# The private e-scooter in the Netherlands

## Assessing the willingness to use the private e-scooter for the first-mile of train trips

Master thesis

Wouter van der Veer

Delft University of Technology

TU Delft

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by

Wouter van der Veer

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| Thesis committee: | Dr. ir. N. Van Oort, | TU Delft | Chair |
| | Dr. ir. W. Daamen, | TU Delft | Daily supervisor |
| | Dr. ir. G. Correia, | TU Delft | Daily supervisor |
| | Ir. B. Donners | RHDHV | Company supervisor |

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# Preface

In this thesis, I explore the potential of integrating private e-scooters with daily train commuting to improve urban mobility in the Netherlands. Combining these two modes of transport offers an exciting solution for bridging the "first and last mile" between the train station and the destination, especially within the unique context of Dutch urban and transportation infrastructure. As cities in the Netherlands grow, the need for sustainable and flexible transportation options becomes increasingly essential. I hope this research will show how private e-scooters can support daily train users and provide a more seamless commuting experience. This work aims to enhance the understanding of how such multimodal approaches, including the e-scooter, are perceived in the Netherlands.

Completing this thesis has been essential in my journey through the Transport & Planning master's program at TU Delft. Throughout my education, I have developed a deep interest in understanding and enhancing transportation systems to create more efficient and sustainable mobility solutions. This research allowed me to apply the theoretical foundations and analytical skills gained during my coursework to a real-world challenge in urban transportation. By focusing on integrating private e-scooters with train commuting in the Netherlands, I explored a topic at the intersection of technology, urban planning, and sustainability—areas central to my studies and aspirations in the field of transport and planning.

While writing my thesis, I struggled to bring my thoughts and ideas to paper. I am grateful for the invaluable assistance ChatGPT-4, and Grammarly provided throughout my writing enhancement. ChatGPT -4's ability to offer real-time feedback, suggest improvements and provide diverse perspectives, combined with Grammarly's precise grammar and style corrections, has significantly refined my work, making it more accurate, engaging, and polished. Together, they allowed me to focus on creativity while ensuring the technical accuracy, coherence, and professionalism of my writing. This collaboration has been an indispensable part of my journey, and I sincerely appreciate their role in helping me realize my vision.

I would like to sincerely thank my family and my girlfriend for their support during my thesis. My family's encouragement and understanding helped me stay focused and committed. I am also grateful to my girlfriend for her patience and for being there through each step, providing motivation and balance. This work would not have been possible without their steady support.

Finally, I would like to express my deepest gratitude to my guidance committee members, Niels van Oort, Winnie Daamen, Gonçalo Correia from TU Delft, and Barth Donners from RHDHV. Their combined expertise, encouragement, and valuable feedback have been essential to completing this thesis. I would especially like to thank Winnie, whose insights during our meetings were crucial in helping me refine my research and bring focus to my ideas. I am also profoundly grateful to Barth for his patience and the time he invested in guiding me—our meetings were invaluable, providing the motivation and support I needed to keep pushing forward. This work would not have been possible without their guidance and belief in my potential.

*Wouter van der Veer*
*Delft, November 2024*

# Abstract

In recent years, e-scooters have gained significant traction as a sustainable mode of transportation across Europe. While countries like Germany and Belgium quickly embraced e-scooters, the Netherlands initially approached their adoption with caution. However, in 2023, a pivotal shift occurred when the Dutch government made a landmark decision: the House of Representatives approved legislation establishing a regulatory framework for light electric vehicles, including e-scooters. This milestone was further solidified in October of the same year when the Senate passed the bill.

E-scooters share several similarities with bicycles in urban mobility. Both are eco-friendly, enhance manoeuvrability in traffic, and offer cost-effective transportation alternatives. They promote an active lifestyle, require minimal storage space, and are often accessible through sharing services in many cities. In other countries, e-scooters frequently utilise similar infrastructure, such as bike lanes, and adhere to comparable regulations.

The Netherlands has a deeply ingrained bicycle culture, which has made the bicycle a central part of daily life. Approximately 28% of all journeys in the country are made by bicycle, and for trips between 0-5 km, this figure exceeds 50%. Compared to other European nations, the Netherlands leads in bicycle usage as the primary mode of transport and tops the daily use rankings. This extensive cycling culture has evolved over the years, positioning the bicycle as an integral part of Dutch life. The combination of this culture and the similarities between bicycles and e-scooters creates a promising potential for a high mode share of e-scooters in the Netherlands.

For many travellers, the journey begins at home in the morning, where they make crucial decisions about their mode of transportation before stepping outside. This initial choice significantly influences the rest of the journey, impacting factors like convenience, travel time, and overall satisfaction. The decision of how to reach the starting point of a trip, such as a train station, is particularly critical, as it sets the tone for the entire travel experience.

## The research

This research focuses on this ”first-mile” segment of a journey, particularly the first mile towards train stations—a common travel scenario in the Netherlands. For many Dutch travellers, reaching a train station is the first leg of their trip, whether by foot, bicycle, or other modes. This stage is not only about reaching the train but also involves considerations such as accessibility, cost, comfort, and reliability. In this context, the study specifically examines the role of e-scooters in the first-mile journey, comparing them to other active modes like walking and cycling while excluding buses and cars from the analysis. To clarify, the e-scooter in the research is presumed to be a carry-on vehicle. This means the e-scooter can be folded and taken onto public transport.

A survey with a stated preference choice experiment was executed to investigate the possible number of e-scooter users once the e-scooters are legal in the Netherlands. A stated preference was used to collect data on potential e-scooter users in the Netherlands because e-scooters are not yet legal for widespread use on public roads. As a result, data cannot be observed of actual behaviour or conducted via a revealed preference survey, as this relies on data from real-world choices.
In this experiment, participants were asked to choose between familiar modes and the e-scooter in six scenarios. The sample of respondents is 174, of which 156 remained after thoroughly assessing the data quality. The participants in the survey were asked how they would travel to a train station in the six different scenarios. As mentioned, the e-scooter is one of the possible modes of travel. The other travel modes available for these scenarios are taken from the participants' answers to earlier questions in the survey to reflect better the current travel possibilities that those participants have daily. This way,

the participants chose between familiar modes and the e-scooter. The other modes consist of walking, cycling, e-bikes and moped-scooters. Within the six provided scenarios, three relevant attributes were varied. These attributes included carry-on ticket cost, parking time (or time saved for the e-scooter), and travel time. These relevant attributes were selected based on reference research and papers.

