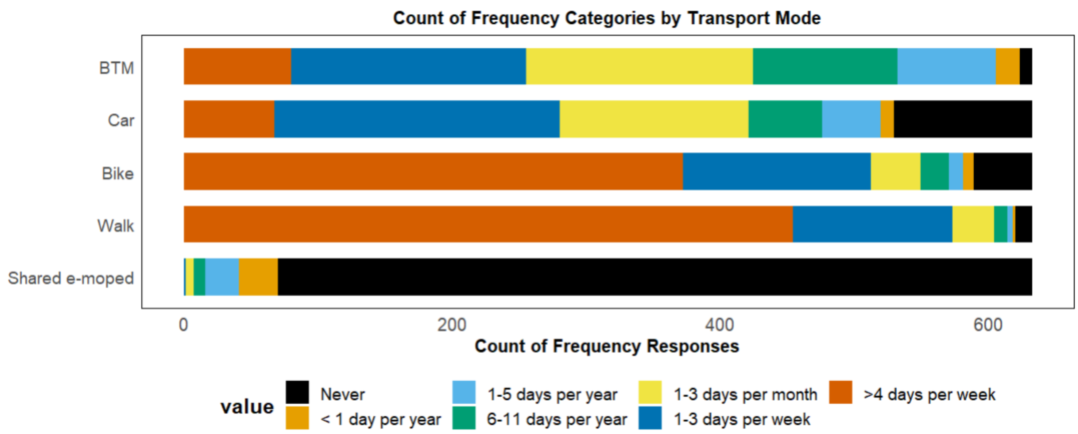


Figure 5.3: Frequency of Use by Transport Mode

User Characteristics

To get a view on the shared e-moped user characteristics, the characteristics of the people who have used the shared e-moped before are investigated. This is done with a multivariate logistic regression model. The previous use of the shared e-moped is taken (yes or no) as dependent variable. Different variables were added, and the significant ones are shown in table 5.5.

The logistic regression model can be described by the following formula:

$$\begin{aligned}\text{Previous use} \sim \beta_0 &+ \beta_{\text{Age}} \cdot \text{Age} + \beta_{\text{Gender}} \cdot \text{Gender} + \beta_{\text{Education}} \cdot \text{Education level}\\ &+ \beta_{\text{MopedPoss}} \cdot \text{Moped possession} + \beta_{\text{MotorPoss}} \cdot \text{Motor possession} + \beta_{\text{CarPoss}} \cdot \text{Car possession}\\ &+ \beta_{\text{CarFreq}} \cdot \text{Car frequency} + \beta_{\text{WalkFreq}} \cdot \text{Walk frequency}\\ &+ \beta_{\text{BikeFreq}} \cdot \text{Bike frequency} + \beta_{\text{EmotionalSatisf}} \cdot \text{Emotional satisfaction (Shared e-moped)}\\ &+ \beta_{\text{PerksSatisf}} \cdot \text{Perks satisfaction (Shared e-moped)}\end{aligned}$$

Table 5.5: Logistic Regression Coefficients

Beta	Estimate	Std. Error	p-value
β_0	-10.497	0.912	0.000
β_{Age}	-0.555	0.048	0.000
β_{Gender}	0.674	0.123	0.000
$\beta_{\text{Education}}$	0.276	0.121	0.023
$\beta_{\text{MopedPoss}}$	0.829	0.251	0.001
$\beta_{\text{MotorPoss}}$	1.036	0.353	0.003
β_{CarPoss}	-0.294	0.139	0.034
β_{CarFreq}	0.146	0.042	0.001
β_{WalkFreq}	0.394	0.096	0.000
β_{BikeFreq}	0.140	0.049	0.004
$\beta_{\text{EmotionalSatisf}}$	0.589	0.064	0.000
$\beta_{\text{PerksSatisf}}$	0.504	0.061	0.000

Age is a significant factor, with younger individuals showing higher usage rates of shared e-mopeds. This trend may be influenced by younger people's greater familiarity with technology and different lifestyle choices compared to older generations. This finding is consistent with previous studies (Aguilera-García et al., 2021; Van Kuijk et al., 2022).

Gender differences were examined, revealing that males have a larger share in the group of shared e-moped users, aligning with findings from other studies (Garritsen, 2022; Hoobroeckx et al., 2023; Vega-Gonzalo et al., 2024).

Education is found to be significant, with shared e-moped users having higher education levels.

Individuals who own motorcycles or mopeds are more represented in the group who have used shared e-mopeds, possibly due to their comfort with similar vehicles. Conversely, car owners have a lower share in the previous user group.

Regarding travel frequency, significant differences were observed. People who tend to use the car, bike, or walk more often are positively correlated with shared e-moped use. However, the use of other modes of transport, such as buses, trams, metros (BTM), and trains, does not significantly influence this behavior.

Perceptions of shared e-mopeds, derived from factor analysis, significantly impact previous use. Individuals with more positive perceptions are more likely to have used shared e-mopeds before.

First and Last Mile

Among all respondents, 4.7% have used a shared e-moped once or more for the first mile of their journey, while 6.3% have used it in the last mile. Of these people, nobody uses the shared e-moped weekly. This gives an indication of the very low current modal share of the shared e-moped in the first and last mile transportation. More people have tried it in the last mile than in the first mile. This aligns with previous research, which shows that shared e-mopeds are more commonly used for the last mile rather than the first mile (de Wit, 2023).

Respondents were asked about their reasons for using the shared e-moped for the first and last mile.

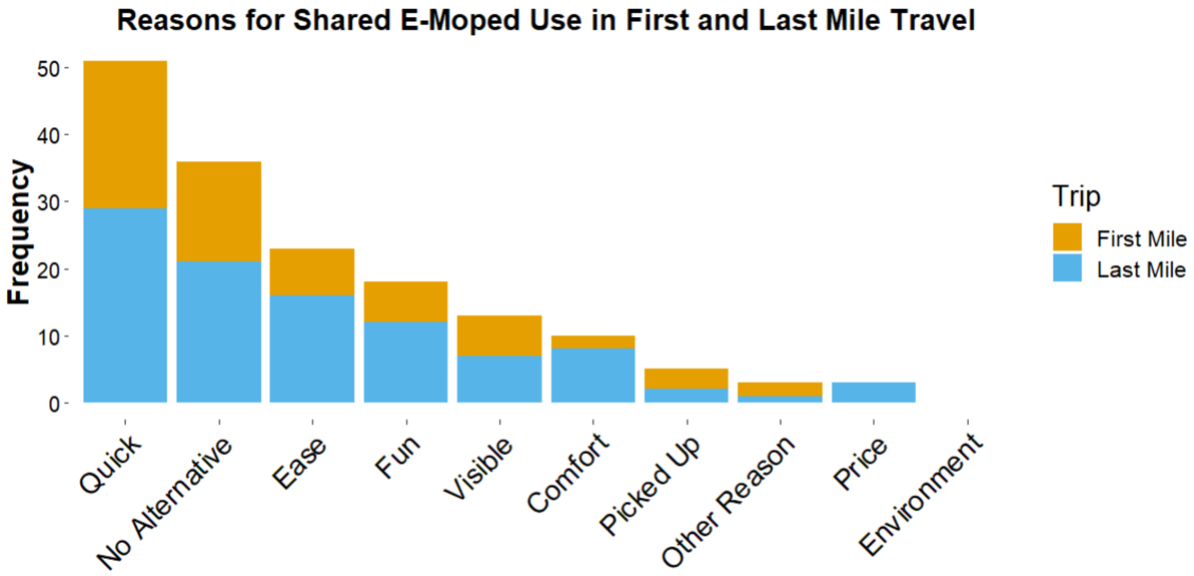


Figure 5.4: Reasons for Shared E-Moped Use in First and Last Mile Travel

The reasons for shared e-moped use are equally distributed over the two trips. The most frequently mentioned reason for using shared e-mopeds was the fast travel characteristic. The plot illustrates that fast travel and the lack of alternative transportation options are the primary reasons for the use of shared e-mopeds in both first and last mile segments of travel. While ease of use and the fun aspect also play significant roles, comfort, visibility, and being picked up contribute to a lesser extent. Interestingly, environmental concerns are never chosen as a reason to use the shared e-moped. Other reasons that were mentioned were: 'To carry luggage'.

The table below, labeled as Table 5.6, presents the trip purposes for using shared e-mopeds in the first and last mile of a journey. The data is categorized into three main trip purposes: leisure, work/school, and unknown.

Trip Purpose	First mile	Last mile
Leisure	66.7%	63.1%
Work / school	31.6%	31.0%
Unknown	1.75%	5.95%

Table 5.6: Trip Purposes in the first and last mile

For the first mile and last mile, leisure trips constitute the majority. This suggests that a significant number of users prefer shared e-mopeds for recreational activities. On the other hand, the table shows that a substantial portion of users rely on shared e-mopeds for their daily commutes.

Since train travelers seem relatively uninterested in using shared e-mopeds for the first and last mile, Among those who have never used an e-moped, 72.4% stated that they would never use a shared e-moped in the first mile, regardless of the circumstances. In the last mile, this percentage is 64.7%. This suggests a general preference for using shared e-mopeds in the last mile over the first mile. For the remaining respondents, it is useful to examine the factors that are preventing their shared e-moped use. The factors that were questioned are expressed in one word, and described here:

Barrier	Respondent would take the shared e-moped if..
Other modes	If no other means of transportation are available
High price	If the price is lower than is currently the case
Driver's license	If I have a (moped) driver's license
Availability	If a shared scooter is available
App Usability	If I have the app on my phone
Helmet	If there is no helmet requirement
Distance Home / Destination	If it is closer to my house / destination than is currently the case
Distance to station	If I can park it closer to the station than is currently the case
Other barriers	Open question

Table 5.7: Barriers in the Consideration of Shared E-Mopeds

The analysis focuses on the barriers faced by the remaining respondents who have not used shared e-mopeds for the first or last mile of their journey. This includes considering the obstacles for both the first and last mile.

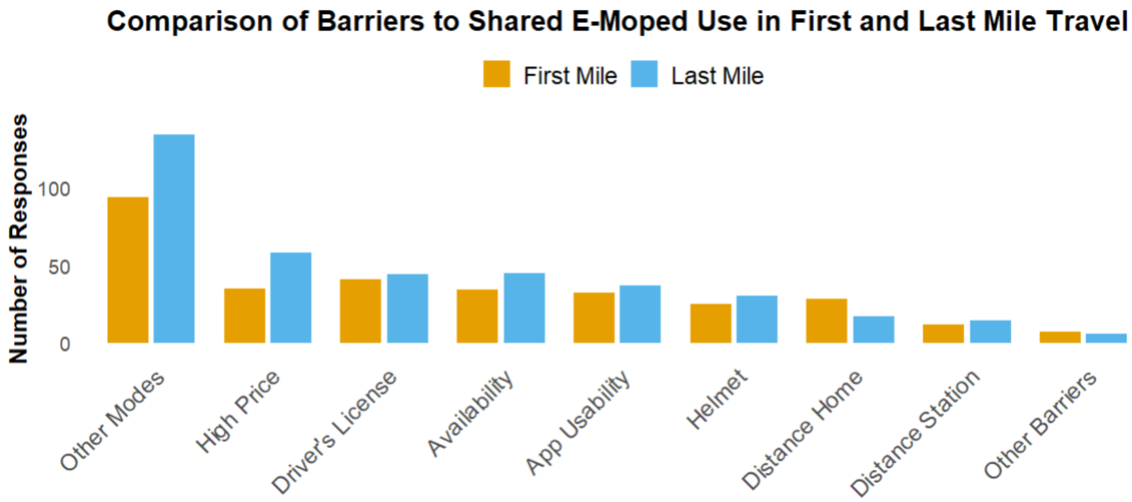


Figure 5.5: Barriers preventing shared e-moped use in the first and last mile

The shared e-moped is most frequently considered when there are no other available modes of transport. This is mentioned more in the last mile than in the first mile. Price is also mentioned relatively often for the last mile. Other barriers were mentioned with similar frequency.

5.3. Summary

The shared e-moped is not a popular mode of transport among train travelers. Only 10.9% of the respondents have ever used a shared e-moped. Among those who have never used an e-moped, 72.4% stated they would never use one for the first mile, regardless of the circumstances. For the last mile, this percentage is 64.7%. The shared e-moped use is significantly more in the last mile than in the first mile. Generally, people have a more negative than positive view of shared e-mopeds, with most holding a neutral opinion. Shared e-mopeds are the least used mode of transport, and even among those who have used them, the frequency of use is very low. Users of shared e-mopeds tend to be young, highly educated males with a positive perception of the service. The reasons for using shared e-mopeds are similar for both the first and last mile, primarily due to their speed or when no other modes are available. Other transport modes were the most commonly mentioned barrier, preventing people from using shared e-mopeds. Additional barriers included the high price and the lack of a driver's license. Owning motorcycles or mopeds are positively correlated the previous use of the shared e-moped, while owning a car is negatively influencing the chance of having previously used the shared e-moped. The frequency of using the car, bike, or walking. The purpose of trips made with shared e-mopeds is consistent across both the first and last mile, with approximately 67% of trips being leisure-related and 33% related to work or school.

6

Choice experiment

The data from the stated preference experiment has been analyzed. Table 6.1 displays the frequency with which each alternative was selected.

Table 6.1: Overview of choices in the Stated Preference Experiment

	Walk	Shared Bike	Shared E-moped	BTM
Times available	3792	3792	3792	3792
Times chosen	1191	786	112	1703
Percentage chosen overall (%)	31.41	20.73	2.95	44.91

The shared e-moped is chosen in less than 3% of cases. To identify the characteristics of these potential shared e-moped users, a latent class model was created to segment the sample into different groups. This segmentation helps in drawing conclusions about the distinct groups. This will be done after making Multinomial Logit to get the first insights on the mode choice behaviour.

6.1. Mode Choice Behaviour

The Multinomial Logit (MNL) model serves as the foundation in the study of mode choice behaviour, providing insights into factors that influence these decisions. At the heart of the MNL model are the utility functions, which represent the perceived total utility that an individual derives from choosing a particular option. The utility for each mode is modeled as a function of various explanatory variables.

The utility functions for different transportation modes in the context of this study are expressed as follows:

$$
\begin{aligned}
U_{\text{walk}} &= \text{ASC}_{\text{walk.1,5}} + \text{ASC}_{\text{walk.3}} + \epsilon \\
U_{\text{mop}} &= \text{ASC}_{\text{mop.1,5}} + \text{ASC}_{\text{mop.3}} + \beta_{\text{mop.conv}} \cdot \text{Conv}_{\text{mop}} + \beta_{\text{mop.walk}} \cdot \text{Walk}_{\text{mop}} + \beta_{\text{mop.cost}} \cdot \text{Cost}_{\text{mop}} + \epsilon \\
U_{\text{bike}} &= \text{ASC}_{\text{bike.1,5}} + \text{ASC}_{\text{bike.3}} + \beta_{\text{bike.conv}} \cdot \text{Conv}_{\text{bike}} + \beta_{\text{bike.walk}} \cdot \text{Walk}_{\text{bike}} + \beta_{\text{bike.cost}} \cdot \text{Cost}_{\text{bike}} + \epsilon \\
U_{\text{btm}} &= \text{ASC}_{\text{btm.1,5}} + \text{ASC}_{\text{btm.3}} + \beta_{\text{btm.conv}} \cdot \text{Conv}_{\text{btm}} + \beta_{\text{btm.walk}} \cdot \text{Walk}_{\text{btm}} + \beta_{\text{btm.cost}} \cdot \text{Cost}_{\text{btm}} + \epsilon
\end{aligned}
$$

U_{walk}	: Walking mode utility
U_{mop}	: Shared e-moped mode utility
U_{bike}	: Shared bike mode utility
U_{btm}	: Bus/tram/metro mode utility
$\text{ASC}_{\text{mode.x}}$	: Alternative Specific Constant per mode (x = 1.5 or 3 km)
$\beta_{\text{mode.conv}}$	: Coefficient for the convenience factor per mode
$\beta_{\text{mode.walk}}$	: Coefficient for walking time per mode
$\beta_{\text{mode.cost}}$	: Coefficient for the costs per mode
Conv_{mop}	: Shared E-moped reservation time
$\text{Conv}_{\text{bike}}$	: Shared Bike reservation time
Conv_{btm}	: BTM waiting time
Walk_{mop}	: Walking time to the shared e-moped
$\text{Walk}_{\text{bike}}$	: Walking time to the shared bike
Walk_{btm}	: Walking time to the BTM
Cost_{mop}	: Shared e-moped costs
$\text{Cost}_{\text{bike}}$	: Shared bike costs
Cost_{btm}	: BTM costs
ϵ	Random error

The model assumes that individuals choose the mode with the highest utility, though the presence of the error term acknowledges the stochastic nature of decision-making. By estimating the parameters of these utility functions using observed choices, the MNL model allows to infer the relative importance of different factors influencing mode choice decisions.

Table 6.2: Model Estimates for MNL Model

Attribute	MNL Estimate (t-ratio)
$ASC_{walk.1,5}$	0.000
$ASC_{bike.1,5}$	0.081 (0.34)
$ASC_{mop.1,5}$	0.157 (0.41)
$ASC_{btm.1,5}$	0.392 (1.17)
$ASC_{walk.3}$	0.000
$ASC_{bike.3}$	3.139 (12.07)*
$ASC_{mop.3}$	4.464 (6.15)*
$ASC_{btm.3}$	3.447 (9.26)*
$\beta_{mop.conv}$	-0.246 (-1.63)
$\beta_{mop.walk}$	-0.158 (-2.78)*
$\beta_{mop.cost}$	-1.174 (7.65)*
$\beta_{bike.conv}$	-0.182 (-3.35)*
$\beta_{bike.walk}$	-0.065 (-2.37)*
$\beta_{bike.cost}$	-0.378 (-9.38)*
$\beta_{btm.conv}$	-0.066 (-3.29)*
$\beta_{btm.walk}$	-0.083 (-2.62)*
$\beta_{btm.cost}$	-0.279 (-2.75)*
Log-likelihood	-3591.380
Rho-squared	0.175

*Note: * indicates significance at $p<0.05$*

In analyzing the mode choice behaviour for different trip lengths using a MNL model, focus on the role of alternative-specific constants (ASCs) assesses the inherent preferences across various transport modes. These constants represent the preferences for each mode when all other variables are held at zero, and their significance levels help gauge the confidence in these estimates.

For trips spanning 1.5 km, the analysis reveals no statistically significant ASCs across the examined modes of transport. This lack of significant inherent preference suggests that the choice of transport mode for shorter distances may be predominantly influenced by factors such as cost, convenience, and walking distance rather than any intrinsic appeal of a particular mode.

Conversely, trips of 3 km exhibit a distinct pattern, with significant ASCs indicating a strong inherent preference for mopeds, bikes, and buses/trains/metros (btm). This implies that for moderately longer distances, these modes become more appealing due to attributes like comfort or speed, which may outweigh the advantages of walking.

The MNL model further includes the influence of various attributes through the β coefficients, where the negative values detract from it. The results underscore cost as a dominant factor affecting mode choice across all options. The coefficients associated with cost are consistently larger than those for other variables. Since the shared e-moped is the most expensive mode of transport, it heavily impacts the decision to choose this option.

Additionally, the impact of walking distance on mode utility is negative across all modes, with varying degrees of sensitivity. Notably, mopeds exhibit a higher sensitivity to walking distance compared to bicycles and btm, indicating that the inconvenience of longer walks significantly deters moped use.

The effect of convenience varies significantly between different modes of transport, as it depends on the specific features and characteristics of each mode. For shared e-mopeds, there is not enough evidence to reject the null hypothesis at the 5% significance level. However, it is close to the 10% significance level, indicating that we have some uncertainty about this outcome. For BTM (bus, tram, metro), convenience has less impact on mode choice compared to the walking time to reach BTM. This makes sense because for BTM, convenience means waiting, whereas walking involves physical movement.

6.2. Modeling Classes

The LC model identifies distinct classes within the population, each with unique preferences and sensitivities to the attributes of the different modes of transport.

6.2.1. Model fit

In the process of developing and evaluating the models, it is essential to compare the performance of different model specifications. Table 6.3 presents the model comparison metrics for various models evaluated in this study. The metrics include Log-Likelihood (LL), Rho-squared, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). These metrics provide insights into the goodness-of-fit and the relative quality of the models.

Table 6.3: Model Comparison Metrics

Model	LL	Rho-squared	AIC	BIC
MNL	-3591.38	0.176	7212.75	7306.36
LC 2 classes	-3570.76	0.177	7203.51	7396.97
LC 2 classes (panel)	-3087.45	0.286	6242.9	6455.08
LC 3 classes (panel)	-2849.85	0.338	6345.97	6477.32
LC 3 classes (panel), 1 factor in CM	-2843.69	0.338	5785.37	6091.16
LC 3 classes (panel), 2 factors in CM	-2894.79	0.326	5895.57	6226.33
LC 3 classes (panel), 3 factors in CM	-2828.36	0.341	5762.72	6093.47
LC 3 classes (panel), 4 factors in CM	-2814.43	0.344	5738.86	6082.10
LC 3 classes (panel), 5 factors in CM	-2812.57	0.344	5739.13	6094.85

Adding latent classes and panel effects improves model performance significantly. The Latent Class (LC) models with panel data consistently show better fit metrics. Among these, the LC model with 3 classes and 4 factors in class membership provides the best fit, evidenced by the highest LL (-2814.43), highest Rho-squared (0.344), and the lowest AIC (5738.86) and BIC (6082.10).

The first factor included in the class membership model was the shared e-moped perception factor (emotional satisfaction), identified through factor analysis. This was done to determine differences in preferences regarding the shared e-moped among different classes. Subsequent factors, which were all found to be correlated with shared e-moped use in previous studies, were added. There was no excessive correlation between the factors, and the combination of the four factors -age, education, perception, and familiarity— provided the best model fit results. The second factor on perception was also added to the model, but no significant differences between the classes were found, and the model comparison metrics did not improve. This is why it was chosen to exclude this factor from the class membership model.

6.2.2. Estimation results

Table 6.4 summarizes the estimation results for both the MNL and LC models. Additionally, the table shows the parameters for the class membership model, which explains the probability of an individual belonging to each latent class based on variables such as age, education, perception, and familiarity with mopeds.

The LC model results divided the MNL model into three classes, each representing a group of individuals with similar mode choice behavior. The estimates (coefficients) and their corresponding t-ratios (in parentheses) indicate the significance and strength of each attribute in influencing mode choice decisions. The class allocation percentages shows the distribution of the population across the three latent classes.

Table 6.4: Model Estimates for MNL and LC Models

Attribute	**MNL**	**LCM**		
		Class 1	**Class 2**	**Class 3**
	Estimate (t-ratio)	**Estimate (t-ratio)**	**Estimate (t-ratio)**	**Estimate (t-ratio)**
$ASC_{walk.1,5}$	0.000	0.000	0.000	0.000
$ASC_{bike.1,5}$	0.081 (0.34)	5.708 (1.82)*	1.537 (4.12)**	1.147 (1.11)
$ASC_{mop.1,5}$	0.157 (0.41)	6.314 (0.04)	0.641 (1.20)	2.211 (2.49)**
$ASC_{btm.1,5}$	0.392 (1.17)	-1.366 (-2.07)**	1.827 (2.38)**	3.645 (2.97)**
$ASC_{walk.3}$	0.000	0.000	0.000	0.000
$ASC_{bike.3}$	3.139 (12.07)**	7.643 (2.52)**	6.735 (11.43)**	3.755 (3.29)**
$ASC_{mop.3}$	4.464 (6.15)**	0.872 (0.00)	7.382 (7.00)**	7.186 (3.33)**
$ASC_{btm.3}$	3.447 (9.26)**	2.911 (4.26)**	7.384 (8.15)**	6.752 (4.47)**
$\beta_{mop.conv}$	-0.246 (-1.63)	-3.000 (-0.01)	-0.237 (-1.41)	0.537 (0.94)
$\beta_{mop.walk}$	-0.158 (-2.78)**	-0.305 (-0.62)	-0.197 (-2.65)**	-0.053 (-0.39)
$\beta_{mop.cost}$	-1.174 (7.65)**	-6.344 (-0.03)	-1.156 (-6.49)**	-2.452 (-2.62)**
$\beta_{bike.conv}$	-0.182 (-3.35)**	-1.811 (-2.66)**	-0.445 (-4.78)**	-0.165 (-0.73)
$\beta_{bike.walk}$	-0.065 (-2.37)**	-0.827 (-2.66)**	-0.068 (-1.50)	-0.130 (-1.17)
$\beta_{bike.cost}$	-0.378 (-9.38)**	-1.520 (-2.81)**	-0.462 (-7.99)**	-0.369 (-2.37)**
$\beta_{btm.conv}$	-0.066 (-3.29)**	-0.020 (-0.47)	-0.298 (-6.35)**	-0.072 (-0.99)
$\beta_{btm.walk}$	-0.083 (-2.62)**	-0.214 (-3.20)**	-0.218 (-2.91)**	-0.145 (-1.21)
$\beta_{btm.cost}$	-0.279 (-2.75)**	-0.310 (-1.55)	-1.037 (-4.60)**	-0.387 (-1.10)
Class membership				
Constant		0.000	-1.227 (-2.72)**	-1.457 (-2.96)**
Age		0.000	-0.091 (-1.66)*	-0.021 (-0.38)
Education		0.000	0.464 (2.06)**	-0.678 (-3.03)**
Perception (moped)		0.000	0.326 (3.05)**	0.246 (2.10)**
Familiar (moped)		0.000	1.081 (3.98)**	0.572 (2.09)**
Class allocation		0.3167	0.3996	0.2837

*Note: * indicates significance at $p<0.1$, ** indicates significance at $p<0.05$*

When considering all classes, convenience does not appear to influence the choice of shared e-mopeds. Class 1 is not sensitive to the convenience of public transportation (BTM) but experiences the largest negative influence of convenience on the utility for shared bikes. This suggests that they do not prefer shared bikes due to the complexity of renting them. Class 2 values convenience more negatively compared to walking when choosing BTM and shared bikes. This indicates that this class does not like to wait or spend more time on reservations than on walking.

The walking distance is also valued differently per class. Class 1 does not prefer to walk to their modes of transport. Class 2 does not mind the minutes spent walking to their modes, especially for the shared bike. Class 3 does not feel influenced by walking distance, as these values are not significant.

When comparing the travel costs across different classes, various perspectives on travel expenses emerge. Class 1 is generally not sensitive to costs, except when it comes to choosing the shared bike, indicating a reluctance towards sharing. This class does not choose the shared e-moped, so its cost influence on this class cannot be determined. For Class 2, travel costs are more important than other factors. The costs associated with shared e-mopeds negatively influence their mode choice more than other factors. However, they are less concerned about costs when choosing the shared bike. Class 3 is the most sensitive to costs. They do not care about the walking time or convenience. However, they do not appear to be influenced by public transportation (BTM) costs. For choosing the e-moped, costs are the only factor that affects the choice for the shared e-moped in this group.

6.2.3. Class description

When looking at the estimates of the LC model, the classes seem to each have their own travel patterns. These patterns are caught into the following class descriptions:

Class 1: Conservative travelers

The 'Conservative travelers' prioritize simplicity and practicality in their daily transportation choices. For short distances, they prefer walking and generally avoid using public transportation modes such as buses, trams, and metros (BTM). Bicycles are their preferred option, but only if there is no hassle and no additional costs.

For longer trips, these individuals also prefer cycling but are reluctant to use bike rental services that require mobile apps or involve long walks to access the bikes. They are not willing to adopt new transport modes that require new tasks, so for longer distances, they are more likely to choose traditional public transportation options.

Class 2: Mode Adapters

Members of the 'Mode Adapters' group prefer using different modes of transportation instead of walking. For a 1.5 km trip, they prefer to use a bike or public transportation. However, if these options take too long or are too expensive, they choose to walk. For trips around 3 km, walking is considered too far for this group. They are generally open to trying new things, including shared transportation.

Class 3: Cost-Sensitive Adapters

This group prefers being transported without any physical effort. They favor local public transport (BTM) over walking and biking for short distances. Shared e-mopeds are their preferred option for short distances, but only if there are no costs involved. For longer distances, they also prefer shared e-mopeds, although their preference strongly depends on competitive pricing. Public transport becomes their preferred mode of transportation, as they show minimal concern for factors that might typically affect BTM usage.

6.2.4. Class allocation

The class allocation percentages (0.317, 0.399, and 0.284 for Classes 1, 2, and 3, respectively) indicate the proportion of the population that falls into each class. This distribution reflects the variety in transportation preferences among the population.

Each respondent can be assigned to one of these classes based on their class membership. By assigning respondents to the class where they have the highest probability of belonging, the classes become distinct groups that can be analyzed. The demographics of these classes are shown in Table 6.5.

Table 6.5: Class demographics

Characteristic	Conservative Travelers (n = 133)	Mode Adapters (n = 321)	Cost-sensitive Adapters (n = 172)
Gender			
Female	50%	47%	42%
Male	50%	53%	58%
Age			
18-35 years	9%	50%	54%
36-55 years	20%	30%	19%
55+ years	71%	20%	27%
Occupation			
Employed	41%	64%	29%
Retired	41%	9.3%	15%
Student	5.3%	17%	33%
Unemployed	5.3%	1.6%	7.6%
Unknown	6.8%	8.4%	16%
Education			
Level 1	–	–	2%
Level 2	32%	10%	98%
Level 3	68%	90%	–
Urbanity			
Not urbanised	9.1%	6.9%	5.8%
Hardly urbanised	9.8%	7.2%	9.3%
Moderately urbanised	14%	12.2%	15.7%
Strongly urbanised	34%	28.4%	33.1%
Extremely urbanised	32%	43.3%	27.3%
Unknown	1%	2.8%	8.7%
Drivers license			
Yes	77%	83%	57%
No	23%	17%	43%

The table already shows the differences in demographics between the classes. To gain more detailed information about the people in each class, factors influencing mode choice were analyzed and tested for differences between the classes. Chi-squared and Wilcoxon tests were used for this analysis. The significant values were identified and incorporated into the description of the characteristics of each class.

Conservative travelers' characteristics

Individuals in the ”Conservative travelers” class are typically older than those in other classes. This group has the biggest share of retired people. Most people in this class own a car, and they are not frequent train travelers. When they travel, they have the highest share of 1st class travelers compared to the other classes. Most people in the class have never used an OV-bike.

The Conservative Travelers show the strongest resistance to using shared e-mopeds. Although some individuals in this class would use shared e-mopeds if no other modes were available, this willingness is significantly lower compared to the other classes. They tend to have a negative perception of shared e-mopeds, often considering them less safe and less environmentally friendly compared to the opinion of the other classes. Additionally, many are not even aware of shared e-mopeds.

In summary, the ”Conservative travelers” are characterized by their preference for personal, straightforward transportation methods, particularly cycling and walking, and their disinterest in new transportation options like shared or app-based transportation solutions.

Mode Adapters' characteristics

Most people in this class are between 18 and 44 years old and are predominantly employed. Additionally, they are the highest educated class. They tend to live in more crowded areas, such as city centers, compared to other classes.

Members of this class are open to try new modes. Most have used shared OV-bikes before, and all previous shared e-moped users fall into this class. They also own the most bikes among the different classes and have the most positive attitude towards shared e-mopeds.

In summary, ”Mode Adapters” are characterized by their preference for using various transportation modes over walking, their positive attitude towards shared services, and their high level of education and employment, often living in busy urban areas.

Cost-Sensitive Adapters' characteristics

Most people in this group are young, with the age range of 18-24 years being the most represented. They have the lowest education levels compared to other classes. Many in this group do not possess a driver’s license, which restricts their use of e-mopeds. Additionally, they do not own cars and have the least bike possession among all classes.

The biggest share of the Cost-sensitive Adapters are not into trying the shared e-moped. They highlight the availability of alternative modes as a key barrier. Major barriers for this class include high price, driver’s license, and helmet requirements, reflecting their sensitivity to costs and the importance of social image.

In summary, ”Cost-Sensitive Adapters” are young individuals who prefer public transportation and shared e-mopeds over walking, but only if the shared e-mopeds are the cheapest option. They have lower education levels, lack driver’s licenses, and own fewer personal vehicles and bikes. Their transportation choices are influenced by social perceptions and pricing competitiveness.

6.3. Mode Choice Probability

To predict future mode choices and understand how changes in certain variables might impact these choices, a mode choice model is constructed for each class. This model involves several steps and calculations:

For each class and mode, utility values are calculated using provided coefficients and average attribute values. Choice probabilities for each mode are then derived by normalizing the exponentiated utilities across all modes, ensuring the probabilities sum up to one. The final probabilities for each mode are found by combining the class-specific probabilities, weighted by how likely an individual is to belong to each class. This accounts for the fact that individuals are not entirely in one class.

This model enables to interpret and predict the future mode choices of individuals, taking into account changes in key variables. For example, by adjusting the coefficients, a forecast can be made on how these changes might influence the likelihood of choosing different transportation modes.

Figure 6.1 shows the distribution of mode choices among the different classes for trips of 1.5km and 3km when all variables are set to their average or equal to each other.

Mode	1.5 km			3 km		
	Convenience (min)	Walking time (min)	Cost (euro)	Convenience (min)	Walking time (min)	Cost (euro)
Moped	2	4	2.00	2	4	4.00
Bike	2	4	2.80	2	4	3.00
Bus/Tram/Metro	6	4	1.40	6	4	1.70

Table 6.6: Mode choice data input for 1.5 km and 3 km distances

For each class, the figure presents the probability for individuals selecting each mode of transport per class.

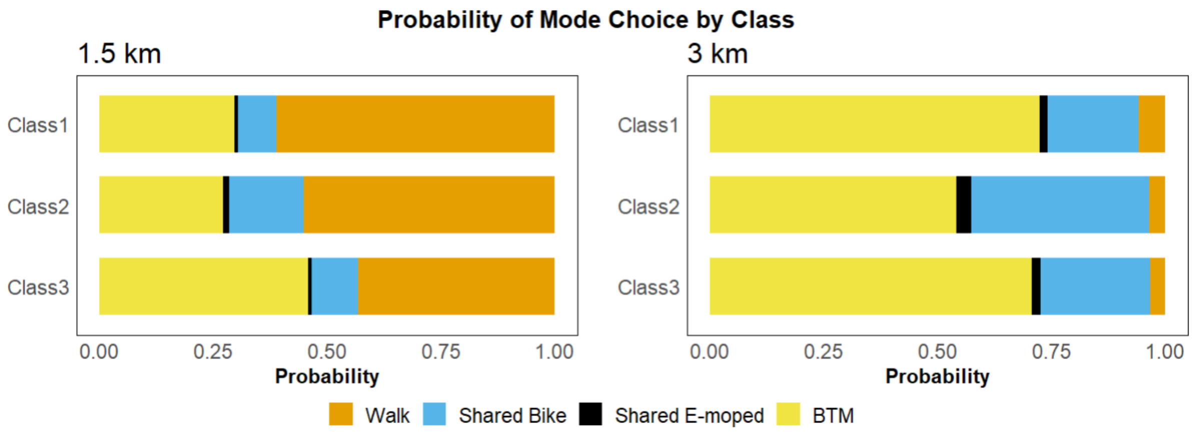
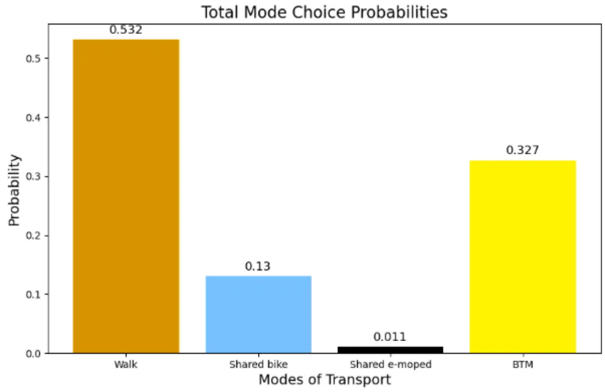
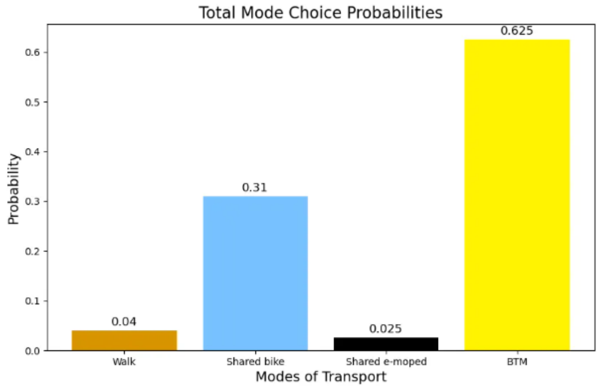


Figure 6.1: Stated preference experiment choices per class

The likelihood of choosing a shared e-moped for a 1.5 km trip ranges from 0.07% (Conservative Travelers) to 0.14% (Mode Adapters). For a 3 km trip, this probability increases to between 1.6% (Cost-sensitive Adapters) and 3.2%. The total mode choice probability in this situation is shown in figure 6.2.



((a)) 1.5 km



((b)) 3 km

Figure 6.2: Total mode choice probability within the scenario (1.5km on the left side, 3km on the right side)

The 3 km trip the shared e-moped mode choice probability is higher than for the 1.5 km trip.

6.3.1. Impact of the Attributes

To understand the impact of various attributes on the probability of choosing a shared e-moped, we use a reference situation. In this situation, the attributes of the shared e-moped are modified for both a 1.5 km trip and a 3 km trip, while keeping other attributes constant. This analysis examines different classes when changing the attributes, providing insight into their impact.

Walking distance

Walking distance is particularly interesting to see its impact because it is an area where policy makers such as government and railway station owners can have a direct impact. By spatially integrating shared e-moped parking spaces closer to their stations where possible, the policy makers are able to reduce the walking time. A minimum walking distance of 1 minute is assumed, as shared e-mopeds cannot be parked within the stations. The impact of changing the walking distance to the shared e-moped parking is measured for both 1.5 km and 3 km trips. These results are shown in figure 6.3 and figure 6.4. Class 1 represents Conservative Travelers, Class 2 represents Mode Adapters, and Class 3 represents Cost-sensitive Adapters.