## Results and conclussions

The data from this survey were first analysed using rough statistics and then further defined using a multinomial logit model. The Multinomial Logit (MNL) model is well-suited for analysing choice situations, as it models the probability of each choice being selected. It effectively captures how different attributes of each alternative, such as cost, travel time, or parking time, influence the likelihood of being chosen.

The final model of the MNL reveals a cohesive story about travel behaviour and preferences, categorised into four key insights that work together to shape the choices people make.

First, the model highlights a baseline preference for certain modes of transport through the alternative specific constants (ASC) for e-scooters, bikes, walking, e-bikes, and moped scooters, with values ranging from 3.095 to 8.296. These values suggest that people are generally more inclined to choose these options over not travelling, underscoring their attractiveness and role in meeting mobility needs.

Next, the influence of resource-related factors—cost and time—emerges as a crucial consideration in travel decisions. As expected, higher time and price make a trip less desirable, reflecting the tendency to avoid longer or more expensive journeys. However, the model also reveals a gender-specific nuance: the positive effect of travel time for biking among males suggests that they are less deterred by longer biking distances than females, indicating variations in how time is perceived across different groups.

Experience with a transport mode is another influential factor, as seen in the positive effect of having used an e-scooter before. Those who previously used an e-scooter are likelier to choose it again, suggesting familiarity breeds comfort and confidence. This finding hints at the potential for increased e-scooter adoption as more people become accustomed to this mode of transport.

Lastly, the role of past behaviour in shaping future choices ties the model's story together. The significant positive impact of previous usage of walking, biking, and e-biking (with effects ranging from 0.757 to 2.317) shows that once a mode becomes part of a person's routine, it tends to remain a preferred choice. This likely stems from comfort, habit formation, and satisfaction with past experiences.

The model's findings were used to simulate a percentage of how many people would choose the e-scooter when consulting a representative sample of the Netherlands.From this simulation a prediction per centage in create. For the group inexperienced user, both a low and high extreme scenario is displayed in the Figure 1 and 2. In the figures, both scenarios show the modes of walking and cycling compared to the e-scooter.

The two figures illustrate how user preferences for walking, cycling, and e-scooter use change over varying distances, based on the choice model estimates combined with the representative sample of Dutch train travellers. The simulation compares an "Extreme Low" scenario, with a cost of 1 euro and a parking time of 3 minutes, to an "Extreme High" scenario, where no fee is involved, and parking time is extended to 9 minutes. Across both scenarios, distance plays a crucial role in shaping transportation choices. Walking is preferred at shorter distances (around 0.5 km) but quickly loses favour as distances increase, with users turning to other modes. In the "Extreme Low" scenario, cycling rapidly becomes the dominant choice beyond short distances, while e-scooters see a moderate increase in use. However, in the "Extreme High" scenario, where e-scooters are free and don't have the adverse effects of longer parking times, they become significantly more attractive, particularly for distances beyond 1.5 km, surpassing both walking and cycling.

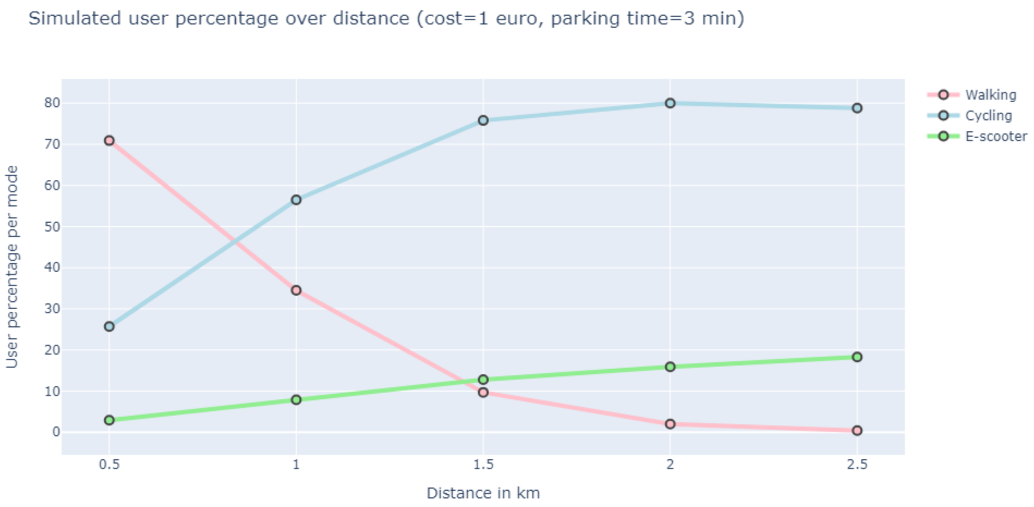



Figure 1: Extreme "Low" scenario for participants with no experience

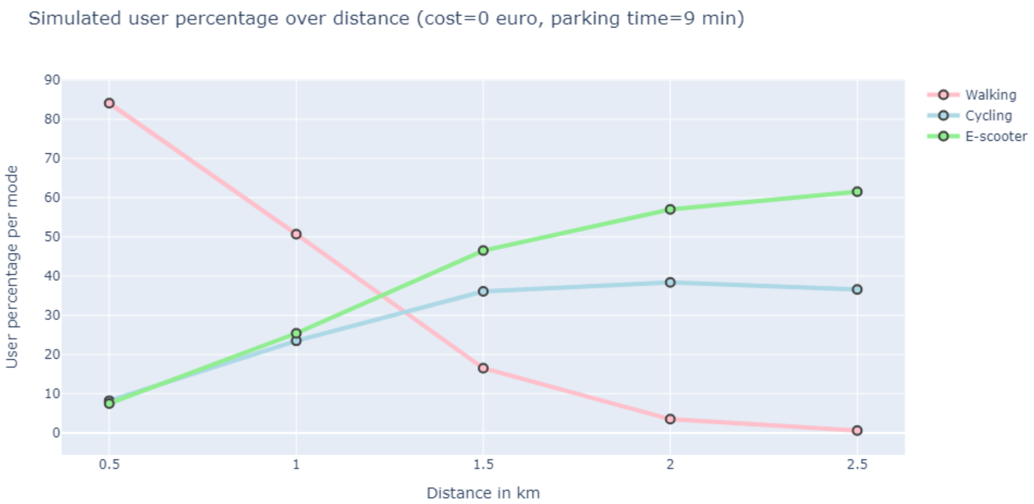



Figure 2: Extreme "High" scenario for participants with no experience

Overall, the simulation highlights that user preferences are highly sensitive to economic factors like cost and the convenience of not having to park. While cycling consistently remains a viable option across distances, its appeal diminishes when the cost barrier for e-scooters is removed. In contrast, e-scooters, which become more appealing when their use is economically advantageous, dominate the longer-distance choices in the "Extreme High" scenario. These results underscore how variations in pricing and convenience can shift user behaviour, with e-scooters emerging as an exceptionally competitive option when such factors are favourable.

The research provided valuable insights into e-scooters; however, it fell short when analysing other modes of transportation included in the study. The choice experiment incorporated moped scooters, but during data validation, it became evident that the sample size of moped scooter users was too small to draw meaningful conclusions about their estimated attributes. No estimates could be made in one of the validation models because no moped scooters were selected, resulting in an error in the MNL model. To address this limitation, the experiment could be repeated with a larger participant pool, increasing the likelihood of including more moped-scooter users and thus overcoming this shortcoming.

In a follow-up study, the retail price of the e-scooter can be included. For this research, it was assumed that people would have the e-scooter available. However, the influence of ticket prices on the participants' choices raises the question of whether they would be willing to buy an e-scooter. The small increases in ticket cost for using the e-scooter in combination with the train made many participants switch to other modes. This begs the question of whether they are willing to invest in a new mode of transport.

A second follow-up study could focus on making the travel distance included in the experiment more tailored to the participants. In the current research, the participants got three distances (500, 1000, and 1500); however, only one distance is typically travelled daily from home to the train station. This distance generally does not vary; tailoring to the participants' distance gives a more realistic choice when considering the alternatives. However, switching to individual distance would a different approach in collecting participants. The goal should remain to get data over short and longer distances towards the train station.

# Contents

# 1 Introduction

In recent years, Europe has seen the emergence of e-scooters as a viable mode of transportation. The government was initially hesitant in the Netherlands compared to neighbouring countries such as Germany and Belgium, which quickly adopted e-scooters. This hesitation originated from an accident with a light electric-powered vehicle in the Netherlands. This accident led to stricter legislation on the introduction of electric-powered vehicles. However, in 2023, the Dutch House of Representatives approved new legislation establishing a regulatory framework for introducing light electric vehicles, including e-scooters. Subsequently, on October 24th of the same year, the bill successfully passed through the Senate (Eerstekamer.nl, 2023).

The bicycle and the e-scooter share several similarities in urban mobility: both are eco-friendly, enhance manoeuvrability in traffic, and offer cost-effective transportation alternatives. They promote an active lifestyle, require minimal space for storage, and are accessible through sharing services in many cities. Additionally, they often utilise similar infrastructure, like bike lanes, and are subject to comparable regulations.
Bicycle use is highly integrated into daily life in the Netherlands. Approximately 28% of all journeys in the country are made by bicycle, and for trips between 0-5 km, this percentage is just above 50 per cent (KiM, 2024). Compared to other European countries, the Netherlands lead in bicycle use as the primary mode and in the daily use ranking (Yanatma, 2023). The high numbers in the Netherlands are related to the cycling culture that the country has developed over the years (Dekker, 2021).
Combining this Dutch bicycle culture and the similarity between e-scooters and bicycles creates a potential high mode share for e-scooters in the Netherlands. This research aims to investigate the possible e-scooter share in the Netherlands so policymakers and regulators can better prepare for the Netherlands with e-scooters present.

## 1.1. Research gap

During the exploratory research before the study, reference papers on the Internet were mainly on shared e-scooters. A more in-depth look at the ability to gather data on shared vs. private e-scooters, it is plausible that when e-scooters are introduced in the Netherlands, data on shared e-scooters will be more accessible to collect than data on private e-scooters. Shared e-scooters are typically operated by large companies in cities, which require detailed tracking for fleet management, compliance with local regulations, and safety measures. These companies collect vast amounts of data on scooter usage, trip durations, routes, frequency, and user demographics. As a result, shared e-scooter data is readily accessible, can be extensively analysed faster, and contributes to research on urban mobility trends.

In contrast, private e-scooters lack this level of centralised data collection. Owners use their scooters independently, and there is no requirement to report usage patterns or performance data. This creates a fragmented data landscape, with only small-scale surveys, self-reported data, or isolated studies available. Consequently, comprehensive data on daily private e-scooter usage numbers is more complex, leading to a disparity in the richness and availability of data between shared and private e-scooter systems.

Therefore, the current and future gap regarding e-scooters in the Netherlands is expected to be larger for private e-scooters than their shared counterparts. As a result, this research will focus on privately owned e-scooters.

## 1.2. Context and scope

For the definition and boundaries of what an e-scooter should adhere to, the definition of an e-scooter according to the Dutch framework for LEVs (light electric vehicles) will be used. The framework used for the Netherlands is based on its German counterpart (IenW, 2022). More on the specific boundaries an e-scooter in the Netherlands has to adhere to once the e-scooters are legalised in the Netherlands is included in subsection 3.1.1 of the literature study.
Further, the e-scooter models in this study can be folded and taken with one on a train trip. This means users can use the e-scooter for first- and last-mile trips.
As stated within the research gap, the shared e-scooter research mainly includes shared e-scooters. Those research and the associated user patterns show that within shared e-scooter research, e-scooter trips related to public transport trips are primarily last-mile trips. Therefore, this study focuses on privately owned e-scooters and their use in the first-mile segments of a trip. This is done to limit the scope of the research. Here, it is assumed that behaviour and preference for distance and use for the last mile follow the same characteristics for private as for sharing. Secondly, to limit the complexity of the data collection, the first-mile choice is discontinued from the last-mile choice. However, the participants in the data collection are made aware of the possibility of using the e-scooter for both the first-mile trip and the last-mile trip, as the e-scooter is formulated in this research as mentioned above as a foldable carry-on mode for train travel.

## 1.3. Research objective and research questions

Within the context and the defined scope boundaries, this research aims to estimate a mode share for private e-scooters for the first mile of train travel in the Netherlands. The objective is to formulate a number based on current travel behaviour and preferences. The main research question to guide this objective is formulated as follows:

> ”What is the willingness among inhabitants of the Netherlands to adopt private e-scooters for the first leg of their journey when travelling by train?”