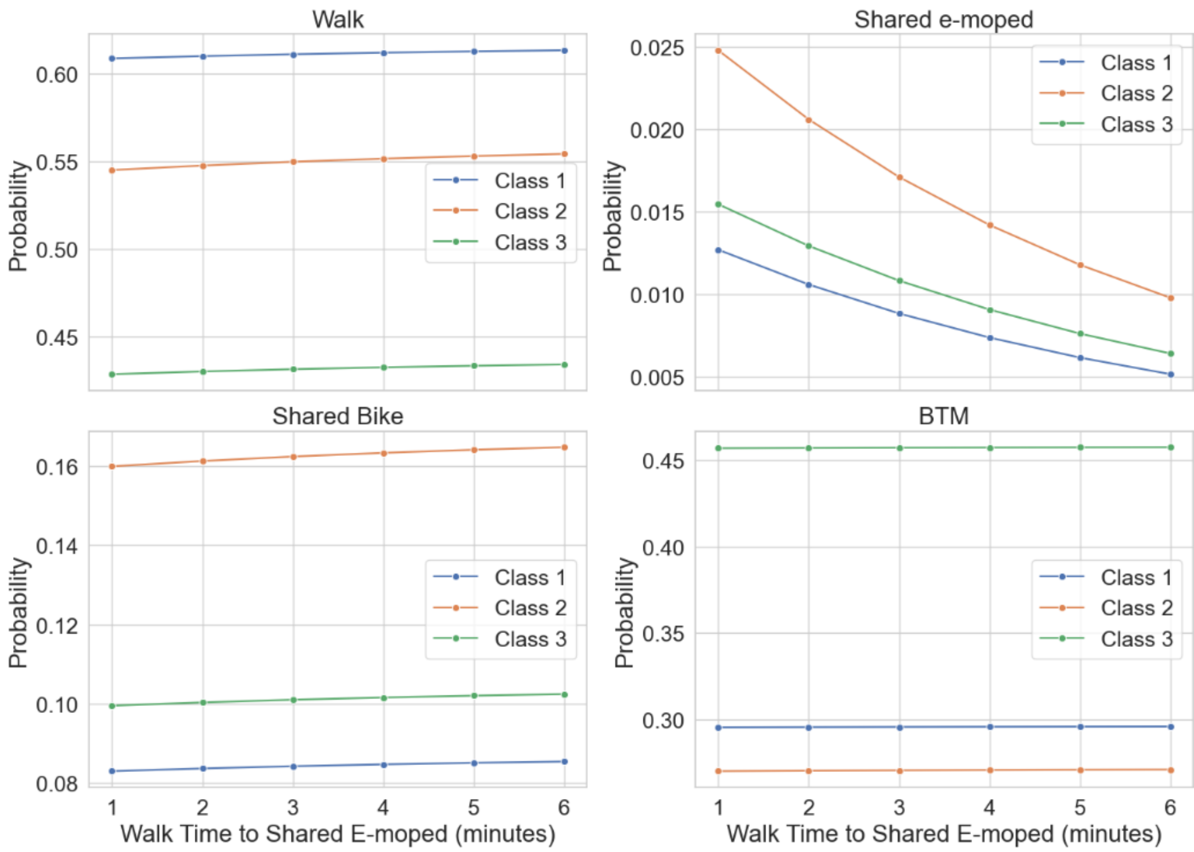


Figure 6.3: Impact of changing the shared e-moped walking time in the 1.5 km trip

The probability of choosing a shared e-moped consistently decreases as the walking time to the shared e-moped increases. This trend is observed across all classes, with Mode Adapters (Class 2) showing the highest initial probability, followed by Cost-sensitive Adapters (Class 3) and Conservative Travelers (Class 1).

The probabilities of choosing shared bike and walking modes decrease, with a reduction of 0.015 and 0.010 in probability for Class 2, respectively, when the shared e-moped walking distance decreases from 6 to 1 minute.

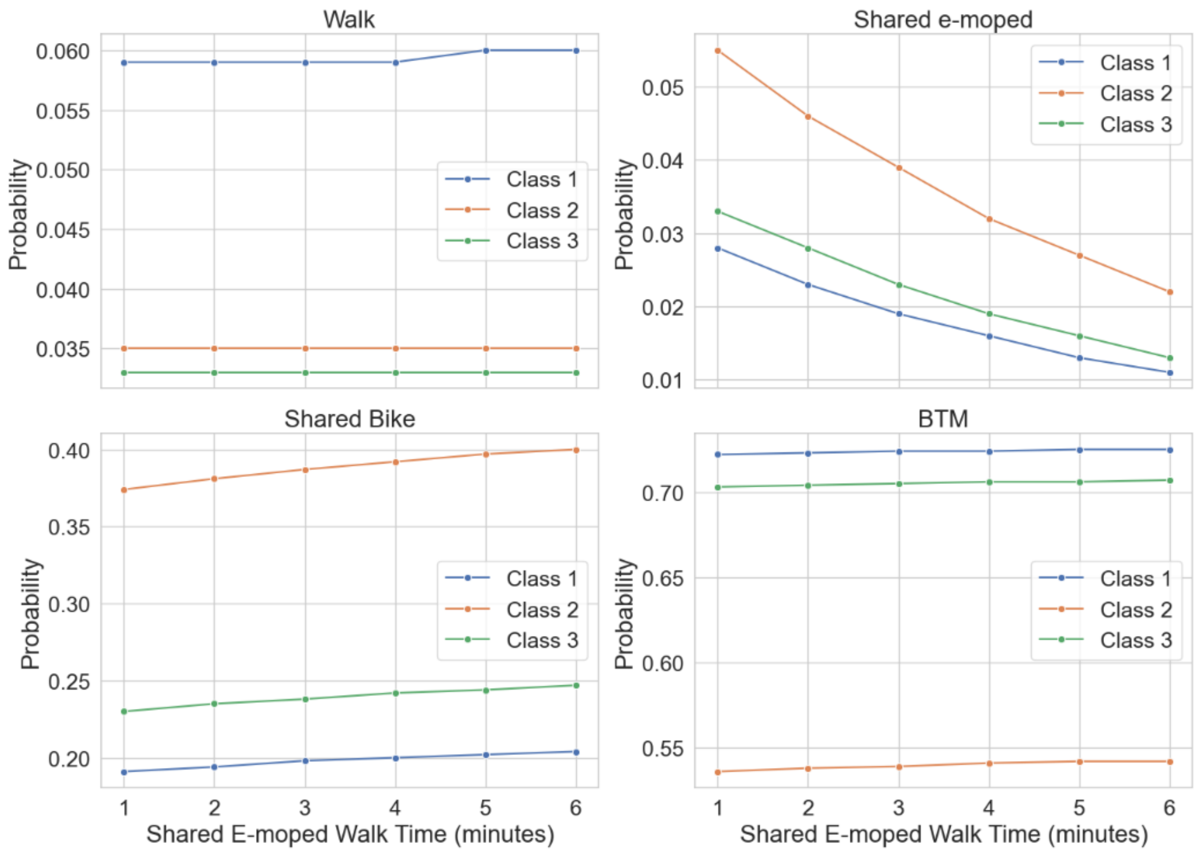


Figure 6.4: Impact of changing the shared e-moped walking time in the 3 km trip

When the walking time to a shared e-moped is reduced, the likelihood of choosing the shared e-moped increases. For the Mode Adapters (Class 2), the difference in probability between walking 1 minute and 6 minutes is the greatest, at 0.033. The shared bike sees the largest decrease in its share, losing 0.026, followed by BTM losing 0.006, and walking losing 0.001.

In other classes, the shared bike also loses the most in mode choice probability. This indicates that if NS integrates the shared e-moped closer to their entrance, the use of shared bikes would decline the most.

In conclusion, reducing walking time increases the probability of choosing a shared e-moped for all classes, especially for Class 2, the Mode Adapters. When these classes are combined, reducing the walking time from 4 minutes to 1 minute increases the probability of choosing a shared e-moped from 0.011 to 0.02 for a 1.5 km trip, and from 0.025 to 0.043 for a 3 km trip.

For the hypothetical station, this change would result in 1.15% of trips being made by shared e-mopeds for the last mile. Reducing the walking time from 4 minutes to 1 minute would increase the number of shared e-moped trips in the reference scenario from 59 to 115 trips, nearly doubling the number of trips.

Trip costs

Since the convenience of the shared e-moped does not significantly influence mode choice, this factor will not be modified for analysis. Although NS does not directly influence the trip costs of shared e-mopeds, it is interesting to examine the impact of changes in these costs. This experiment focuses on a 3 km trip, with other variables remaining constant. For the 1.5 km trip, the shared e-moped costs range from 1 euro to 3 euros. The model does not consider costs above 3 euros, as the probability of choosing the e-moped becomes negligible.

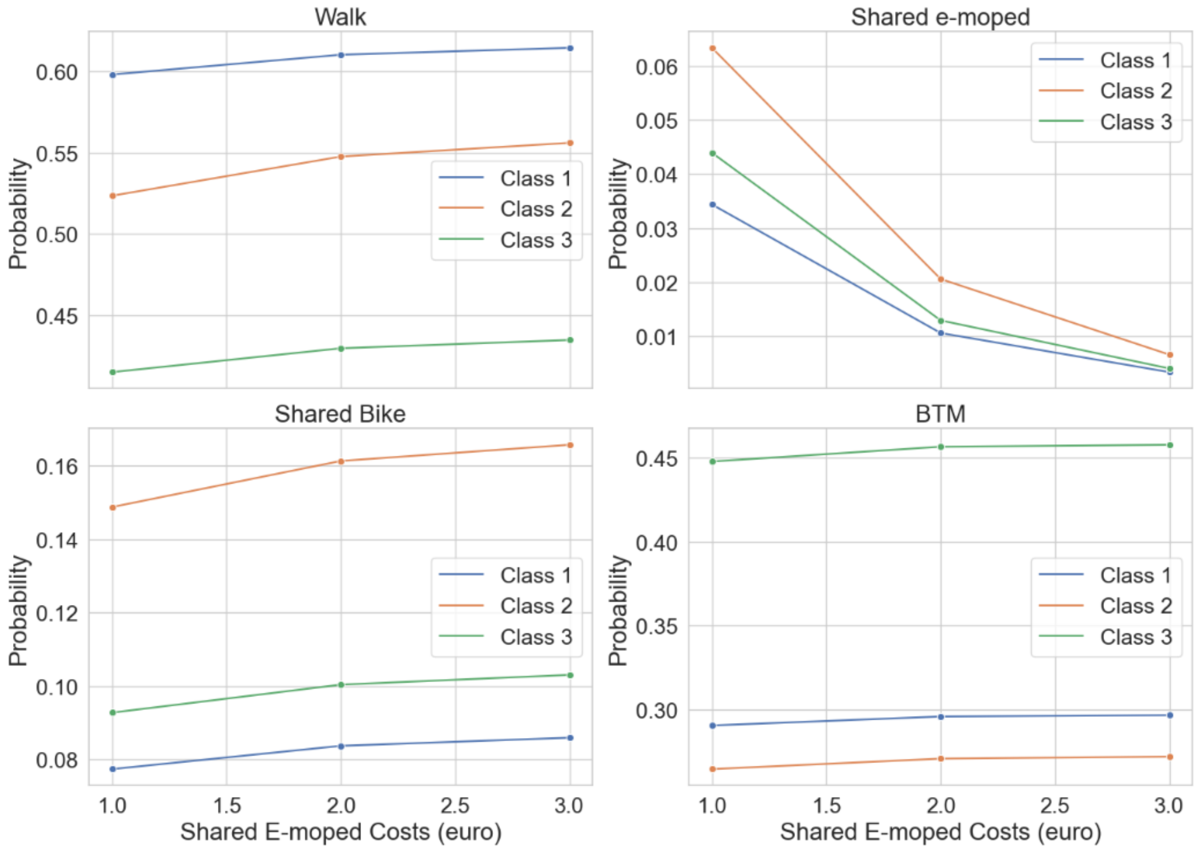


Figure 6.5: Impact of changing the shared e-moped costs in the 1.5 km trip

It can be concluded that the shared e-moped trip costs affect mode choice probabilities. Reducing the costs by 2 euros (to 1 euro) increases the probability of Mode Adapters choosing the e-moped by more than 0.056, Conservative Travelers by 0.03, and Cost-sensitive Adapters by 0.04. For all classes, this increase is mainly at the expense of the walking probability, followed by the shared bike, and to a lesser extent, BTM.

Changing the costs of the shared e-moped for the 3 km trip covers a wider range of euros since people are willing to pay more for longer distances.

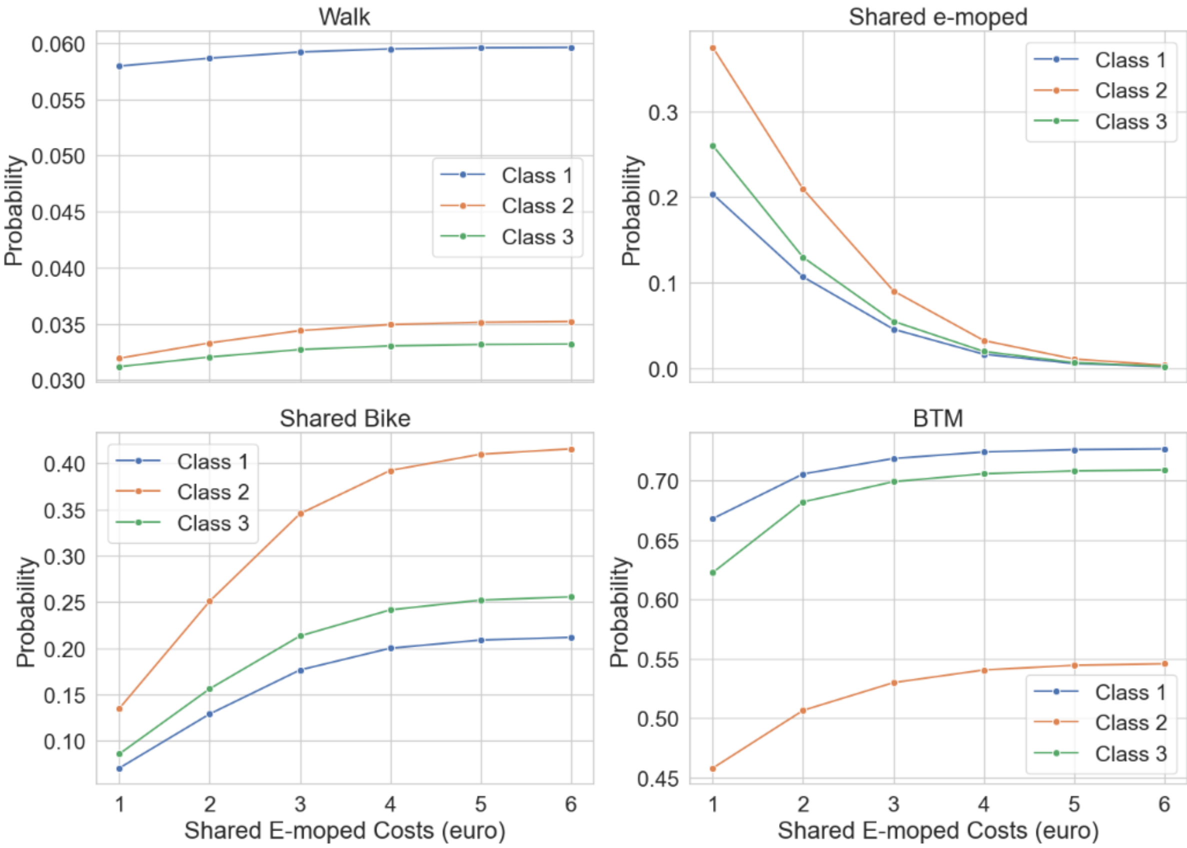


Figure 6.6: Impact of changing the shared e-moped costs on the 3 km trip

Similar to the other experiments, the probability of choosing the shared e-moped increases the most for Mode Adapters when costs are lowered. When reducing the cost to 1 euro while keeping other factors constant, the probability of using the shared e-moped in this group exceeds 0.35. For all classes, this cost reduction has the greatest impact on the probability of choosing the shared bike, followed by BTM (Bus, Tram, Metro).

When lowering the cost by 1 euro for both distances at the hypothetical station, the probability of choosing the shared e-moped will increase. For the 1.5 km trip, reducing the price from 2 euros to 1 euro will increase the probability from 0.011 to 0.038. For the 3 km trip, reducing the price from 4 euros to 3 euros will increase the probability from 0.025 to 0.071.

At the hypothetical station, this change would result in 1.82% of trips being made by shared e-mopeds for the last mile. Reducing the trip cost by 1 euro would increase the minimum number of shared e-moped trips in the reference scenario from 59 to 182 trips per day.

Using this model, the mode choice probabilities for all four modes can be calculated with different input values. However, to understand the impact of these changes on the number of shared e-moped trips, it is important to examine cases with real trip numbers.

6.3.2. Studying an example

When taking a railway station where shared e-mopeds and shared bikes are available, it would be interesting what will happen if the parking spots are brought closer to the station. In this example, The Hague Central is taken as case study. Figure 6.7 shows a map of The Hague Central, with the locations of the shared bike (S), bus stop (B), and Tram stop (T). They are all within a 2 min walk. The shared e-moped parking area is located on a 5 minute walk. When deciding to move theses parking spots in front of the station, this walk will shift from 5 to 2 minutes.

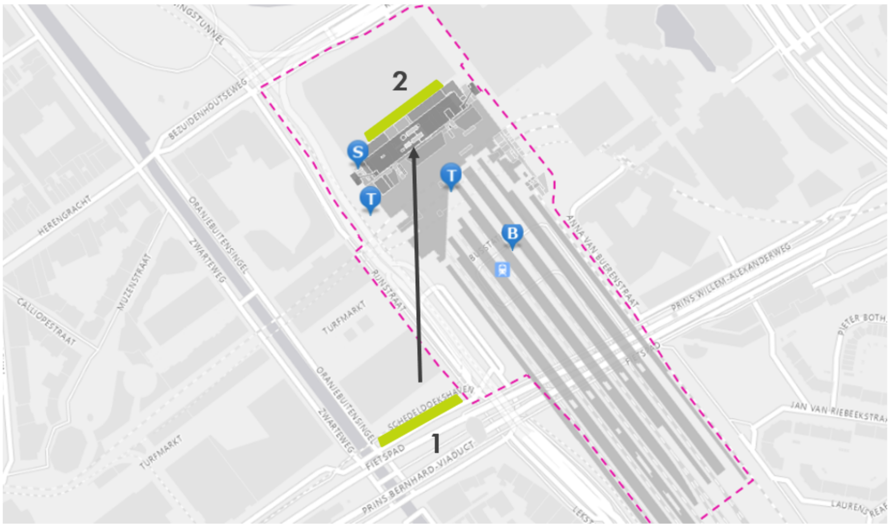


Figure 6.7: Moving the shared e-moped parking spot towards the station

For a 1.5 km trip, the shared e-moped mode choice from 0.9% to 1.6%. For the 3 km trip, the shared e-moped mode choice changes from 1.9% en 3.3%. Appendix F shows how this is measured with the model.

6.4. Summary

Traveler segments

Analysing the results of the stated preference experiment, latent class modeling revealed distinct attitudes and behaviors toward shared e-mopeds among different groups of train travelers. The 'Conservative Travelers' prefer traditional modes of transport and are hesitant to adopt new technologies. In contrast, 'Mode Adapters' are the most enthusiastic users of shared e-mopeds, reflecting their openness to innovation. Cost-sensitive adapters show potential interest driven by social and economic factors but have not yet extensively embraced shared e-mopeds. Age, education, perception of shared e-mopeds, and previous use of shared e-mopeds influence the classification of individuals into these segments.

Conservative Travelers are the group least likely to choose shared e-mopeds for the last mile of their journey. This group is typically older and has a negative perception of shared e-mopeds, viewing them as less safe and less environmentally friendly. Most members of this group are retired, primarily own cars, and seldom travel by train. They are also the least familiar with shared e-mopeds.

Mode Adapters are the group most likely to choose shared e-mopeds for the last mile of their journey. This group is generally younger, more highly educated, and more familiar with shared e-mopeds. They have a more positive perception of shared e-mopeds compared to other groups. Other characteristics of this group include being mostly employed, owning the most bikes, and frequently using OV-bikes. The reservation time for shared e-mopeds (convenience) does not influence mode choice for train travelers.

Cost-Sensitive Adapters prefer transportation methods that do not require physical effort. Most people in this group are young, with the lowest education levels compared to other classes. Regarding shared e-mopeds, this group places significant importance on the social image associated with using them. While they are aware of shared e-mopeds, they have not used them primarily. They have lower education levels, many do not have driver's licenses, and they own fewer personal vehicles and bikes. Their transportation choices are only influenced by pricing competitiveness.

Choice probability model

For a 3 km trip in the last mile, the shared e-moped has a higher probability of being chosen compared to a 1.5 km trip in the last mile, aligning with previous research (de Wit, 2023; Hoobroeckx et al., 2023). Reducing the walking distance to the shared e-moped or the trip costs increases its likelihood of being chosen for all classes, with the most significant impact on the Mode Adapters. Reducing the travel cost of the shared e-moped also increases its likelihood of being chosen for all classes.

Overall, the shared bike is chosen over the shared e-moped. The shared e-moped is generally less preferred compared to shared bicycles when considering average attributes. This is consistent with previous research, where Van Kuijk et al. (2022) found that in Utrecht, shared e-scooters and shared bikes were favored over shared e-mopeds for the first and last mile from public transport.

7
Modal shift

To understand which modes of transportation were potentially being replaced by shared e-mopeds for the first and last mile, different perspectives were considered. First, the modes that were currently being replaced in trips where shared e-mopeds were already used for the first or last mile were identified. Second, the mode substitution for the last mile from the Stated Preference Experiment was analyzed, particularly when the shared e-moped was made more attractive. Third, individuals who did not choose to 'never' use shared e-mopeds for these purposes were analyzed. While some explicitly indicated they would not consider using shared e-mopeds for the first and last mile, the group that did not choose 'never' (or did not cite other modes as barrier) showed a potential willingness to use shared e-mopeds.

7.1. Shared e-moped users

When asking the train travelers which mode they replaced with using the shared e-moped in the first or last mile, these were the answers given.

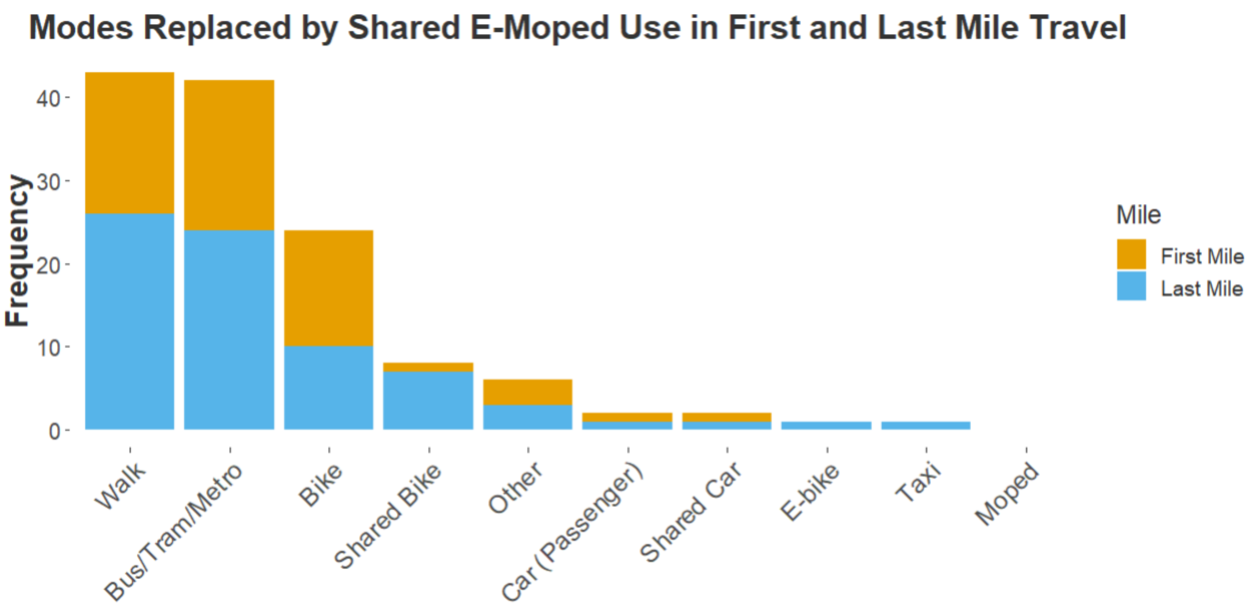


Figure 7.1: Modes Replaced by Shared E-Moped Use in First and Last Mile Travel

The data indicates that walking and using public transportation (bus, tram, metro) are the most commonly replaced modes in the first and last mile. Other modes such as shared bikes, other forms of transport, passenger cars, shared cars, e-bikes, and taxis are replaced less frequently, with a gradual decrease in frequency, reaching nearly negligible levels for e-bikes and taxis.

The plot shows that shared e-mopeds most often replace walking, bicycles, and public transportation for first-mile travel. For last-mile travel, they mainly replace walking and public transportation.

7.2. Last mile substitution

When examining the potential modal shift resulting from making shared e-mopeds more attractive, two key factors are considered: lowering the walking distance to access the shared e-mopeds and reducing their costs. The figures of these adjustments can be seen in the Mode Choice Probability model section. Each of these adjustments impacts the mode choice probabilities differently, shedding light on which transport modes might be replaced by the shared e-mopeds in the last mile.

7.2.1. Lowering the Walking Distance

- **Walking Distance for 1.5 km trip:** By reducing the walking distance to access a shared e-moped for the 1.5 km trip, the data indicates a slight decrease in the probability of choosing a shared bike. Walking also sees a minor decline. Interestingly, the probability of using BTM (Bus, Tram, Metro) remains unaffected.
- **Walking Distance for 3 km trip:** When the walking distance is further reduced for the 3 km trip, the shared bike is almost entirely substituted by the shared e-moped. In this scenario, neither BTM nor walking modes show significant changes in their probabilities. This shift underscores the shared bike as the primary competitor to shared e-mopeds when walking distance is minimized, likely due to their similar convenience and speed for short trips.

7.2.2. Reducing the Costs

- **Costs for 1.5 km trip:** Lowering the costs associated with using a shared e-moped for a distance of 1.5 km primarily affects walking. Many users who would have opted to walk now prefer the shared e-moped, finding it a more attractive option due to the reduced cost. Shared bikes are the next most affected, though to a lesser extent than walking. This suggests that cost reductions make the e-moped a viable alternative for those seeking a balance between convenience and affordability.
- **Costs for 3 km trip:** When the costs are lowered for a distance of 3 km, the shared bike sees the most significant decrease in probability, indicating that users are likely to switch from shared bikes to shared e-mopeds for longer trips as well. BTM is the second most affected mode, highlighting that cost reductions make the shared e-moped competitive even against more traditional public transport options.

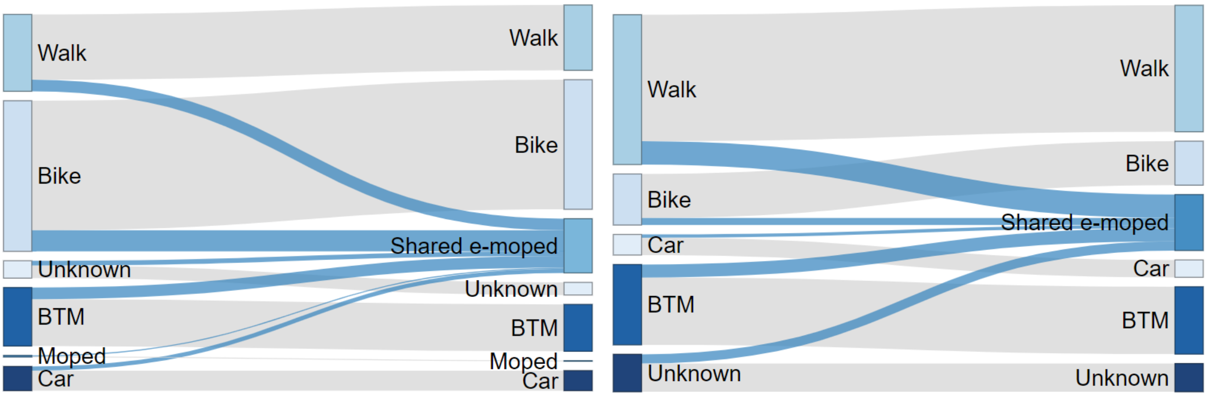
In summary, making shared e-mopeds more attractive by lowering walking distances or reducing costs leads to a noticeable modal shift. Shorter walking distances primarily draw users from shared bikes, whereas cost reductions attract users from both walking and shared bikes for shorter trips and from shared bikes and BTM for longer trips.

7.3. Breaking barriers

When considering a potential shift in transportation modes among individuals who currently do not choose to ”never” use a shared e-moped but are hindered by barriers (other than ”no alternative”), it is important to focus on those who might be persuaded to use shared e-mopeds if these barriers are removed. Here, also the people who have filled in they would only use the shared e-moped when no other modes are available are left out, since they would not have the option to shift from that other mode. This group includes people who could be convinced to use shared e-mopeds if certain obstacles are eliminated.

People who might consider using shared e-mopeds are most commonly represented among those who use bicycles for the first mile. Bus, train, and metro (BTM) and walking have equal shares. The last mile is predominantly covered by walking, suggesting that shared e-mopeds are more appealing for shorter, walkable distances. The modal split of people considering shared e-mopeds, assuming no barriers, is as follows.

In chapter 5, the modal split of the respondents were compared to that of the train traveler from NS 2023 data. Here the first mile in the sample was overrepresented with bikes, and the last mile



((a)) First mile **((b))** Last mile

Figure 7.2: Modal shift when barriers are taken away

Mode	First Mile (N = 103)	Last Mile (N = 103)
Bike	40 (38.8%)	13 (12.6%)
BTM	22 (21.3%)	24 (23.3%)
Car	8 (7.7%)	6 (5.8%)
Moped / Taxi	2 (1.9%)	0 (0%)
Unknown	9 (8.7%)	17 (16.5%)
Walk	22 (21.3%)	43 (41.7%)

Table 7.1: Mode Choice for First and Last Mile

underrepresented in walking. This indicates that the percentages of bike in the first mile will be smaller, and the percentage of walking in the last mile will be higher.

For both the first and last mile, the distribution of people does not significantly differ from the overall modal split of the total sample. This indicates that no specific mode user in the first or last mile values the shared e-moped more than others.

7.4. Summary

Analyzing the modal shift from three perspectives provides an overview of the modes that could be replaced by the shared e-moped. Firstly, the modes that are already replaced in previous trips indicate that walking, BTM, and biking are the most commonly replaced in the first and last mile. Additionally, the shared bike is also commonly replaced in the last mile. This trend is further supported by the second perspective, which analyzes the SP experiment on the last mile trip. It shows that making the shared e-moped more attractive by reducing walking time or trip costs will mostly replace the shared bike or walking. The third perspective examines individuals who currently face barriers but are willing to use the shared e-moped. These individuals currently use various modes of transport, so no specific conclusions can be drawn about a particular mode being replaced.

The most replaced modes are walking, BTM, and biking for the first mile, with shared bikes also being replaced in the last mile. Literature on shared mobility indicates that shared electric modes emit more CO2 than the transport modes they replace (Reck et al., 2022). This aligns with the finding that shared e-mopeds will mostly replace walking, BTM (bus, tram, metro), and bikes in the first mile, and shared bikes in the last mile.

8 Discussion

This chapter interprets the results from the previous three chapters. To provide a clearer understanding of these results, it first interprets them and compares them with findings from related studies. Next, it discusses the methodological limitations of this study. Finally, it addresses the generalizability of the results.

8.1. Interpretation and comparison with literature

The percentage of respondents who have previously used shared e-mopeds (10.7%) is significantly higher than the national average reported in the national traveler survey (5% in 2022) (Rijksoverheid, 2022). This discrepancy could be attributed to the busier travel behavior of train travelers compared to the average person. This is supported by the findings that frequent use of bikes, walking, and cars positively influences previous use of shared e-mopeds.

Conversely, car ownership negatively influences the likelihood of being a previous user. Therefore, shared e-moped users typically do not own a car but frequently travel by car. This could be explained by either traveling as a car passenger or using shared cars, indicating an openness to sharing. In addition to showing the influence of car ownership and travel frequencies, this study contributes to the literature by identifying that moped and motorcycle ownership positively influences previous use of shared e-mopeds.

This study examines the variation among the latent classes which is a novel perspective within the field of shared e-mopeds. (Garritsen, 2022) investigated numerous traveler characteristics influencing the use of shared e-mopeds for the first and last mile but did not differentiate between population groups or classes. By introducing different classes, this study provides valuable insights for policymakers who aim to target their policies more effectively and understand the varying preferences of different groups.

The classes made can be fit into the model made by (Rogers, 1962) about the diffusion of innovation. The identified classes show overlap with the different sections Rogers made. The mode adopters (40%) are the 'early adopters' and a big part of the 'early majority'. The 10% who have already used the shared e-moped before can be seen as the 'innovators' and a part of the 'early adapters'. These who are younger and have previously tried other shared modes of transport. The cost-sensitive adopters (31%) can be seen as part of the early and late majority, consisting of individuals who are open to using shared e-mopeds but are not yet ready to do so. Conservative travelers (28%) are the least likely to adopt this mode of transport as they are older and have a negative perception of shared e-mopeds. The question is whether these factors will ever change enough for them to adopt shared e-mopeds in the future. The key factors Rogers stated for an innovation being adopted show if the shared e-moped could have potential in the first and last mile.

- **Relative Advantage** - Shared e-mopeds have a relatively small advantage over the curren shared bikes for the user, which are better spatial integrated at railway stations. The shared e-mopeds are more often a "free-floating model", and do not need any effort of the user, which can be also seen as a disadvantage.

- **Compatibility** - Shared e-mopeds align well with the values of train travelers who value transport sharing and sustainability.
- **Complexity** - The usability of shared e-mopeds is relatively straightforward, especially with user-friendly apps for booking and unlocking the vehicles. However, potential adopters may need to develop riding skills if they are unfamiliar with mopeds.
- **Trialability** - Shared e-mopeds are highly trialable, as users can easily rent them for short periods to test their convenience and suitability before deciding to make them a regular part of their transport routine.
- **Observability** - The benefits of shared e-mopeds, such as reduced travel time and convenience, are easily observable. Users can see others using them, and the positive outcomes can be quickly recognized, encouraging further adoption.

In general, following Rogers' diffusion of adoption theory, shared e-mopeds could be adopted by train travelers, but only under certain circumstances. There has to be a relative advantage over the other modes, which is not the case when not spatial integrated at a railway station. Conservative Travelers are less likely to adopt them because they may experience higher complexity and lower relative advantages. Future adoption is possible, but not for all classes. At the same time, the shared e-moped is competing with other shared innovations that are currently better integrated into the railway system.

To validate the choice model, one can assess whether the predicted range of mode share is realistic. The observed trip numbers for shared e-mopeds at a hypothetical station seem reasonable. To compare these numbers with real data, there has been looked at Amsterdam Sloterdijk station. In 2021, an average weekday saw 24,411 train travelers entering and exiting this station (NS data, 2021). This suggests that 12,211 travelers might be involved in last-mile travel at this station. Applying the model, which incorporates variables such as walking distances and costs, we find that 12,211 * 0.056 results in a minimum of 68 trips per day when only four options are available. In reality, a report from the municipality of Amsterdam indicated around 58 trips per day in the second half of 2021, suggesting that the model's range is accurate (RWS, 2024). The model can be adapted to other stations, but it requires fine-tuning for each unique location. This includes setting variables like walking distances and costs specific to each station. Additionally, each station has distinct travel patterns, populations, and first and last-mile mode options, leading to unique modal splits. Therefore, it is most practical to maintain the model's general applicability. According to de Wit (2023), the mode share for shared e-mopeds in cities ranges between 0.06% and 2.5%, which aligns with the model's output range when using average input data.

The impact of the attributes 'walking distance,' 'trip costs,' and 'convenience' on the choice of shared e-mopeds was measured. While walking distance and trip cost align with findings from previous studies on shared e-mopeds in general (Chen et al., 2023), the convenience of shared e-mopeds does not significantly influence the choice of this mode at the 5% significance level. However, other research has identified convenience as a significant factor (Hector, 2022; Loudon et al., 2023). It was even found to be even more influential than time and cost in the context of using shared modes (J. Ye et al., 2020). In that study, participants were asked if they hoped to use the new mode for more convenient travel, which differs from considering it as a time constraint in the stated preference experiment.

The replaced modes indicate that modes being replaced by the shared e-moped are generally more spatially efficient and environmentally friendly. (Loudon et al., 2023) found that the shared e-moped could be competitive with cars. Aguilera-García et al. (2021) and Wortmann et al. (2021) also stated that the desire for sustainable transportation is a significant reason for using the shared e-moped. However, in a survey of train travelers, sustainability was not mentioned at all, and the shared e-moped rarely replaced car trips. The main reason for this difference could be that Aguilera-García et al. (2021), Loudon et al. (2023), and Wortmann et al. (2021) did not focus on train travelers in the first and last mile, but on trips in general. Only a small percentage of people use a car in combination with the train. According to the survey data on modes replaced by shared e-moped use, the car was mentioned only a few times. This can be interpreted as most people using cars do not live in urban areas where the shared e-moped is available.

Other differences from literature

Garritsen (2022) showed the social influence having impact on the use of the shared e-moped. He found that the extent to which users perceive to be influenced by others, like friends, family, or other authority figures was the most influencing predictor for the shared e-moped use. This does not align with the train travelers preference. Only the Cost-sensitive adapters do care about social image, but they do not use the shared e-moped often.