To support the main research question, five sub-questions are drawn up. Three of the five questions are aimed at reference papers and investigating the effects influencing the choice between e-scooters and traditional first (and last) mile modes for train travel. The fourth question looks at how the intensified factors affect the mode choice for the e-scooter; this will be done with the help of a stated preference survey. The last question focuses on how these choices of the stated preference translate to a bigger group, like train travellers in the Netherlands. As mentioned, the e-scooter is a new mode of transportation in the Netherlands and is currently not legal on public roads. This leads to not everyone having had the chance to use one yet or has only used one in another country. Assessing the difference between people with and without experience can indicate a hidden preference or, for example, an over-prediction by nescience. The methods for answering these questions are indicated by every sub-question listed below. The methods themselves are explained in chapter 2

1. What are the spatial and technical conditions for introducing e-scooters to train travel in the Netherlands?
   - literature study
2. What factors influence the choice of the e-scooter when taking a first (or last) mile trip for train travel?
   - literature study
3. What is the current mode choice for a first (or last) mile trip for train travel in the Netherlands?
   - literature study

4. What is the effect of the identified factors on the mode choice when considering the e-scooter for first-mile travel in the Netherlands?
    - Stated preference survey & Model study
5. How do the estimated effects translate to the current first-mile train travel in the Netherlands when simulated for train travellers in the Netherlands?
    - Simulation

With the combined answers to each of the four sub-research questions, the main research question defined as before, ”What is the willingness to use private e-scooters for the Netherlands' first mile for train travel?” will be answered using the outputs of the model study and current travel behaviour in a simulation in chapter 7. The methodology of this simulation will be explained in chapter 2

## 1.4. Scientific and societal value

This study provides significant societal value by predicting the potential adoption and usage of e-scooters in the Netherlands. Given the recent positive development in the form of a proposed change in regulations for e-scooters in the Netherlands, there is still considerable uncertainty about how extensively they will be utilised once fully legalised. This research aims to mitigate this uncertainty by offering predictions that will aid policymakers, advisors, and administrators understand the potential impacts of e-scooter integration into the urban landscape. For lawmakers, the findings of this study are crucial as they provide a data-driven basis for establishing regulations concerning e-scooter use, particularly focusing on ensuring safety within cycle lanes. Advisors can use the research outcomes to provide municipalities with strategic guidance on accommodating this new mode of transportation and identifying necessary modifications to existing infrastructure. Furthermore, for administrators, such as those in public transportation, the data can inform strategies to manage potential increases in demand and prevent overcrowding, as e-scooters may be brought onto public transport vehicles.

The research into private e-scooter usage in the Netherlands brings scientific value by creating the opportunity to develop e-scooter research further in the Netherlands. This brings scientific value as the unique Dutch cycling culture (Dekker, 2021) provides a unique context for studying e-scooter usage patterns. By understanding how Dutch cyclists adapt to and interact with e-scooters, researchers can extrapolate data to predict user behaviour, optimise infrastructure design, and enhance safety measures in diverse urban settings, ultimately fostering more sustainable and efficient transportation ecosystems globally.

## 1.5. Thesis outline

This thesis is divided into five parts. The first part sets up the research with the methodology in chapter 2 and describes the methods used in detail. The second part will continue with the context and further address the current state of legislation on e-scooters in the Netherlands, how e-scooters are used outside of the Netherlands, and how the current state of first-mile travel in the Netherlands is in chapter 3. The third part, consisting of chapter 4, details the survey, how the questions are formulated and which information from the literature study is included in the question. The fourth part of this research consists of the data collection and the descriptive statics of that data in chapter 5, and the analysis conducted on the data to answer the research questions in chapter 6. Lastly, the simulation to predict a user percentage of the e-scooters in the Netherlands for the first mile of train travel in chapter 7.
The last part of this research consists of the conclusion, discussion in chapter 8 and further recommendations in chapter 9.

# 2 Methodology

The methodology consists of five methods: a literature review, a survey, a data analysis, a model study, and a simulation. The literature review aimed to give insight into three subjects: What were the precise boundaries of introducing e-scooters in the Netherlands, how were e-scooters used outside the Netherlands, and what was the current status of first-mile travel in the Netherlands? These insights drew characteristics that frame the potential boundaries for introducing e-scooters in the Netherlands. This frame was used to formulate the questions within the second method: the survey.

The survey aimed to gain insight into how the people of the Netherlands thought about the introduction of e-scooters and whether they were willing to use them. The willingness to use was tested via a choice experiment. The third method was a data analysis of the collected data via the survey. The fourth method is choice model estimation, where attributes from the choice experiment are estimated via a multinomial logit model. The last method, the simulation, combined these estimates with travel data from the Netherlands to compose a mode share prediction.

The overview of how these five research methods fit into the total research approach is shown in Figure 2.1. Here, the start of the approach was defined by a preliminary literature review, which fed into a research proposal. This initial proposal formed the basis for the literature review, resulting in the characteristics needed for the survey. The survey, once conducted, delivered the required data for the last two methods before the conclusion could be made.