Aguilera-García et al. (2021) also concluded that students were the most likely users of the shared e-moped. This does not align with this study's results. Here, students are more represented in the Cost-sensitive class, where respondents are sensitive to the high costs of the shared e-moped, which is logical given their financial situation. This class also has the highest proportion of people without a driver's license, which acts as a barrier to using the shared e-moped.

8.2. Methodological limitations

The survey participants were individuals more willing to express their opinions, often having higher educational levels, which may skew the results. Additionally, the socio-demographic information for the NS panel could have been completed up to six months prior, potentially leading to inaccuracies.

The number of respondents who had previously used shared e-mopeds for the first and last mile was too small to conduct analyses beyond exploratory data analysis. The survey also did not ask why respondents would never consider using shared e-mopeds, leaving a gap in understanding specific barriers.

Regarding the survey design, the estimated priors for shared e-mopeds were set too high, resulting in fewer respondents choosing this mode and thereby limiting the data on shared e-mopeds.

It is important to recognize the inherent limitations of this stated preference experiment, particularly because of its hypothetical nature (Welling et al., 2023). It may only provide a surface-level understanding of motivations, as it relies on closed-ended questions, potentially restricting insights (Coughlan et al., 2009). The stated preference (SP) experiment conducted as part of this research introduced several biases that should be considered when interpreting the results. The results are specifically relevant to the 'last mile' segment of travel, particularly for distances of 1.5 km and 3 km. Since the SP experiment was conducted in the context of an unspecified city, the findings are applicable to multiple station types typically found in urban areas. The study did not account for weather variations, encompassing all possible weather conditions.

The comparison in the SP experiment was limited to a few modes of transport: walking, shared bikes, bus/tram/metro (BTM), and shared e-mopeds. It is important to note that the focus was on shared e-mopeds with a speed of 45 km/h, which might not fully represent the diverse usage patterns of e-mopeds.

The results of the SP experiment offer new insights into travelers' preferences regarding shared mopeds. This includes insights from individuals who have not yet used them, which allows examining factors for both current users and non-users.

The reasons given by previous users for using shared e-mopeds are illustrated in a stacked bar plot, combining the first and last mile per reason. While this provides a comprehensive overview of the main reasons, it does not allow for a detailed comparison between the first and last mile reasons. This is because the number of respondents is too low, while some people have used the shared e-moped in both the first and last mile, and some only in one of the cases.

The primary reason, 'Fast travel,' could be further divided into multiple reasons, as done in previous research. Studies by Aguilera-García et al. (2021), Garritsen (2022), and Wortmann et al. (2021), who investigated reasons for using shared e-mopeds in general, also identified 'Time-saving,' 'Travel directly,' and 'Congestion avoidance' as reasons. These categories offer more detailed insights and are easier to interpret than the broader category of 'Fast travel'.

When comparing trip purposes to other literature, the categories used in this study differ. For instance, de Wit (2023) included a 'home' category that encompassed both home-work trips and visits to family and friends. However, the proportion of his 'work' and 'education' categories (30%) relative to the 'leisure' category (16%) aligns with the findings in this thesis. Aguilera-García et al. (2021) also examined trip purposes, distinguishing between frequent and infrequent shared e-moped users. Unfortunately, the number of respondents who had used shared e-mopeds for the first and last mile was too small to make this distinction in the current study.

The survey results showed that a significant number of respondents selected 'neutral' regarding their perception of shared e-mopeds. This might be due to a lack of familiarity with shared e-mopeds among the respondents. A limitation of the survey is that it did not explain the concept of shared e-mopeds before asking questions about them.

Initially, the plan was to incorporate 6 psychological factors when creating the classes in the latent class model. However, the perception questions were found to be highly correlated. Including all these psychological factors in the model could lead to multicollinearity issues. As a result, a factor analysis was done to extract 2 non-correlating factors.

8.3. Generalisability

This study examines train travelers and notes significant demographic differences between the survey´s sample data and the actual train traveler population. These differences, particularly in age, occupation, education, and driver's license ownership, suggest that the sample may not fully represent the train traveler population. The sample includes an older age distribution than the actual train traveler population, which could result in a lower proportion of shared e-moped users since younger individuals are more likely to use them. Differences in occupational composition and education levels could also influence the study outcomes. Since shared e-moped users tend to be more highly educated, this could lead to a higher proportion of shared e-moped users in the sample. Additionally, the sample has more individuals without a driver's license, indicating that a greater number of people in the sample face a barrier to using shared e-mopeds, potentially leading to a lower proportion of shared e-moped users.

This thesis focuses on the Netherlands, based on a survey conducted among Dutch people. So the results of the survey are only applicable to the train traveler in the Netherlands. The railways, modal split, built environment, regulations on shared modes, and shared modes offered differ per country.

The primary focus of this research is on access and egress trips to and from railway stations. Other transit nodes, such as bus stations, tram stations, and metro stations, have distinct characteristics that influence mode choice decisions differently, so the findings of this thesis are specific to railway stations.

Although the emphasis is on shared e-mopeds, the methods and theories presented can be extended to other emerging transportation modes when considering their integration with railway stations.

While the unique characteristics of different countries, transit hubs, and shared modes are acknowledged, the methods and theories developed in this research can be used to adapt for studies for studying new transportation modes in combination with transit hubs.

The choice model can be applied at stations in the Netherlands where the following four modes of transportation are available: 'walking,' 'shared bikes,' 'bus/tram/metro (BTM),' and 'shared e-mopeds.' It can also be used to analyze stations where these modes are not currently available to assess the potential impact if they were added.

To evaluate the impact of walking distance or costs when these factors change, the choice model can only be used at stations that already have shared e-mopeds and shared bikes. This model is valid only if no other modes besides 'walking,' 'shared bikes,' 'bus/tram/metro (BTM),' and 'shared e-mopeds' are considered in the choice set.

It is important to note that each station has its unique travel patterns and traveler behaviors. Therefore, the choice model is primarily hypothetical and not specific to any particular station. When applied to a specific station, tailored assumptions should be made for that station.

9
Conclusion & Recommendations

This study investigated the travel behavior and preferences of train travelers during the beginning and end segments of their journeys. Factors influencing the choice of transportation mode for these segments were identified through a literature review. These factors were then included in a survey conducted among train travelers. Using exploratory data analysis and a model derived from a stated preference experiment, an overview of the preferences and behaviors of train travelers was developed.

9.1. Conclusion

The main research question, ”How do shared electric mopeds impact the travel behavior of train travelers for first and last-mile transportation?” will be answered by addressing the four subquestions.

What are the key factors influencing travelers' decisions to choose a mode for railway station access/egress?

The factors that influence travelers' choices for accessing and leaving railway stations are varied and can be divided into several main categories. Traveler characteristics such as gender, age, education, occupation, previous experience, possession of a driver's license, and vehicle ownership play a significant role. Trip characteristics, including trip distance, trip purpose, and travel cost, also affect mode choice. Additionally, mode characteristics like walking distance and convenience are important considerations. Psychological factors, including social influence, environmental awareness, safety perception, attitude towards the service, and habits, further contribute to the decision-making process. Understanding these factors is crucial for developing policies and services that cater to different traveler segments.

Category	Factors
Traveler Characteristics	Gender, Age, Education, Occupation, Previous Experience, Driver's License, Own Vehicle
Trip Characteristics	Trip Distance, Trip Purpose, Trip Cost
Mode Characteristics	Walking Distance, Convenience
Psychological Factors	Social Influence, Environmental Awareness, Safety Perception, Attitude Towards the Service, Habits

Table 9.1: Factors Influencing Mode Choice

What is the current travel behaviour and perception of train travelers regarding shared e-moped use?
Travel behavior and perceptions of train travelers regarding shared e-mopeds indicate that only a small fraction has previously used this mode, primarily for leisure rather than daily commutes. Most travelers hold a neutral to negative view of e-mopeds. Many travelers prefer not to use e-mopeds under any circumstances, with resistance to using shared e-mopeds being greater at the start of the journey than at the end. Many non-users are hesitant to consider them due to the availability of other transportation options, perceived high costs, the requirement for a driver's license, and limited availability of shared e-mopeds in certain areas. The most frequently mentioned barriers, aside from the availability of other modes, include the high price, the need for a driver's license, and the lack of shared e-mopeds nearby.

How do key factors contribute to the likelihood of choosing shared e-mopeds for railway station access/egress?
When studying the impact of key factors, several factors significantly influence traveler choices. Firstly, walking distance from the stations towards the shared e-moped and the cost of trips are major determinants. Lowering the walking distance and lower travel costs increase the likelihood of travelers choosing this mode, particularly among mode adapters, which are young, employed, high educated people who have a positive perception on sharing, including the shared bike and shared e-moped.

By identifying different traveler segments, it becomes clear which groups are influenced by shared e-mopeds, both positively and negatively. 'Conservative Travelers' (31.7%) are the least likely to adopt shared e-mopeds, while 'Mode Adapters' (40%) are the most enthusiastic, and 'Cost-Sensitive Adapters' (28%) show potential interest. However, whether everyone will adapt to using shared e-mopeds remains uncertain, particularly since the need among train travelers seems low which may be a key factor needed for adoption in the first and last mile.

Which modes are substituted by the shared e-moped use in first/last mile transportation when integrated at NS stations?
The integration of shared e-mopeds at railway stations mostly leads to the substitution of walking and biking, especially for shorter trips. For longer distances, the BTM is replaced the most. Reductions in e-moped costs or shorter walking distances relatively draw most users away from walking and the shared bike users in the last mile. The people who are willing to use are open to sharing in general, so also for bike sharing.

This study aimed to explore the preference and travel behaviour regarding shared e-mopeds in the first and last mile. The main research question was:

How do shared electric mopeds impact the travel behavior of train travelers for first and last-mile transportation?

Shared electric mopeds have the potential to significantly alter the travel behavior of train travelers. Not all traveler segments are open to adopt a relatively new mode like this. While shared e-mopeds are not yet a prevalent mode of transport for first and last-mile travel, they could become more influential if they are more spatial integrated at stations, trip costs are lowered, or barriers are addressed.

9.2. Recommendations

Based on the findings and conclusions of this thesis, several recommendations can be proposed for NS regarding the use of shared e-mopeds. Additionally, suggestions for further research are made.

9.2.1. Recommendations for the NS

The NS aims to provide a seamless door-to-door experience for its passengers, including offering various transportation options. This section provides recommendations on whether to incorporate shared e-mopeds more extensively into their system.

Several policy considerations should be taken into account regarding the integration of shared e-mopeds. At present, there are some stations where the NS owns the surrounding land and can decide where to place parking spots for shared e-mopeds. Additionally, improving the app or system used for integrating shared e-mopeds should be considered. Currently, the cooperation with shared e-moped providers only includes showing the location of the shared e-mopeds to the users. It could be helpful to create an option where app users can also rent an e-moped through the app to make it more user-friendly.

Since there is a segment of travelers willing to use the shared e-moped, NS could see this as a beneficial addition to the current modal options. However, these 'Mode adapters' are also the train travelers who are open to using the OV-fiets. While most train travelers prefer the shared bike over the shared e-moped, this would partly replace the OV-fiets.

Considering the modes replaced by the shared e-moped, there are several reasons why NS should not further integrate the shared e-moped into their system, both digitally and spatially. Firstly, from an environmental perspective, the shared e-moped does not seem to replace more harmful modes of transport, such as private cars or traditional mopeds.

Secondly, the shared e-moped does not effectively address spatial (parking) issues. Walking, public transport, and (shared) bikes are more space-efficient compared to shared e-mopeds. Although replacing private bikes in the first mile could improve spatial efficiency, this requires further research.

If it is decided to spatially integrate shared e-mopeds at specific railway stations, it is recommended to consider the production and attraction rate of the station.

In summary, the recommendation is to prioritize more space and environmentally efficient transportation modes while considering shared e-mopeds as a supplementary option only in strategic locations where it might enhance overall accessibility.

9.2.2. Future Research Directions

Future research in the field of shared e-mopeds could explore various approaches to gain better insights and understanding.

Firstly, one important approach is to conduct long-term studies to track changes in user behavior and preferences over time. These studies can provide deeper insights into the lasting impact of shared e-mopeds. They can help answer questions such as whether the current generation is particularly inclined to use shared services or if this trend will continue in the future. Additionally, it is worth exploring whether the willingness to use shared modes declines among specific population segments as they age, or if they will continue to use shared modes as they grow older.

Secondly, investigating the spatial impact of shared e-mopeds at NS stations is also important. Key questions include how many parking spaces are needed for shared e-mopeds at different types of NS stations and whether dedicating space to these vehicles is better than building new bicycle parking spots. Additionally, understanding the potential impacts on station accessibility and congestion can inform infrastructure planning and policy decisions.

Additionally, examining whether shared e-mopeds could attract more train users and increase revenue would provide valuable insights. This perspective could offer a different view on the role of shared e-mopeds.

Finally, studying user behavior on longer trip distances can help us understand how shared e-mopeds could enhance or replace other transportation options. By analyzing how the availability of shared e-mopeds influences transportation choices for longer distances and identifying the factors that encourage or discourage their use on extended journeys, we can create better services that meet diverse mobility needs.

By addressing these areas, future research can significantly broaden our understanding of shared e-moped systems and their role in urban mobility, helping to shape policies and practices that support sustainable and efficient transport solutions.

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A

Shared e-moped integration at NS stations

Figure A.1: Measurements of distance from entrance (blue letter) towards shared e-moped parking (green) opposed to private mopeds (purple) (Up left: Rotterdam. Up right: 's Hertogenbosch. Down left: Amsterdam. Down right: Amsterdam Muiderpoort

B

Stated preference experiment design

```
? This will generate a sequential orthogonal factorial design
Design
;alts = moped, bike, BTM
;rows = 6
;eff = (MNL,d)
;block = 2
;model:
U(moped) = b1[-0.15] * conv_mop[1,2,3] + b2[-0.169] * walk_mop[2,4,6] + b3[-0.231] * cost_mop
    [1,2,3] /
U(bike) = b4[-0.15] * conv_bike[1,2,3] + b5[-0.169] * walk_bike[2,4,6] + b6[-0.231] *
    cost_bike[1.10,2.80,4.50] /
U(BTM) = b7[-0.112] * conv_BTM[3,6,9] + b8[-0.169] * walk_BTM[2,4,6] + b9[-0.231] * cost_BTM
    [0.80,1.40,2]
? U(walk) = (fixed)

(3km, different cost variables)
$
```

Table B.1: MNL Efficiency Measures (1.5km)

Measure	Value
D error	0.508242
A error	1.217534
B estimate	26.981478
S estimate	312.857815

Table B.2: Prior Estimates and t-ratios (1.5km)

Prior	b1	b2	b3	b4	b5	b6	b7	b8	b9
Fixed prior value	-0.15	-0.169	-0.231	-0.15	-0.169	-0.231	-0.15	-0.169	-0.231
Sp estimates	246.7	48.4	105.6	274.0	55.1	65.2	38.3	65.2	312.9
Sp t-ratios	0.125	0.282	0.191	0.118	0.264	0.294	0.317	0.243	0.111

1.5km Design

Choice	Moped			Bike			BTM			Block
	conv	walk	cost	conv	walk	cost	conv	walk	cost	
1	3	4	2	3	2	1.1	6	6	0.8	2
2	2	4	3	1	2	4.5	9	4	0.8	1
3	2	6	2	1	6	1.1	3	6	1.4	1
4	1	2	3	3	6	2.8	3	2	2	2
5	3	2	1	2	4	2.8	6	4	2	1
6	1	6	1	2	4	4.5	9	2	1.4	2

Table B.3: 1.5km Design

3km Design

Choice	Moped			Bike			BTM			Block
	conv	walk	cost	conv	walk	cost	conv	walk	cost	
1	2	4	5	3	2	1.5	6	4	2.4	2
2	2	6	3	1	2	3.0	9	4	1.7	1
3	3	4	3	2	4	4.5	3	2	2.4	1
4	3	2	4	1	6	1.5	6	6	1.7	2
5	1	6	4	2	4	4.5	3	6	1.0	2
6	1	2	5	3	6	3.0	9	2	1.0	1

Table B.4: 3km Design

C

Survey

NS Panel

0%

Hartelijk dank voor uw deelname aan deze vragenlijst.

Uw deelname stelt de NS in staat om inzicht te krijgen in het gebruik van deelscooters in combinatie met de trein.

De vragenlijst is opgedeeld in drie delen. In het eerste deel zullen enkele vragen over uw voorkeur voor vervoersmiddelen en uw mening over deelscooters worden gesteld. In het tweede deel wordt u gevraagd om een vervoersoptie te selecteren in verschillende hypothetische situaties. Het laatste deel bestaat uit vragen over uw huidige reisgedrag.

Klik op 'volgende' om te starten.

< Terug | Volgende >

NS Panel

3%

Deze vragenlijst gaat over de deelscooter.

Een deelscooter is een huurscooter die tegen betaling beschikbaar is voor algemeen gebruik zonder dat u de eigenaar bent. U kunt een deelscooter vinden en huren via een app op uw telefoon. Bekende aanbieders van deze service zijn onder andere Felyx, Go Sharing en Check.

Hoe bekend bent u met het concept deelscooter?

- ○ Ik heb wel eens een deelscooter gebruikt
- ○ Ik heb van deelscooters gehoord maar nooit gebruikt
- ○ Ik heb nog nooit van deelscooters gehoord

< Terug | Volgende >

8%

Hieronder ziet u een aantal stellingen over uw huidige reisgedrag. Wilt u voor elke stelling aangeven in welke mate u het met die stelling eens bent?

	Helemaal oneens	Oneens	Neutraal	Eens	Helemaal eens	Weet niet / n.v.t.
Ik reis graag met de trein						
Ik loop graag						
Ik reis graag met de deelscooter						
Ik reis graag met de auto						
Ik reis graag met de bus/tram/metro						
Ik fiets graag						

Terug Volgende

11%

Wilt u voor elk vervoermiddel aangeven hoe vaak u het gebruikt?

	Nooit	Minder dan 1 dag per jaar	1 tot 5 dagen per jaar	6 tot 11 dagen per jaar	1 tot 3 dagen per maand	1 tot 3 dagen per week	4 of meer dagen per week	Weet niet / n.v.t.
De deelscooter								
Lopen								
De auto								
De fiets								
De bus/tram/metro								

Terug Volgende

14%

Hieronder ziet u een aantal stellingen over de deelscooter. Wilt u voor elke stelling aangeven in welke mate u het met die stelling eens bent?