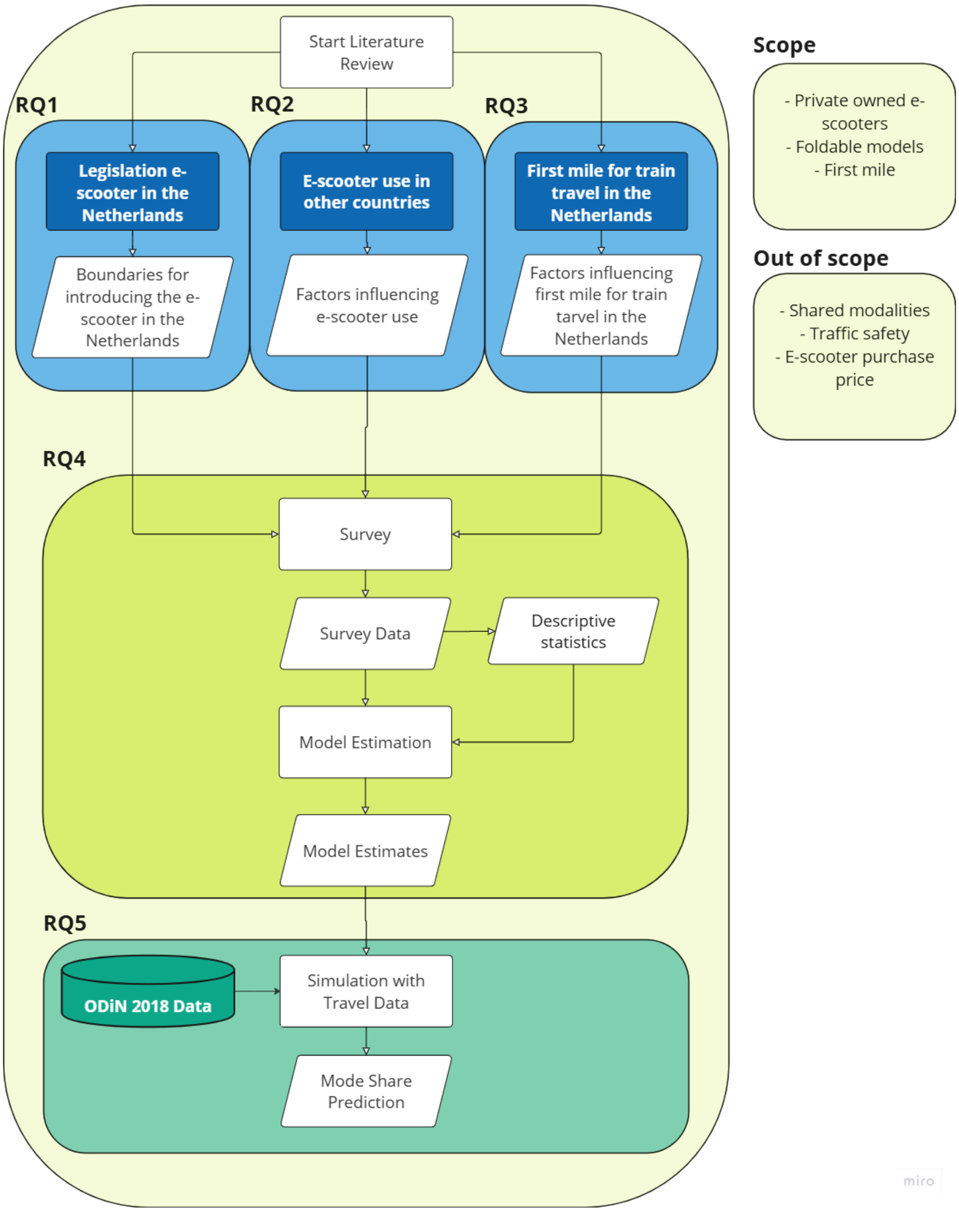



Figure 2.1: Overview research approach

## 2.1. Literature study

The literature study is the first method in chapter 3. The literature study consists of three sections. Boundaries for introducing the e-scooter in the Netherlands, E-scooter use in other countries, and First mile for train travel in the Netherlands.

For the first section connected to the first research question: "What are the spatial and technical conditions for introducing e-scooters to train travel in the Netherlands?", a targeted approach to gathering literature has been taken. This entails that the relevant governmental websites (e.g. www.government.nl) and websites of transport operators (e.g. NS (Dutch railways) and operators from other countries) have been used to search for information regarding e-scooters or other modes that are or are not allowed to be taken onto public transport. If the e-scooters are permitted, they are also assessed for which conditions.

The process for the second and third sections consists of four steps.

1. Database searches Within the first step, academic databases such as Google Scholar and Sco-

pus were consulted for peer-reviewed articles. At the same time, governmental websites connected to the research subject or subjects of the literature section were searched for, and their relevance was assessed.

2. Keyword strategy and snowballing For the second step of the literature methodology, based on the earlier found article, the search terms for the new reference paper are enchanted with relevant keywords to the literature sections.

3. synthesis In the third step of the methodology, the found papers were grouped and organised on theme and relevance for the literature sections

4. Review The last step consisted of validation. The groups for the last step were reassessed. Papers that survived this reassessment are incorporated in the literature review.

This methodology provided a comprehensive understanding of the potential for e-scooters to improve first-mile travel to train stations in the Netherlands by systematically reviewing and analysing literature from these three sections. These insights will be used as input for the survey and her choice experiment.

## 2.2. Survey

The second method used is a stated preference survey. A stated preference survey was used to collect data on potential e-scooter users in the Netherlands because e-scooters are not yet legal for widespread use on public roads. As a result, e-scooter data cannot be observed in an actual behaviour or collected by a revealed preference survey as this relies on data from real-world choices.

In such cases where a mode of transport is not yet available or legal, a stated preference survey is an effective method for understanding potential user behaviour. It allows researchers to create hypothetical scenarios and ask respondents how they would react or what choices they would make if e-scooters became legal and viable. This type of survey helps to simulate future conditions. It provides insights into how people might incorporate e-scooters into their travel patterns, especially for the first mile of their journey, such as travelling to train stations.

By using a stated preference survey, valuable information on factors such as the potential demand for e-scooters, the preferences for various attributes (like cost, travel time, or convenience), and how e-scooters might compete with or complement other modes of transport can be gathered.

As mentioned under the literature review, the literature review gives input for the survey. From this input, attributes were selected, and the attributes and levels were created. These levels were put in Ngene, and the choice experiment was set up with a D-efficient design using the Fedorov algorithm. This advanced statistical method optimises the design by minimising correlation among the variables, thus ensuring the independence and significance of each scenario presented within the survey. Applying this algorithm develops a structured choice experiment that includes six unique scenarios. These scenarios are specifically engineered to minimise redundancy and overlap, thereby maximising the efficiency of the experimental design and enhancing the quality of the data collected. This means that this research can reach significance on its parameter with a smaller sample size than would have been needed if a more convenient algorithm was used.

In the initial section of the survey, before participants reach the choice experiment, participants will be asked to provide details about the transportation modes they possess at home and their typical commuting methods. This data will be utilised to assemble a customised set of transportation options, ensuring that each participant is presented with choices that are relevant and familiar to them. Consequently, when participants are asked to choose between an e-scooter and other modes of transportation, they make informed decisions based on the options they already know and use. This approach helps ensure that their choices better reflect their preferences and experiences with the included modes.

After the choice experiment, the later section concluded the survey and asked the participants for their socio-demographic background with typical characteristics, including age, gender, income, and education level. These background statistics were used for model calibration in the following chapters

## 2.3. Descriptive statistics

The data analysis started with descriptive statistics, which provided a foundational understanding of the data set and its characteristics. The process of understanding the data was split into three parts. The first part focused on the collection and duration of the survey. Here, the quality of the survey answers is assessed. This was done by looking at the given answers as well as by looking at the distribution channels.

The second part examined the sample's composition, including statistical tests for the subgroups in the data set. And looking at how representative the subgroups were.

The last part of the descriptive statistic involved a deep dive into the choice experiment. Here, the choices made in the experiment were explained. On a deeper level, the social demographics in the sample were assessed on the subgroup level, and the choices between the subgroups were analysed. Significant choice differences between the subgroups were listed and noted to be later used for the choice modelling.

## 2.4. Choice modelling

The methodology employed for the chapter model estimation in this research followed a detailed and structured approach designed to accurately capture the factors influencing individual choice behaviour based on the survey data. The process involved several vital steps that progressively refined the model to ensure it reflected both the attributes of the choice experiment and the socio-demographic and conditional factors affecting participants' decision-making.

Base Model Construction The first step involved developing a base model. A Multinomial Logit (MNL) model was selected for this base model. The MNL model was chosen because it is well-suited for scenarios with multiple discrete choices, such as the various transport modes offered in the choice experiment (e.g., walking, cycling, e-scooter, etc.). For the development of the base model, the forward step-wise method was used to build up the MNL model. This method began by evaluating the individual attributes from the choice experiment, such as travel time, parking time, travel cost, and in-vehicle time. Each attribute was incorporated into a single attribute model to assess its impact on choice behaviour. These models were ranked based on performance. The performance was measured using the adjusted Rho-square values. Once the highest-ranked attribute model was identified, other attributes were added sequentially in descending order of performance to the model. The process continued iteratively: with each new attribute added, the model was reassessed to determine if its performance improved. It was discarded if the newly added attribute did not enhance the model's quality. This resulted in a final base model that captured the most significant predictors of participants' choices from the choice experiment.

Socio-Demographic Variables Integration After establishing the base model, the next step was to incorporate socio-demographic factors into the model to account for differences in choice behaviour across various population subgroups. The socio-demographic variables, such as age, gender, income level, education, and prior experience, were derived from the descriptive analysis. The same forward step-wise method was used as with the base model. Each identified socio-demographic group was added as a single attribute to the base model to test whether it significantly influenced the choice behaviour. For instance, age groups might show differing preferences for specific modes of transport, or income levels could affect sensitivity to travel costs. These socio-demographic factors were tested in addition to the base model attributes, and only those that improved the model's performance were retained. If a socio-demographic variable did not enhance the model or was found to be insignificant, it was excluded from the final model. The result of socio-demographic integration was a more nuanced model that reflects the variations in choice behaviour among different demographic groups. Conditional Logit Model Integration In the third phase, a Conditional Logit (CL) model was incorporated into the existing MNL to address conditional factors affecting choice behaviour. Two primary conditional factors were considered: vehicle ownership and current usage patterns. These conditional variables were necessary to account for the specific transport options available to participants in the choice experiment.

**Vehicle Ownership:** This step evaluated how the ownership of specific transport modes, such as bikes or e-scooters, influenced the likelihood of selecting these modes. The CL model adjusted the utility functions for each mode to reflect these availability conditions, ensuring that the final model captured the influence of ownership on transport choices.

**Current Usage:** The model also considered participants' travel behaviour in addition to ownership. This variable assessed whether individuals who regularly used a specific mode of transport, such as cycling or walking, were more likely to choose that mode in the choice scenarios. By incorporating current usage patterns into the model, it was possible to account for habitual behaviours.

After the addition of the CL, the total model was reassessed, and socio-demographic variables that were no longer deemed significant due to the addition of conditional logit were removed from the model. This resulted in the final model used for the next chapter, the simulation.

## 2.5. Simulation

This chapter employed a simulation-based methodology to model the potential adaptation of e-scooters as a transportation mode for trips to the train station. The simulation was structured around travel data from the ODiN 2018 dataset, which provides a comprehensive view of travel patterns in the Netherlands. To align the simulation with the research objectives, the dataset was filtered to include only trips where the primary mode of transport was a train and only for travellers aged 18 and older. This ensured that the focus remained on a relevant subsample of adult train travellers whose behaviour was most pertinent to the study. After filtering the relevant data, travellers were grouped into subgroups based on key demographic and behavioural variables. These subgroups were formed by the choice models estimated in Chapter 6, which considered gender, ownership and use of bicycles or mopeds. A total of 26 subgroups were generated through this process. These subgroups represented distinct segments of the population, each differing in their likelihood of adopting e-scooters based on the models' estimates. It is important to note that the simulation did not consider opt-out options or alternative trips not taken, as the focus was exclusively on modelling actual trips to train stations. Trips made differently don't fit this scope. The model's parameters, as estimated in Chapter 6, were then applied to these subgroups to simulate e-scooter usage per subgroup. The overall user percentage for e-scooter adoption was calculated by combining these mode choice probabilities from the choice model with the rate that each subgroup represented in the sample from ODiN 2018.

In the first stage, a base simulation was run with the assumption of zero cost for e-scooter use and a minimal parking time of three minutes. This base simulation provided a benchmark for estimating the proportion of e-scooter users across the different subgroups, revealing how factors like travel distance and experience with e-scooters affect mode choice. Subsequent stages introduced variations in cost and parking time to simulate different scenarios.

In the second stage, these variations were modelled to observe how changes in these variables affected e-scooter adoption, particularly between inexperienced and experienced users. The goal was to determine the sensitivity of e-scooter uptake to practical factors like increased costs or longer parking times. This stage demonstrated the impact of reduced costs and time savings associated with e-scooters, especially in cases where parking times for alternative modes (e.g., bicycles) were significantly higher.

In the third and final stage, extreme scenarios were simulated to assess the upper and lower bounds of e-scooter adoption. These extreme cases, such as zero cost and long parking times, provided insights into the maximum possible market share of e-scooters under ideal conditions, contrasting this with scenarios where high costs and minimal parking time savings limited adoption. The results of these simulations were compared across both experienced and inexperienced e-scooter users to illustrate further how familiarity with the mode affected behaviour.

# 3

# Literature study

Within this chapter, the reference literature will be assessed. This consists of three major subjects: The spatial and technical conditions of the concept of the e-scooter in Dutch train travel, coherent with research question 1; the use of e-scooters in other countries, coherent with research question 2; and the current state of first-mile train travel in the Netherlands, coherent with research question 3. These three subjects give the base for setting up the survey in chapter 4.

## 3.1. Spatial and technical conditions for introducing the e-scooter in the Netherlands for train travel

Within the scope of this research, boundaries created by legalisation and boundaries created (or present) by the public transport operator for introducing the e-scooter in the Netherlands are distinguished. The first set of boundaries concerns why currently available models in stores are unsuitable for public roads and where they must differ to comply with the Dutch market. The second set of boundaries regards the current policy of taking vehicles with one onto the train. Here, the policy of the NS (Dutch train operator) will be highlighted, and the place of the e-scooter will be assessed. In addition, the policy of the NS will be compared to the current policies of other public transport operators in different countries.