	Helemaal oneens	Oneens	Neutraal	Eens	Helemaal eens	Weet niet / n.v.t.
De deelscooter gebruiken is goed voor mijn imago						
Ik ben blij dat de deelscooter er is						
Ik ben positief over de deelscooter						
De deelscooter is milieuvriendelijk						
De deelscooter is veilig						
De deelscooter is makkelijk te gebruiken						

Terug Volgende

17%

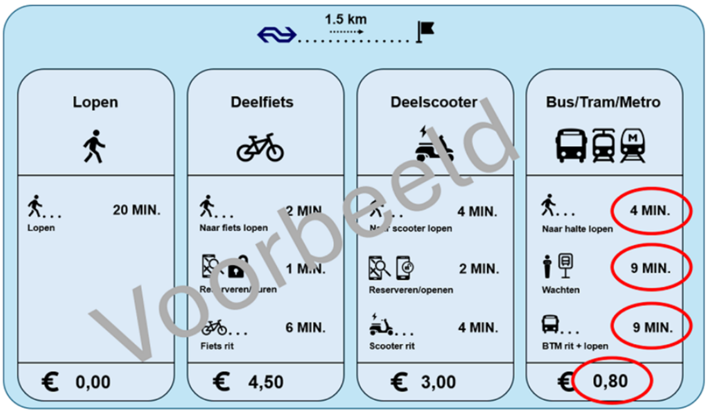
We gaan een experiment doen waarin u gevraagd wordt om zes keer uw vervoersvoorkeur aan te geven in verschillende reissituaties.

Dit zijn situaties waarin u reist vanaf het station waar u aankomt naar uw bestemming. De beschikbare vervoersopties zijn lopen, de deelscooter, bus/tram/metro en de deelfiets.

Meer uitleg over de deelfiets:
Een deelfiets is een fiets die u kunt huren zonder eigenaar te zijn. Dit zijn zowel fietsen die u bij een station kunt huren en terugbrengen, als fietsen die u via een app kunt vinden en huren. Voorbeelden van deelfietsaanbieders zijn de OV-fiets (rechts) en Donkey Republic (links).

19%

Hierna volgen 6 keuze experimenten. Hieronder ziet u een voorbeeld. De tijden en kosten per vervoermiddel zullen per experiment telkens variëren (in het voorbeeld voor Bus/Tram/Metro rood omcirkeld).



47%

Nu volgen er wat vragen over uw huidige reisgedrag.

Bent u in het bezit van een rijbewijs?

- Ja
- Nee

Terug | Volgende

50%

Welke vervoermiddelen heeft u in bezit of tot uw beschikking?

- [ ] Geen
- [ ] Fiets
- [ ] Auto
- [ ] Scooter, brommer of bromfiets
- [ ] Motor
- [ ] Anders, namelijk:

Terug | Volgende

53%

Heeft u wel eens de deelscooter gebruikt om naar het station te komen waar uw treinreis begint?

- ( ) Ja
- ( ) Nee

Terug | Volgende

57%

Om welke redenen heeft u de deelscooter gebruikt om naar het station te komen? U kunt meerdere antwoorden kiezen.

- [ ] De scooter stond in het zicht
- [ ] Gebruiksgemak
- [ ] Lage prijs
- [ ] Comfort
- [ ] Geen andere vervoersmiddelen beschikbaar
- [ ] Plezier
- [ ] Ik werd opgehaald
- [ ] Snel
- [ ] Duurzaamheid
- [ ] Anders, namelijk:

60%

Wat was uw reisdoel bij deze trip(s)? Er zijn meerdere antwoorden mogelijk.

- ☐ Van en naar mijn werk / vrijwilligerswerk
- ☐ Zaken-, dienstreis, bezoek congres en dergelijke, anders dan van en naar mijn werk
- ☐ Van en naar school, studie, opleiding, stage
- ☐ Bezoek aan familie, vrienden, kennissen
- ☐ Voor hobby, sport, verenigingsbezoek
- ☐ Oppassen, kinderen halen/brengen, boodschappen doen of andere zorgtaken
- ☐ Vakantie, uitstapje met minimaal 1 overnachting
- ☐ Winkelen
- ☐ Stad bezoeken
- ☐ Wandelen of fietsen
- ☐ Museumbezoek, tentoonstelling, festival of ander cultureel uitje
- ☐ Ander dagje of avondje uit
- ☐ Ander doel

63%

Welk vervoermiddel zou u naar het station hebben gebruikt als de deelscooter op dat moment niet beschikbaar was? Er zijn meerdere antwoorden mogelijk.

- ☐ Lopend
- ☐ Fiets
- ☐ Elektrische fiets
- ☐ Deelfiets
- ☐ Brommer/scooter
- ☐ Motor
- ☐ Auto (bestuurder)
- ☐ Auto (passagier)
- ☐ Deelauto
- ☐ Bus/tram/metro
- ☐ Taxi
- ☐ Anders

63%

Welk vervoermiddel zou u naar het station hebben gebruikt als de deelscooter op dat moment niet beschikbaar was? Er zijn meerdere antwoorden mogelijk.

- [ ] Lopend
- [ ] Fiets
- [ ] Elektrische fiets
- [ ] Deelfiets
- [ ] Brommer/scooter
- [ ] Motor
- [ ] Auto (bestuurder)
- [ ] Auto (passagier)
- [ ] Deelauto
- [ ] Bus/tram/metro
- [ ] Taxi
- [ ] Anders

69%

Heeft u wel eens de deelscooter gebruikt vanaf het station waar u aankomt naar de eindbestemming?

- ○ Ja
- ○ Nee

72%

Om welke redenen heeft u de deelscooter gebruikt om naar de eindbestemming te reizen? U kunt meerdere antwoorden geven.

- [ ] Plezier
- [ ] Gebruiksgemak
- [ ] Geen andere vervoersmiddelen beschikbaar
- [ ] Ik werd opgehaald
- [ ] Duurzaamheid
- [ ] Lage prijs
- [ ] Snel
- [ ] De scooter stond in het zicht
- [ ] Comfort
- [ ] Anders, namelijk:

76%

Wat was uw reisdoel bij deze trip(s)? Er zijn meerdere antwoorden mogelijk.

- [ ] Van en naar mijn werk / vrijwilligerswerk
- [ ] Zaken-, dienstreis, bezoek congres en dergelijke, anders dan van en naar mijn werk
- [ ] Van en naar school, studie, opleiding, stage
- [ ] Bezoek aan familie, vrienden, kennissen
- [ ] Voor hobby, sport, verenigingsbezoek
- [ ] Oppassen, kinderen halen/brengen, boodschappen doen of andere zorgtaken
- [ ] Vakantie, uitstapje met minimaal 1 overnachting
- [ ] Winkelen
- [ ] Stad bezoeken
- [ ] Wandelen of fietsen
- [ ] Museumbezoek, tentoonstelling, festival of ander cultureel uitje
- [ ] Ander dagje of avondje uit
- [ ] Ander doel

79%

Welk vervoermiddel zou u hebben gebruikt als de deelscooter op dat moment niet beschikbaar was? Er zijn meerdere antwoorden mogelijk.

- ☐ Lopend
- ☐ Fiets
- ☐ Elektrische fiets
- ☐ Deelfiets
- ☐ Brommer/scooter
- ☐ Auto (passagier)
- ☐ Deelauto
- ☐ Bus/tram/metro
- ☐ Taxi
- ☐ Anders

80%

Om welke redenen zou u overwegen de deelscooter te gebruiken om naar het station te komen waar uw treinreis begint? U kunt meerdere antwoorden kiezen.

- ☐ Geen, ik zou het nooit overwegen
- ☐ Als ik hem dichterbij het station kan parkeren dan nu het geval is
- ☐ Als ik de app op mijn telefoon heb
- ☐ Als er geen andere vervoersmiddelen beschikbaar zijn
- ☐ Als er een deelscooter beschikbaar is
- ☐ Als de prijs lager is dan nu het geval is
- ☐ Als hij dichterbij mijn huis staat dan nu het geval is
- ☐ Als er geen helmplicht is
- ☐ Als ik een (scooter)rijbewijs heb
- ☐ Anders, namelijk:

85%

Om welke redenen zou u overwegen de deelscooter te gebruiken om vanaf het station waar u aankomt naar de eindbestemming te reizen? U kunt meerdere antwoorden kiezen.

- ☐ Geen, ik zou het nooit overwegen
- ☐ Als ik de app op mijn telefoon heb
- ☐ Als hij dichterbij het station staat dan nu het geval is
- ☐ Als er geen andere vervoersmiddelen beschikbaar zijn
- ☐ Als de prijs lager is dan nu het geval is
- ☐ Als ik een (scooter)rijbewijs heb
- ☐ Als ik hem dichterbij de bestemming kan parkeren dan nu het geval is
- ☐ Als er geen helmplicht is
- ☐ Als hij beschikbaar is
- ☐ Anders, namelijk:

92%

Hoe beoordeelt u de vragenlijst die u zojuist heeft ingevuld?

Denk hierbij aan het onderwerp, de formulering, de afwisseling van vragen, de lengte, etc.
(1 = zeer ontevreden, 10 = zeer tevreden)

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7
- ○ 8
- ○ 9
- ○ 10

- ○ Weet niet

D

Data transform

```python

import pandas as pd
import numpy as np

df = pd.read_csv("C:/Users/bouwi/iCloudDrive/Desktop/NS/Master Thesis/Data analysis/Data (640 completes)/2024 04 04 resultaten deelscooter keuzescenarios_totaal.csv", sep=';')


#Mapping for sample composition
#Gender
df['Gender'] = df['PV_Geslacht'].map({'Man':'Male','Vrouw':'Female','Overig':'Unknown','Wil ik liever niet zeggen':'Unknown'})

#Age
df['Age'] = df['PV_Leeftijd_cat_3'].map({'18-35 jaar':'18-35 years','36-55 jaar':'36-55 years','55 jaar en ouder':'55+ years'})

#Age cat
df['Age_cat_1'] = df['PV_Leeftijd_cat_1'].map({'18-24 jaar':'1','25-34 jaar':'2','35-44 jaar':'3','45-54 jaar':'4','55-64 jaar':'5','65-74 jaar':'6','75+':'7'}).astype(int)

#Age cat
df['Age_cat_3'] = df['PV_Leeftijd_cat_3'].map({'18-35 jaar':'1','36-55 jaar':'2','55 jaar en ouder':'3'}).astype(int)


#Occupation
df['Occupation'] = df['PV_Werksituatie'].map({np.nan:'Unknown','Anders, namelijk:':'Unknown', 'Arbeidsongeschikt':'Unemployed','Freelancer of ZZP`er':'Employed',
                                              'Gepensioneerd / VUT':'Retired','Huisvrouw / huisman': 'Unemployed','Schoolgaand / scholier':'Student',
                                              'Studerend / student':'Student','Vrijwilliger':'Employed','Werkloos / werkzoekend / bijstand':'Unemployed',
                                              'Werkzaam bij de overheid':'Employed','Werkzaam in loondienst':'Employed','Zelfstandig ondernemer':'Employed'})

#Education
df['Education'] = df['PV_Hoogst_met_diploma_afgeronde_studie_NIEUW'].map({np.nan:'Unknown','Anders, namelijk':'Unknown', 'Basisonderwijs':'Primary school', 'LBO':'VMBO',  'MULO':'VMBO', 'VMBO':'VMBO','MAVO':'VMBO', 'HAVO':'VWO / HAVO',
                                                                           'VWO (atheneum of gymnasium':'VWO / HAVO','MBO oude stijl':'MBO', 'MBO1':'MBO',
```

```
                                                                    'MBO1':'MBO', 'MBO2/MBO3/MBO4':'MBO', 'HBO (bachelor)':'HBO','HBO (master)':'HBO',
                                                                    'WO Bachelor':'WO', 'WO doctoraal':'WO', 'WO master':'WO'})
#Education
df['Education_number'] = df['Education'].map({'Unknown':'2', 'Primary school':'1','VMBO':'2', 'MBO':'2','VWO / HAVO':'2','HBO':'3','WO':'3'}).astype(int)


#Trip purpose
df['Trip_purpose'] = df['PV_Reismotief'].map({np.nan:'Unknown', 'Van en naar mijn werk / vrijwilligerswerk':'Business','ZakenÂ -, dienstreis, bezoek congres en dergelijke, anders dan van en naar mijn werk':'Business',
                                              'Van en naar school, studie, opleiding, stage':'Education','Museumbezoek, tentoonstelling, festival of ander cultureel uitje':'Leisure',
                                              'Bezoek aan familie, vrienden, kennissen':'Leisure','Stad bezoeken':'Leisure','Vakantie, uitstapje met minimaal 1 overnachting':'Leisure',
                                              'Vakantie, uitstapje met minimaal 1 overnachting':'Leisure','Winkelen':'Leisure','Wandelen of fietsen':'Leisure',
                                              'Voor bezoek aan arts, ziekenhuis of andere medische doeleinden':'Leisure','Voor hobby, sport, verenigingsbezoek':'Leisure',
                                              'Ander dagje of avondje uit':'Leisure','Ander doel, namelijk:':'Unknown', 'Oppassen, kinderen halen/brengen, boodschappen doen of andere zorgtaken':'Leisure'})


#First mile
df['First_mile'] = df['PV_Vervoer_naar_vertrekstation'].map({np.nan:'Unknown','Anders, namelijk:':'Unknown','Lopend':'Walk','Met de auto of motor, als passagier':'Car',
                                                             'Met de auto, als bestuurder':'Car','Met de bus, tram of metro (stad of streek) of de Randstadrail':'BTM',
                                                             'Met de taxi, NS zonetaxi, regiotaxi':'Taxi','Op de elektrische fiets':'Bike','Op de fiets (niet elektrisch)':'Bike',
                                                             'Op de snorfiets, brommer of scooter':'Moped','Op de vouwfiets (niet elektrisch)':'Bike'})

#Last mile
df['Last_mile'] = df['PV_Vervoer_vanaf_aankomststation2'].map({np.nan:'Unknown','Anders, namelijk:':'Unknown','Lopend':'Walk','Met de auto of motor, als passagier':'Car',
                                                             'Met de auto, als bestuurder':'Car','Met de bus, tram of metro (stad of streek) of de Randstadrail':'BTM',
                                                             'Met de taxi, NS zonetaxi, regiotaxi':'Taxi','Op de fiets':'Bike', 'Op de vouwfiets':'Bike'})

df['familiar'] = df['V3'].map({'Ik heb nog nooit van deelscooters gehoord':1,'Ik heb van deelscooters gehoord maar nooit gebruikt':2,'Ik heb wel eens een deelscooter gebruikt':3})
```

```


# Add an ID column to the original data indicating each person
df['ID'] = df.index

# Rename the columns for better understanding
df.rename(columns={
    'V4_1': 'bike.pref',
    'V4_2': 'walk.pref',
    'V4_3': 'btm.pref',
    'V4_4': 'mop.pref',
    'V4_5': 'car.pref',
    'V4_6': 'train.pref',
    'V5_1': 'walk.freq',
    'V5_2': 'bike.freq',
    'V5_3': 'mop.freq',
    'V5_4': 'car.freq',
    'V5_5': 'btm.freq',
    'V6_1': 'mop.safe',
    'V6_2': 'mop.env',
    'V6_3': 'mop.ease',
    'V6_4': 'mop.image',
    'V6_5': 'mop.positive',
    'V6_6': 'mop.happy',
    'V21' : 'driv.lice',
    'V22_A1' : 'pos.none',
    'V22_A2' : 'pos.bike',
    'V22_A3' : 'pos.car',
    'V22_A4' : 'pos.moped',
    'V22_A5' : 'pos.motor',
    'V22_A6' : 'pos.other',
    'V23' : 'use.first.mile',
    'V24_A1' : 'fm.reason.price',
    'V24_A2' : 'fm.reason.fun',
    'V24_A3' : 'fm.reason.quick',
    'V24_A4' : 'fm.reason.comfort',
    'V24_A5' : 'fm.reason.other.modes',
    'V24_A6' : 'fm.reason.picked.up',
    'V24_A7' : 'fm.reason.visible',
    'V24_A8' : 'fm.reason.ease',
    'V24_A9' : 'fm.reason.env.',
    'V24_A10' : 'fm.reason.other',
    'V25_A1' : 'fm.trip.goal.work',
    'V25_A2' : 'fm.trip.goal.business',
    'V25_A3' : 'fm.trip.goal.school',
    'V25_A4' : 'fm.trip.goal.family',
    'V25_A5' : 'fm.trip.goal.hobby',
    'V25_A6' : 'fm.trip.goal.care',
    'V25_A7' : 'fm.trip.goal.holiday',
    'V25_A8' : 'fm.trip.goal.shop',
    'V25_A9' : 'fm.trip.goal.city',
    'V25_A10' : 'fm.trip.goal.sport',
    'V25_A11' : 'fm.trip.goal.event',
    'V25_A12' : 'fm.trip.goal.day.out',
    'V25_A13' : 'fm.trip.goal.other',
    'V26_A1' : 'fm.modal.shift.walk',
    'V26_A2' : 'fm.modal.shift.bike',
    'V26_A3' : 'fm.modal.shift.ebike',
    'V26_A4' : 'fm.modal.shift.shared.bike',
    'V26_A5' : 'fm.modal.shift.moped',
    'V26_A6' : 'fm.modal.shift.motor',
    'V26_A7' : 'fm.modal.shift.car.driver',
    'V26_A8' : 'fm.modal.shift.car.pass',
    'V26_A9' : 'fm.modal.shift.shared.car',
    'V26_A10' : 'fm.modal.shift.btm',
    'V26_A11' : 'fm.modal.shift.taxi',
    'V26_A12' : 'fm.modal.shift.other',
    'V27_A1' : 'fm.barrier.mop.user.never',
    'V27_A2' : 'fm.barrier.mop.user.availabilty',
    'V27_A3' : 'fm.barrier.mop.user.helmet',
    'V27_A4' : 'fm.barrier.mop.user.dis.station',
```

```
    'V27_A5' : 'fm.barrier.mop.user.dis.home',
    'V27_A6' : 'fm.barrier.mop.user.driv.lice',
    'V27_A7' : 'fm.barrier.mop.user.other.modes',
    'V27_A8' : 'fm.barrier.mop.user.app',
    'V27_A9' : 'fm.barrier.mop.user.price',
    'V27_A10' : 'fm.barrier.mop.user.other',
    'V28' : 'use.last.mile',
    'V29_A1' : 'lm.reason.use.price',
    'V29_A2' : 'lm.reason.use.fun',
    'V29_A3' : 'lm.reason.use.quick',
    'V29_A4' : 'lm.reason.use.comfort',
    'V29_A5' : 'lm.reason.use.other.modes',
    'V29_A6' : 'lm.reason.use.picked.up',
    'V29_A7' : 'lm.reason.use.visible',
    'V29_A8' : 'lm.reason.use.ease',
    'V29_A9' : 'lm.reason.use.env.',
    'V29_A10' : 'lm.reason.use.other',
    'V30_A1' : 'lm.trip.goal.work',
    'V30_A2' : 'lm.trip.goal.business',
    'V30_A3' : 'lm.trip.goal.school',
    'V30_A4' : 'lm.trip.goal.family',
    'V30_A5' : 'lm.trip.goal.hobby',
    'V30_A6' : 'lm.trip.goal.care',
    'V30_A7' : 'lm.trip.goal.holiday',
    'V30_A8' : 'lm.trip.goal.shop',
    'V30_A9' : 'lm.trip.goal.city',
    'V30_A10' : 'lm.trip.goal.sport',
    'V30_A11' : 'lm.trip.goal.event',
    'V30_A12' : 'lm.trip.goal.day.out',
    'V30_A13' : 'lm.trip.goal.other',
    'V31_A1' : 'lm.modal.shift.walk',
    'V31_A2' : 'lm.modal.shift.bike',
    'V31_A3' : 'lm.modal.shift.ebike',
    'V31_A4' : 'lm.modal.shift.shared.bike',
    'V31_A5' : 'lm.modal.shift.moped',
    'V31_A6' : 'lm.modal.shift.car.pass',
    'V31_A7' : 'lm.modal.shift.shared.car',
    'V31_A8' : 'lm.modal.shift.btm',
    'V31_A9' : 'lm.modal.shift.taxi',
    'V31_A10' : 'lm.modal.shift.other',
    'V32_A1' : 'lm.barrier.mop.user.never',
    'V32_A2' : 'lm.barrier.mop.user.availabilty',
    'V32_A3' : 'lm.barrier.mop.user.helmet',
    'V32_A4' : 'lm.barrier.mop.user.dis.station',
    'V32_A5' : 'lm.barrier.mop.user.dis.home',
    'V32_A6' : 'lm.barrier.mop.user.driv.lice',
    'V32_A7' : 'lm.barrier.mop.user.other.modes',
    'V32_A8' : 'lm.barrier.mop.user.app',
    'V32_A9' : 'lm.barrier.mop.user.price',
    'V32_A10' : 'lm.barrier.mop.user.other',
    'V33_A1' : 'fm.barrier.non.user.never',
    'V33_A2' : 'fm.barrier.non.user.availabilty',
    'V33_A3' : 'fm.barrier.non.user.helmet',
    'V33_A4' : 'fm.barrier.non.user.dis.station',
    'V33_A5' : 'fm.barrier.non.user.dis.home',
    'V33_A6' : 'fm.barrier.non.user.driv.lice',
    'V33_A7' : 'fm.barrier.non.user.other.modes',
    'V33_A8' : 'fm.barrier.non.user.app',
    'V33_A9' : 'fm.barrier.non.user.price',
    'V33_A10' : 'fm.barrier.non.user.other',
    'V34_A1' : 'lm.barrier.non.user.never',
    'V34_A2' : 'lm.barrier.non.user.availabilty',
    'V34_A3' : 'lm.barrier.non.user.helmet',
    'V34_A4' : 'lm.barrier.non.user.dis.station',
    'V34_A5' : 'lm.barrier.non.user.dis.home',
    'V34_A6' : 'lm.barrier.non.user.driv.lice',
    'V34_A7' : 'lm.barrier.non.user.other.modes',
    'V34_A8' : 'lm.barrier.non.user.app',
    'V34_A9' : 'lm.barrier.non.user.price',
    'V34_A10' : 'lm.barrier.non.user.other',
    'V35' : 'grade.survey',
```

```python
    'V36' : 'comment.survey'
}, inplace=True)


# Map string responses to numeric codes

response_mapping_likert = {
    'Helemaal oneens': 1,
    'Oneens': 2,
    'Neutraal': 3,
    'Eens': 4,
    'Helemaal eens': 5,
    'Weet niet / n.v.t.' : 3,
    'Weet niet/ n.v.t.' : 3}


likert_columns = ['bike.pref','walk.pref','btm.pref','mop.pref','car.pref','train.pref',
                  'mop.safe','mop.env','mop.ease','mop.image','mop.positive', 'mop.happy',]

for column in likert_columns:
    df[column] = df[column].map(response_mapping_likert)


response_mapping_freq = {

    'Nooit': 1,
    'Weet niet / n.v.t.' : 1,
    'Minder dan 1 dag per jaar': 2,
    '1 tot 5 dagen per jaar': 3,
    '6 tot 11 dagen per jaar': 4,
    '1 tot 3 dagen per maand': 5,
    '1 tot 3 dagen per week': 6,
    '4 of meer dagen per week': 7
}

freq_columns = [ 'walk.freq', 'bike.freq', 'mop.freq', 'car.freq', 'btm.freq',]

for column in freq_columns:
    df[column] = df[column].map(response_mapping_freq)


response_mapping_freq_train = {
    np.nan: 0,
    '4 dagen per week of vaker': 7,
    '1-3 dagen per week': 6,
    '1-3 dagen per maand': 5,
    '6-11 dagen in de afgelopen 12 maanden': 4,
    '3-5 dagen in de afgelopen 12 maanden': 3,
    '1 of 2 dagen in de afgelopen 12 maanden': 2,
    'Ik heb de afgelopen 12 maanden niet binnen Nederland met de trein gereisd': 1,
    'Ik reis nooit met de trein binnen Nederland': 1
}

df['train.freq'] = df['PV_Reisfrequentie'].map(response_mapping_freq_train).astype(int)
df['driv.lice'] = df['driv.lice'].map({'Ja': 1, 'Nee': 0})
df['PV_Geslacht'] = df['PV_Geslacht'].map({'Man': 1, 'Vrouw': 0})
df['prev.use'] = df['V3'].map({'Ik heb nog nooit van deelscooters gehoord': 0, 'Ik heb van deelscooters gehoord maar nooit gebruikt': 0, 'Ik heb wel eens een deelscooter gebruikt': 1})
df['V3'] = df['V3'].map({'Ik heb nog nooit van deelscooters gehoord': 1, 'Ik heb van deelscooters gehoord maar nooit gebruikt': 2, 'Ik heb wel eens een deelscooter gebruikt': 3})
df['use.first.mile'] = df['use.first.mile'].map({'Nee': 0, 'Ja': 1})
df['use.last.mile'] = df['use.last.mile'].map({'Nee': 0, 'Ja': 1})
df['use.first.mile'] = df['use.first.mile'].fillna(0)
df['use.last.mile'] = df['use.last.mile'].fillna(0)



# Filter columns for SP experiment
v_columns = [col for col in df.columns if col.startswith(('V9', 'V10', 'V11', 'V12', 'V13', '
```

```
    V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20'))]

data = df.drop(columns=v_columns)

#export csv for sample composition
data.to_csv('EDA.csv')


# Subset the dataframe
data_v = df[v_columns]


# Now, modify the reshaping process to include the ID
choice_data_with_id = pd.DataFrame()

for column in data_v.columns:
    # Extract the experiment number and the alternative from the column name
    exp_number, alternative = column.split('_')
    temp_df = df[[column, 'ID']].copy()
    temp_df['Experiment'] = exp_number
    temp_df['Choice'] = alternative
    temp_df['Value'] = temp_df[column]
    temp_df.drop(columns=[column], inplace=True)
    choice_data_with_id = pd.concat([choice_data_with_id, temp_df], ignore_index=True)

choice_data = choice_data_with_id.sort_values('ID')

# Drop rows whose are not chosen
choice_data = choice_data.dropna(subset=['Value'])
choice_data = choice_data[choice_data['Value'] != 0.0]


# Map experiment numbers
choice_mapping = {'V9': '1', 'V10': '2', 'V11': '3', 'V12': '4', 'V13': '5', 'V14': '6', 'V15
    ': '7', 'V16': '8', 'V17': '9', 'V18': '10', 'V19': '11', 'V20': '12'}
choice_data['Experiment'] = choice_data['Experiment'].map(choice_mapping).astype(int)

# Remove 'A' from the 'Choice' column, retaining only the numerical part
choice_data['Choice'] = choice_data['Choice'].str.replace('A', '').astype(int)

# Sort by PersonID for better organization
choice_data = choice_data.sort_values(by=['ID','Experiment','Choice'])
choice_data = choice_data[['ID','Experiment','Choice']]


# Create the new columns based on 'mode_choice'
choice_data['Walk.choice'] = (choice_data['Choice'] == 1).astype(int)
choice_data['Bike.choice'] = (choice_data['Choice'] == 2).astype(int)
choice_data['Moped.choice'] = (choice_data['Choice'] == 3).astype(int)
choice_data['BTM.choice'] = (choice_data['Choice'] == 4).astype(int)



Choice_attributes = pd.read_csv("C:/Users/bouwi/iCloudDrive/Desktop/NS/Master␣Thesis/Data␣
    analysis/Data␣(640␣completes)/Block␣attributes␣wide␣format.csv", sep=';')


# Merge DataFrames on 'Experiment'
experiment_data = pd.merge(choice_data, Choice_attributes, on=['Experiment'], how='inner')


# Give value on 1.5km experiment and 3km experiment
experiment_data['1.5km'] = np.where(experiment_data['Experiment'].isin([1, 2, 3, 7, 8, 9]),
    1, 0)
experiment_data['3km'] = np.where(experiment_data['Experiment'].isin([4, 5, 6, 10, 11, 12]),
    1, 0)


# Sort by ID for better organization
experiment_data = experiment_data.sort_values(by=['ID','Experiment','Choice'])