### 3.1.1. technical conditions by legalisation

Currently, e-scooters, as defined in the scope of this research, are not legal in the Netherlands. Only kick scooters with electric support are allowed; for these types, there is no license plate requirement, and third-party liability insurance is sufficient. The e-scooters available for purchase in the Netherlands are not allowed on public roads. This is mainly because these e-scooters do not comply with the current legislation for ”Special mopeds” (RDW, 2024)

As mentioned, this contradicts the e-scooters this research envisions. These e-scooters are envisioned as the e-scooters defined in the ”Dutch framework for Light Electric Vehicles (LEVs).” (IenW, 2022). The framework establishes the e-scooter as a type 1b LEV. This entails all light electric vehicles below 55 kg that do not meet the requirements of category 1a. A category 1a LEV is an electric power-assisted cycle (carrier)bike below 75 kg. Figure 3.1 displays the categorisation for LEVs within the framework. Vehicles without hand steering or with a single wheel are not included in the framework due to safety risks. For the 1b LEVs, there is a license plate requirement, a Motor Vehicle Liability Insurance Act is needed, and the minimum age to use is 16. Appendix A provides a complete overview of the framework boundaries for LEVs.

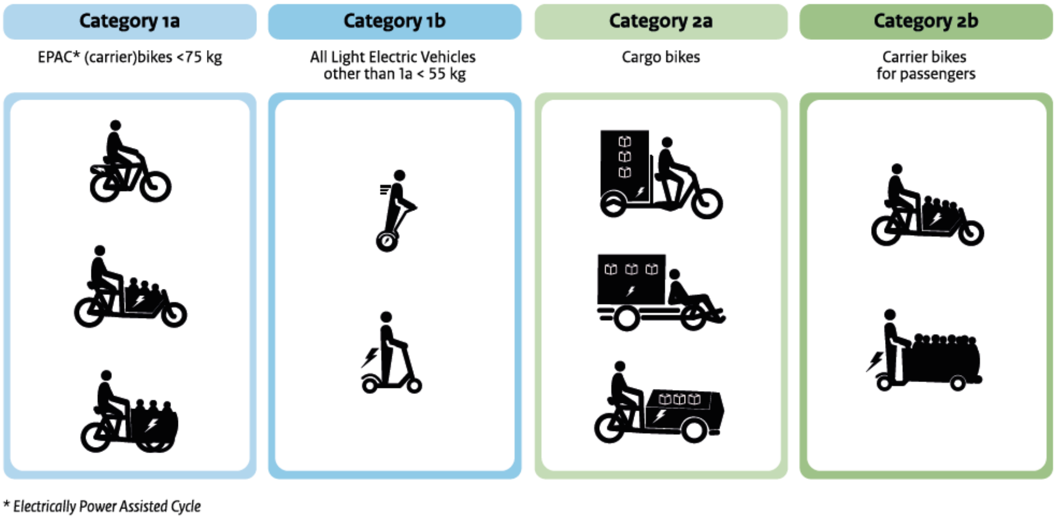



Figure 3.1: Categorisation of LEVs (IenW, 2022)

Category 1b further diversifies from Category 1a in performance. Category 1b vehicles are allowed up to 400W, with a limit for 1a of 250W. As a counter effect, 1b is limited to a single person, so no passengers. The total weight of the driver plus vehicle can not exceed 140 kg. For 1a, this is up to 250 kg, and up to three passengers are allowed.

### 3.1.2. spatial conditions set by operators

Integrating private e-scooters into multimodal train trips presents exciting opportunities for urban mobility, but it also necessitates clear operator regulations since space in carriages is not unlimited. For using e-scooters in combination with the train, it is vital to consider current legislation for bicycles, folding bikes and currently available electric vehicles.

Currently, the NS has a system that classifies bikes and other means of transportation in three different groups. A; Folding bikes, B; regular bikes and C; Bicycles as an aid for disabled travellers (NS, 2024a).
For category A, folding bikes, one does not need a ticket if it complies with the following conditions. A folding bike can not cause hindrances or obstruct seats and pathways. In addition, the folding bike should adhere to the dimensions between 45 cm W x 86 cm L x 80 cm H when folded and should stay folded for the entire trip duration. The folding bikes are also not allowed to be placed at a bicycle spot reserved for category B and C bikes. If a folding bike can not meet these conditions, it can only be taken with you as a category B or C bike. The rules for category B, the regular bike category, are more specific and detailed. This category also contains electric, race, mountain, and disassembled bikes. First, a special bicycle ticket of 7.50 euros for the vehicle is required. Second, bicycles can only be stored in a dedicated spot on the train. If no such place is present or the spot is occupied, one cannot take their bicycle onto the train. In addition, a conductor can, in the context of safety, always decide that a bike is not allowed to entire the train, even if the dedicated spots are still empty. Third, bicycles are only allowed to enter the train during non-peak hours and on the weekends. The only exception here is during the summer months, July and August. During this period, bicycles can be taken onto the train all day. Lastly, when a bike is placed in one of the spots, the owner should remove all other baggage from the bicycle and supervise the bike during the train trip. Category C, the vehicle category that aids disability travellers, does not require a ticket and is not bound by non-peak hours. However, one should mark their vehicle to clarify to the conductor that it concerns a vehicle for disability aid. Further, one should show with the relevant papers that the disability aid is needed. It should be noted that there is a limited number of places for disability aid vehicles. Therefore, it could be that one is to take a train earlier or later than anticipated.

Within the general terms and conditions for vehicles allowed on NS trains, there is no mention of e-scooters. However, on the website under FAQ regarding the bicycle in the train (NS, 2024b), the NS states that one is allowed to take the e-scooter with them as long as it complies with the hand luggage conditions defined in AVR-NS (NS, 2024a). The critical condition for the e-scooter as luggage is that it does not hinder or obstruct seats or pathways. If the e-scooter as luggage does cause hindrance or is expected to cause hindrance, the NS is allowed to refuse you access to the train or require you to leave the train if the luggage has one dimension (width, height, length) more extensive than 85 cm. Currently sold e-scooter models in the Netherlands and models in other countries have a length of more than 85 cm when folded. An e-scooter user is, therefore, warned to adhere to proper vehicle storage inside trains.