```

```

# Remove the choice specific columns from the original data to avoid redundancy
other_columns = df.drop(columns=v_columns + ['ID'])

# Merge the reshaped choice data with the other attributes using PersonID
full_data = pd.merge(experiment_data, other_columns, left_on='ID', right_index=True)

full_data = full_data[['ID', 'Experiment', 'Choice', 'Walk.choice', 'Bike.choice', 'Moped.choice', 'BTM.choice', 'moped.conv_mop', 'moped.walk_mop', 'moped.cost_mop', 'bike.conv_bike', 'bike.walk_bike', 'bike.cost_bike', 'btm.conv_btm', 'btm.walk_btm', 'btm.cost_btm', 'Block', '1.5km', '3km', 'V3', 'prev.use', 'bike.pref', 'walk.pref', 'btm.pref', 'mop.pref', 'car.pref', 'train.pref', 'walk.freq', 'bike.freq', 'mop.freq', 'car.freq', 'btm.freq', 'train.freq', 'mop.safe', 'mop.env', 'mop.ease', 'mop.image', 'mop.positive', 'mop.happy', 'driv.lice', 'pos.none', 'pos.bike', 'pos.car', 'pos.moped', 'pos.motor', 'pos.other', 'OPEN22_6', 'use.first.mile', 'use.last.mile',

                       'fm.trip.goal.work', 'fm.trip.goal.business', 'fm.trip.goal.school', 'fm.trip.goal.family', 'fm.trip.goal.hobby', 'fm.trip.goal.care', 'fm.trip.goal.holiday', 'fm.trip.goal.shop', 'fm.trip.goal.city', 'fm.trip.goal.sport', 'fm.trip.goal.event', 'fm.trip.goal.day.out', 'fm.trip.goal.other',
                       'lm.trip.goal.work', 'lm.trip.goal.business', 'lm.trip.goal.school', 'lm.trip.goal.family', 'lm.trip.goal.hobby', 'lm.trip.goal.care', 'lm.trip.goal.holiday', 'lm.trip.goal.shop', 'lm.trip.goal.city', 'lm.trip.goal.sport', 'lm.trip.goal.event', 'lm.trip.goal.day.out', 'lm.trip.goal.other',

                       'fm.modal.shift.walk', 'fm.modal.shift.bike', 'fm.modal.shift.ebike', 'fm.modal.shift.shared.bike', 'fm.modal.shift.moped', 'fm.modal.shift.motor', 'fm.modal.shift.car.driver', 'fm.modal.shift.car.pass', 'fm.modal.shift.shared.car', 'fm.modal.shift.btm', 'fm.modal.shift.taxi', 'fm.modal.shift.other',
                       'lm.modal.shift.walk', 'lm.modal.shift.bike', 'lm.modal.shift.ebike', 'lm.modal.shift.shared.bike', 'lm.modal.shift.moped', 'lm.modal.shift.car.pass', 'lm.modal.shift.shared.car', 'lm.modal.shift.btm', 'lm.modal.shift.taxi', 'lm.modal.shift.other',

                       'fm.reason.price', 'fm.reason.fun', 'fm.reason.quick', 'fm.reason.comfort', 'fm.reason.other.modes', 'fm.reason.picked.up', 'fm.reason.visible', 'fm.reason.ease', 'fm.reason.env.','fm.reason.other',
                       'lm.reason.use.price', 'lm.reason.use.fun', 'lm.reason.use.quick', 'lm.reason.use.comfort', 'lm.reason.use.other.modes', 'lm.reason.use.picked.up','lm.reason.use.visible', 'lm.reason.use.ease', 'lm.reason.use.env.', 'lm.reason.use.other',

                       'fm.barrier.mop.user.never', 'fm.barrier.mop.user.availabilty', 'fm.barrier.mop.user.helmet', 'fm.barrier.mop.user.dis.station', 'fm.barrier.mop.user.dis.home', 'fm.barrier.mop.user.driv.lice','fm.barrier.mop.user.other.modes', 'fm.barrier.mop.user.app', 'fm.barrier.mop.user.price', 'fm.barrier.mop.user.other',
                       'fm.barrier.non.user.never', 'fm.barrier.non.user.availabilty', 'fm.barrier.non.user.helmet', 'fm.barrier.non.user.dis.station', 'fm.barrier.non.user.dis.home', 'fm.barrier.non.user.driv.lice', 'fm.barrier.non.user.other.modes', 'fm.barrier.non.user.app', 'fm.barrier.non.user.price', 'fm.barrier.non.user.other',

                       'lm.barrier.mop.user.never', 'lm.barrier.mop.user.availabilty', 'lm.barrier.mop.user.helmet', 'lm.barrier.mop.user.dis.station', 'lm.barrier.mop.user.dis.home', 'lm.barrier.mop.user.driv.lice', 'lm.barrier.mop.user.other.modes', 'lm.barrier.mop.user.app', 'lm.barrier.mop.user.price', 'lm.barrier.mop.user.other',
                       'lm.barrier.non.user.never', 'lm.barrier.non.user.availabilty', 'lm.barrier.non.user.helmet', 'lm.barrier.non.user.dis.station', 'lm.barrier.non.user.dis.home', 'lm.barrier.non.user.driv.lice', 'lm.barrier.non.user.other.modes', 'lm.barrier.non.user.app', 'lm.barrier.non.user.price', 'lm.barrier.non.user.other',


```

```
                        'grade.survey',  'comment.survey',       'Route', 'PV_Geslacht', '
                            PV_Leeftijd',  'PV_Leeftijd_cat_1',    'PV_Leeftijd_cat_2',    '
                            PV_Leeftijd_cat_3',    'PV_Reisfrequentie',    'PV_Reismotief',
                                    'PV_Reismotief_Ander_doel_namelijk_OPEN',       '
                            PV_Werksituatie',      'PV_Werksituatie_Anders_namelijk_OPEN', '
                            PV_Postcode',  'PV_Auto_vs_trein',     '
                            PV_Samenstelling_huishouden',  '
                            PV_Samenstelling_huishouden_Anders_namelijk_OPEN',     '
                            PV_Vervoer_naar_vertrekstation',       '
                            PV_Vervoer_naar_vertrekstation_Anders_namelijk_OPEN',  '
                            PV_Vertrekstation',    'PV_Vervoer_vanaf_aankomststation2',    '
                            PV_Vervoer_vanaf_aankomststation2_Anders_namelijk_OPEN',       '
                            PV_Aankomststation', 'PV_Faciliteiten_OV_fiets',       '
                            PV_Faciliteiten_Andere_deelfiets_geen_OV_fiets', '
                            PV_Faciliteiten_Deelscooter',
                        'PV_Hoogst_met_diploma_afgeronde_studie_NIEUW',  '
                            PV_Hoogst_met_diploma_afgeronde_s_Anders_namelijk_OPEN','Gender','
                            Age','Age_cat_1','Age_cat_3','Occupation','Education','
                            Education_number','First_mile','Last_mile','familiar']]

# Export the DataFrame to a CSV file
full_data.to_csv('Fulldata_wide.csv', index=False)
```

E

Choice Probability Model

```python
import numpy as np
import pandas as pd

# Define the utility functions for each class and mode including mop_walk, bike_walk, and
    btm_walk
def utility_walk(row, class_num):
    if class_num == 1:
        return (
            0 * row['ASC_walk_1.5'] + 0 * row['ASC_walk_3']
        )
    elif class_num == 2:
        return (
            0 * row['ASC_walk_1.5'] + 0 * row['ASC_walk_3']
        )
    elif class_num == 3:
        return (
            0 * row['ASC_walk_1.5'] + 0 * row['ASC_walk_3']
        )

def utility_bike(row, class_num):
    if class_num == 1:
        return (
            5.708 * row['ASC_bike_1.5'] +
            7.643 * row['ASC_bike_3'] +
            -1.811 * row['bike_conv'] +
            -0.827 * row['bike_walk'] +
            -1.520 * row['bike_cost']
        )
    elif class_num == 2:
        return (
            1.537 * row['ASC_bike_1.5'] +
            6.735 * row['ASC_bike_3'] +
            -0.445 * row['bike_conv'] +
            0 * row['bike_walk'] +
            -0.462 * row['bike_cost']
        )

    elif class_num == 3:
        return (
            0 * row['ASC_bike_1.5'] +
            3.755 * row['ASC_bike_3'] +
            0 * row['bike_conv'] +
            0 * row['bike_walk'] +
            -0.369 * row['bike_cost']
        )

def utility_moped(row, class_num):
    if class_num == 1:
        return (
            -10 * row['ASC_mop_1.5'] +
```

```
            -10 * row['ASC_mop_3'] +
            0 * row['mop_conv'] +
            0 * row['mop_cost'] +
            0 * row['mop_walk']
        )

    elif class_num == 2:
        return (
            0 * row['ASC_mop_1.5'] +
            7.382 * row['ASC_mop_3'] +
            0 * row['mop_conv'] +
            -0.197 * row['mop_walk'] +
            -1.156 * row['mop_cost']
        )

    elif class_num == 3:
        return (
            2.211 * row['ASC_mop_1.5'] +
            7.186 * row['ASC_mop_3'] +
            0 * row['mop_conv'] +
            0 * row['mop_walk'] +
            -2.452 * row['mop_cost']

        )

def utility_btm(row, class_num):
    if class_num == 1:
        return (
            -1.366 * row['ASC_btm_1.5'] +
            2.911 * row['ASC_btm_3'] +
            0 * row['btm_conv'] +
            -0.214 * row['btm_walk'] +
            0 * row['btm_cost']

        )
    elif class_num == 2:
        return (
            1.827 * row['ASC_btm_1.5'] +
            7.384 * row['ASC_btm_3'] +
            -0.298 * row['btm_conv'] +
            -0.218 * row['btm_walk'] +
            -1.037 * row['btm_cost']

        )
    elif class_num == 3:
        return (
            3.645 * row['ASC_btm_1.5'] +
            6.752 * row['ASC_btm_3'] +
            0 * row['btm_conv'] +
            0 * row['btm_walk'] +
            0 * row['btm_cost']

        )

# Calculate choice probabilities using the multinomial logit model for each individual and
    each mode
def choice_probabilities(row):
    utilities = {
        'walk': [],
        'bike': [],
        'moped': [],
        'btm': []
    }

    for class_num in range(1, 4):
        utilities['walk'].append(utility_walk(row, class_num))
        utilities['bike'].append(utility_bike(row, class_num))
        utilities['moped'].append(utility_moped(row, class_num))
        utilities['btm'].append(utility_btm(row, class_num))

    exp_utilities = {
```

```python
        mode: [np.exp(utility) for utility in utilities[mode]]
        for mode in utilities
    }
    #print(exp_utilities)
    sum_exp_utilities = [
        sum(exp_utilities[mode][i] for mode in utilities)
        for i in range(3)
    ]


    prob_walk = sum(
        row[f'Class_{class_num}_Allocation'] *
        exp_utilities['walk'][class_num-1] / sum_exp_utilities[class_num-1]
        for class_num in range(1, 4)
    )

    prob_moped = sum(
        row[f'Class_{class_num}_Allocation'] *
        exp_utilities['moped'][class_num-1] / sum_exp_utilities[class_num-1]
        for class_num in range(1, 4)
    )


    prob_bike = sum(
        row[f'Class_{class_num}_Allocation'] *
        exp_utilities['bike'][class_num-1] / sum_exp_utilities[class_num-1]
        for class_num in range(1, 4)
    )

    prob_btm = sum(
        #0.3 *
        row[f'Class_{class_num}_Allocation'] *
        exp_utilities['btm'][class_num-1] / sum_exp_utilities[class_num-1]
        for class_num in range(1, 4)
    )

    return prob_walk, prob_moped, prob_bike, prob_btm

# Load the dataset

files = pd.read_csv(r'C:\Users\bouwi\iCloudDrive\Desktop\NS\Master␣Thesis\Data␣analysis\LC_analyse\LC3_␣4␣factoren\Classes.csv', sep=";")

# Select the desired columns
data = files[['Class_1_Allocation', 'Class_2_Allocation', 'Class_3_Allocation', 'Class1', 'Class2', 'Class3']]

# Common future data for mode choice attributes (same for all individuals)
common_attributes = {
    'ASC_walk_1.5': 0,
    'ASC_mop_1.5': 0,
    'ASC_bike_1.5': 0,
    'ASC_btm_1.5': 0,

    'ASC_walk_3': 1,
    'ASC_mop_3': 1,
    'ASC_bike_3': 1,
    'ASC_btm_3': 1,

    'mop_conv': 2,  # Common perceived convenience of using a moped
    'mop_walk': 4,  # Common walking distance to moped
    'mop_cost': 4,  # Common perceived cost of using a moped

    'bike_conv': 2,  # Common perceived convenience of using a bike
    'bike_walk': 4,  # Common walking distance to bike
    'bike_cost': 3.00,  # Common perceived cost of using a bike

    'btm_conv': 6,  # Common perceived convenience of using bus/tram/metro
    'btm_walk': 4,   # Common walking distance to bus/tram/metro
    'btm_cost': 1.70,  # Common perceived cost of using bus/tram/metro
}
```

```

# Number of individuals (based on the length of P_class)
num_individuals = len(data)

# Create a dataframe with the same attributes for all individuals
X = pd.DataFrame([common_attributes] * num_individuals)
data = data.merge(X, left_index=True, right_index=True)

# Calculate the probability of choosing each mode for each individual
data[['prob_walk', 'prob_moped', 'prob_bike', 'prob_btm']] = data.apply(
    lambda row: pd.Series(choice_probabilities(row)), axis=1
)

data = data[['Class1','Class2','Class3','prob_walk', 'prob_bike', 'prob_moped', 'prob_btm']]

# Group by each class and calculate the average for each mode
average_prob_class1 = data.groupby('Class1').mean()
average_prob_class2 = data.groupby('Class2').mean()
average_prob_class3 = data.groupby('Class3').mean()

# Filter rows where Class1, Class2, or Class3 has value 1
filtered_average_prob_class1 = average_prob_class1.loc[average_prob_class1.index == 1]
filtered_average_prob_class2 = average_prob_class2.loc[average_prob_class2.index == 1]
filtered_average_prob_class3 = average_prob_class3.loc[average_prob_class3.index == 1]

(filtered_average_prob_class1, filtered_average_prob_class2, filtered_average_prob_class3)
```

F

Model usage at The Hague Central

Figure F.1: Situation in model for a 1.5 km trip with current walking distances at The Hague Central

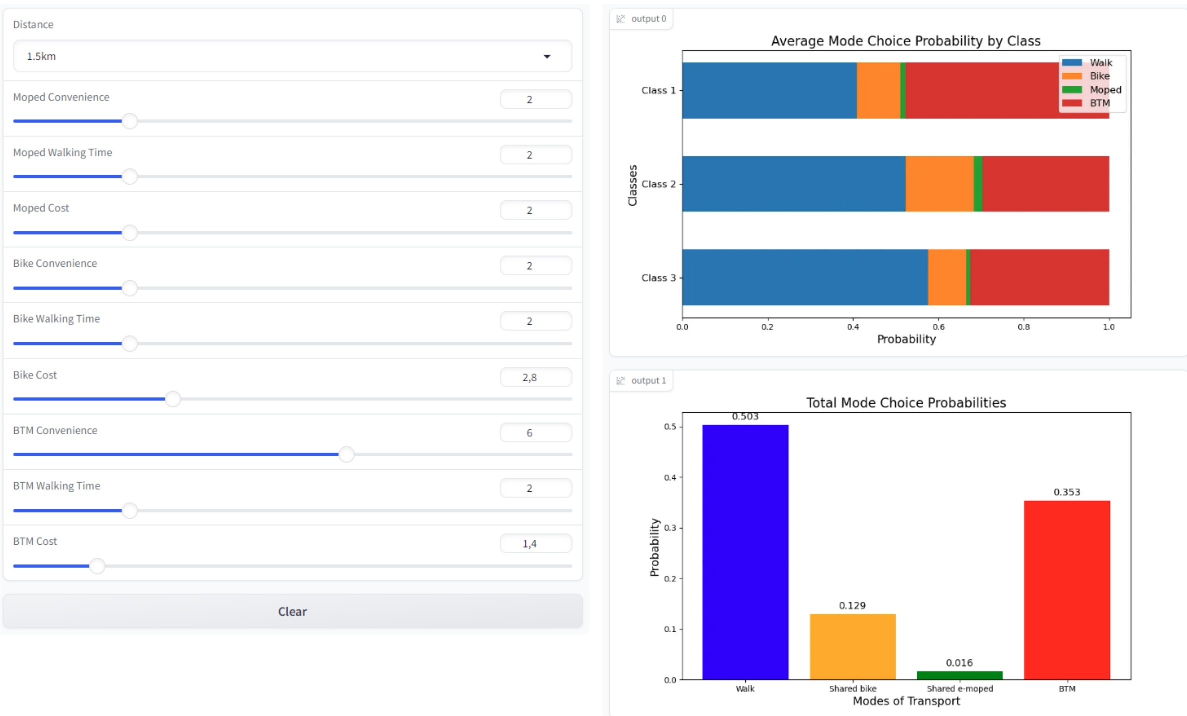


Figure F.2: Situation in model for a 1.5 km trip with shared e-moped parking closer to The Hague Central

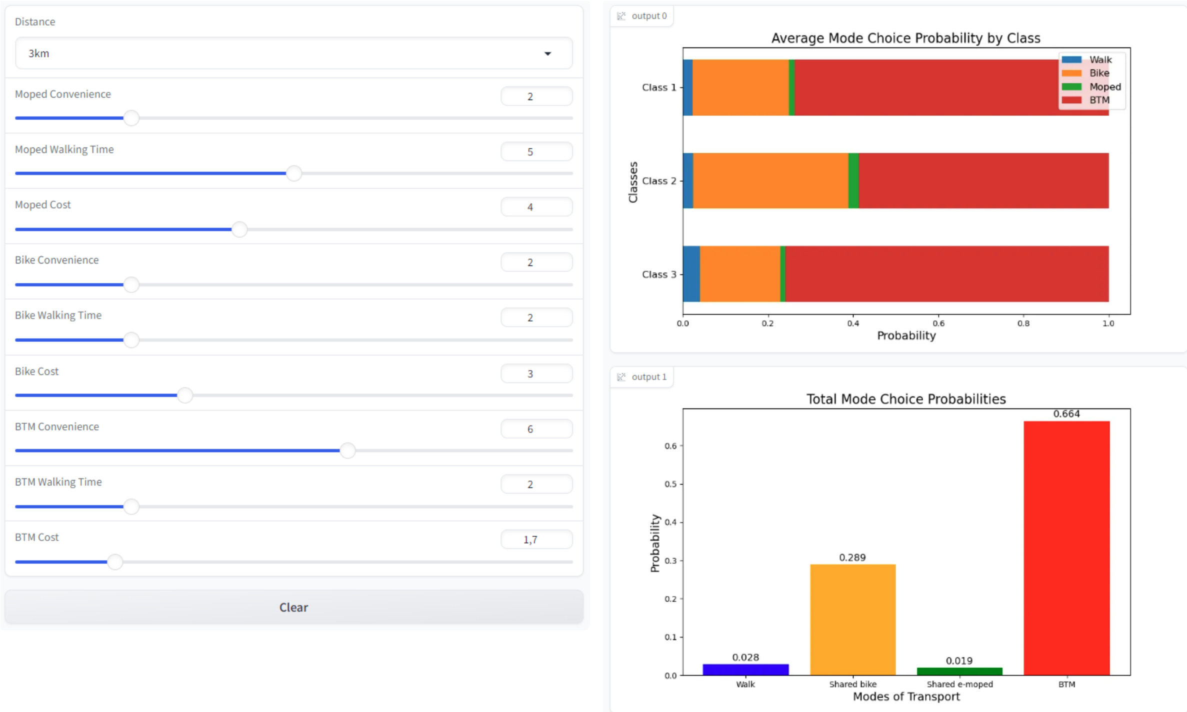


Figure F.3: Situation in model for a 3 km trip with current walking distances at The Hague Central

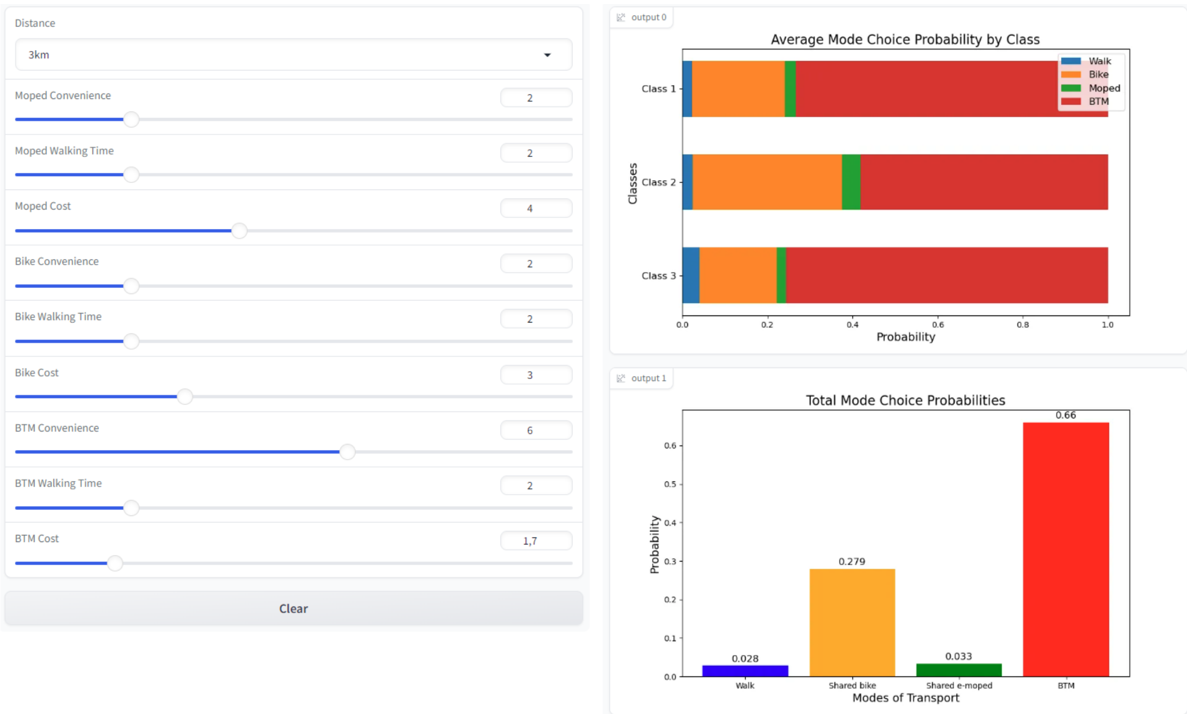
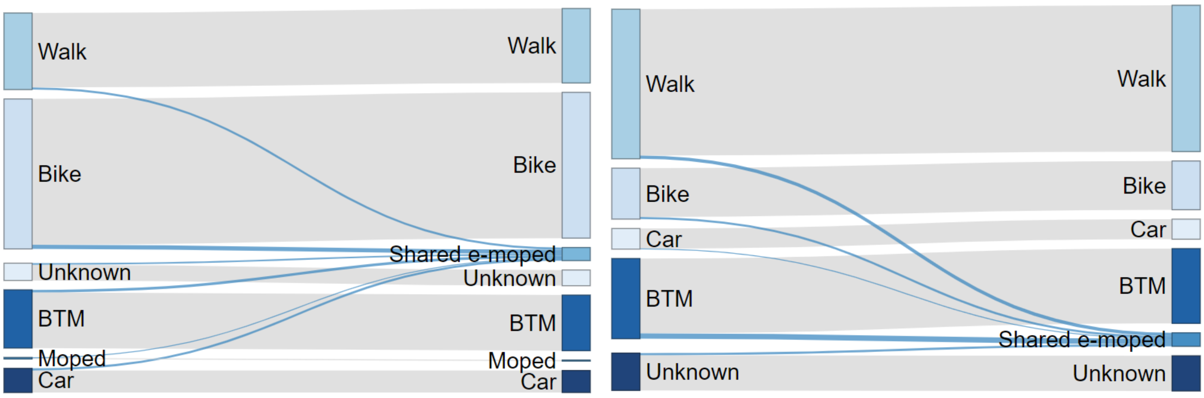


Figure F.4: Situation in model for a 3 km trip with shared e-moped parking closer to The Hague Central

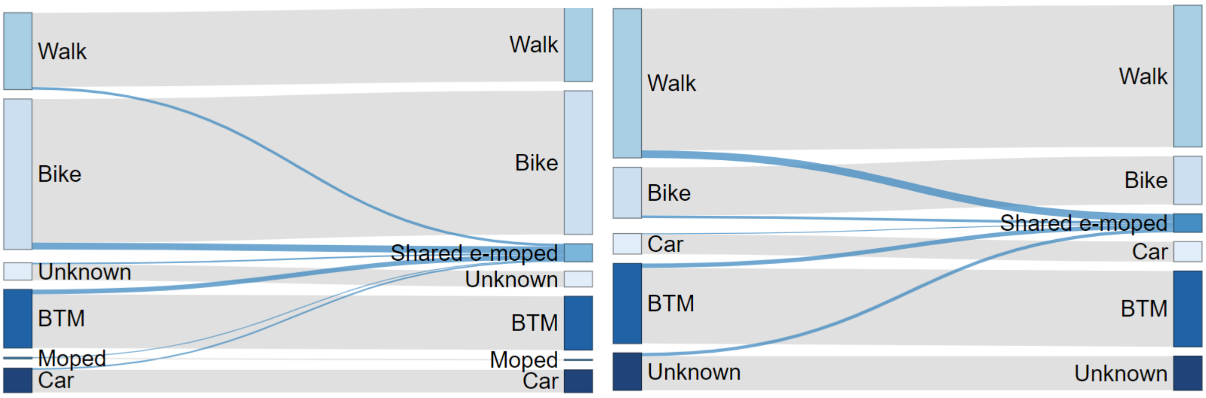
G

Breaking one barrier at the time



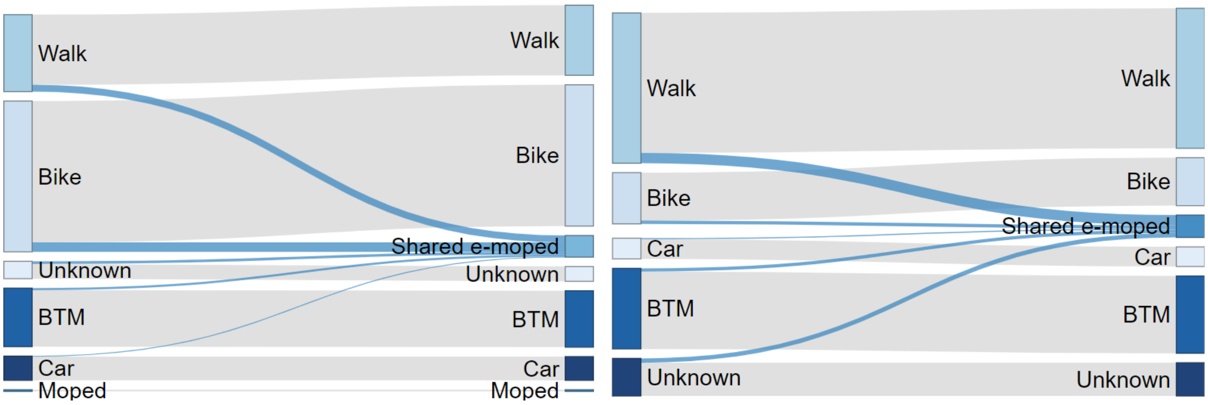
((a)) First mile ((b)) Last mile

Figure G.1: Modal shift when helmet requirement is taken away



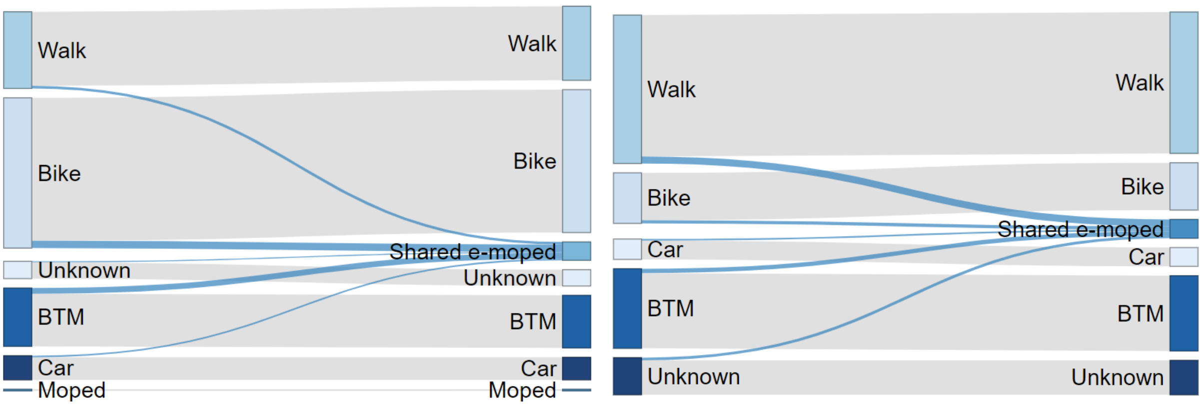
((a)) First mile ((b)) Last mile

Figure G.2: Modal shift when shared e-moped would be available



((a)) First mile ((b)) Last mile

Figure G.3: Modal shift when no drivers license is needed



((a)) First mile ((b)) Last mile

Figure G.4: Modal shift when barrier 'price' is broken