In conclusion, the conditions for travelling with e-scooters on trains must be more elaborated for their successful introduction in the Netherlands. The set condition is that e-scooters are now seen as luggage, while their dimensions are more extensive than luggage, for which one can travel without the fear of being denied entry to the train or kicked off the train. This uncertainty does not contribute to a seamless introduction of e-scooters in combination with train travel. An update to the three-category system that the NS operates to include e-scooters more clearly would be in place to provide clarity. This can be done by extending category A to fit the dimensions of the e-scooter or by creating a new category tailored to the e-scooter. This would also allow the creation of tickets for the e-scooter if the NS deems this necessary. The creation of this ticket would lead to a reevaluation of the goals and function of such a ticket.

Reflecting on the concluded possibilities for the integration of e-scooters on train journeys to other countries and their policies does not give a straight answer on what the best policy could be as e-scooter transport policies on trains vary across Europe, reflecting different approaches to integrating this mode of transport into public systems. In Austria, WESTbahn allows folded e-scooters to be carried as hand luggage without extra charges (WestBahn, 2024). Germany's regulations differ by region; for example, the Verkehrsverbund Region Braunschweig permits folded e-scooters free of charge, while unfolded ones need a ticket (VRB, 2024). In Denmark, a bicycle ticket is required for e-scooters and space reservations are recommended (DOT, 2024b) (DOT, 2024a). Slovenia's rail operator, Slovenske železnice, permits folded e-scooters without additional fees (Slovenske zeleznice, 2024). Meanwhile, in Wales, Transport for Wales generally prohibits e-scooters, with exceptions for mobility aids (TFW, 2024). These regulations highlight the varying accommodation levels for e-scooters across European train services. Yet all countries where the e-scooter is allowed onto train have the condition that the e-scooter can not cause hindrance to other passengers.

## 3.2. E-scooter use in other countries

Introducing e-scooters in the Netherlands presents an exciting opportunity to enhance urban mobility. However, to ensure a successful and sustainable implementation, it is crucial to consider the experiences and lessons learned from other countries where e-scooters are already integrated into the urban landscape. By examining international literature on the subject, valuable insights into best practices, regulatory frameworks, and user acceptance can inform and guide the introduction of e-scooters in the Netherlands. Exploring literature from other countries allows for benefits from diverse perspectives and approaches. Different regions have encountered unique challenges and developed innovative solutions that can be adapted to the Dutch context.

For the reference papers used for travel behaviour with the e-scooter in other countries, the assets papers are primarily on shared e-scooters. The data connected to these e-scooters is more accessible to obtain due to the availability of centralised data and the public nature of shared systems. Companies operating shared e-scooter fleets typically collect extensive data on user behaviour, trip routes, distances travelled, and scooter locations. This data can be aggregated and anonymised, providing a viable source of information for researchers to study mobility patterns. In contrast, private e-scooters are owned and operated by individuals, and no central entity collects data on their usage.

The start of how the e-scooter is used in other countries focuses on who the users are. The socio-demographic findings in relevant research papers are featured to find these users. Research in Vienna indicates that socio-demographics indeed have influences on e-scooter usage. The research respondents and the stated e-scooter users have a high percentage of young to middle-aged males (Laa & Leth, 2020). A study in Germany confirms this socio-demographic group (Degele et al., 2018); however, they also link higher education to the choice of e-scooters. This resonated with research from

Austin, TX (Jiao & Bai, 2020) that finds the same target group as Degele et al., 2018. In addition to the socio-demographics, the research from Vienna also indicated that e-scooter owners are more prone to use shared e-scooters due to their familiarity with the mode compared to non-owners. This familiarity also resonated from Baek et al., 2021, where the experience with the e-scooter positively influenced the choice of e-scooters.
The second focus of e-scooter use in other countries is the distance travelled or duration of e-scooter trips. Li et al., 2022 has analysed e-scooter trips statistically for 40 European cities, finding medians for these cities within the range of 0.91 km and 1.79 km and a range of 5.67 min and 13.77 min, respectively. Other research like Oostendorp and Hardinghaus, 2023 resonates with these ranges. It shows a median for shared e-scooters of around 8 minutes and a higher median for private e-scooters, approaching a median trip duration of 18 minutes.

Oostendorp and Hardinghaus, 2023 further gives insight into the combination of e-scooters with public transport. Of the questioned shared e-scooter users, 23.6 % use the e-scooter as a feeder to a public transport network. For private e-scooters, this is only 14.5 %. In addition, the study found that in 6̃0% of the cases, private e-scooter users make less use of public transport now that they have an e-scooter. The contradiction of competing and completing public transport is also recognised by Aarhaug et al., 2023. This study showed that 2̃0% of the e-scooter trips were connected to PT, but also 35.9 % of e-scooter users admit that they would have used public transport if the e-scooter was not available.

In conclusion, introducing e-scooters in the Netherlands offers significant potential to improve urban mobility. However, achieving a successful and sustainable integration requires careful consideration of international experiences and research. Insights from countries with established e-scooter systems provide valuable lessons on user demographics, travel behaviour, and the interaction between e-scooters and public transport. Understanding the prevalent socio-demographic characteristics, such as the inclination of young, educated males to adopt e-scooters, can help tailor strategies to the Dutch context. Additionally, analysing trip patterns, like distance and duration, offers benchmarks for planning infrastructure and services.

The availability of centralised data from shared e-scooter systems has enabled detailed analyses of user behaviour, making shared systems a key focus for researchers. These insights, including the role of e-scooters as feeders to public transport or as substitutes for it, underscore the dual role of e-scooters in complementing and competing with other modes of transportation. As the Netherlands seeks to introduce e-scooters, applying these international findings can guide effective policies and design choices, ensuring that e-scooters contribute positively to sustainable urban mobility while addressing potential challenges in their adoption.

## 3.3. First mile for train travel in the Netherlands

Before introducing e-scooters in the Netherlands, it is essential to understand the current behaviours of the Dutch first (and last-) mile travel. The first and last miles refer to a journey's beginning and end segments, often involving travel to and from public transportation hubs.

Understanding the current first-mile (and last-mile) behaviours in the Netherlands provides critical insights into the prevalent modes of transportation, user preferences, and challenges commuters face. This information is vital in identifying the specific gaps and opportunities where e-scooters can offer the most value. For example, if many commuters face difficulties accessing public transportation due to long walking distances or lack of convenient options, e-scooters could be a practical and efficient solution to bridge these gaps.

A study from Stam, 2021 emphasises that the combination of cycling and train travel is a popular and sustainable mode of transportation in the Netherlands, offering flexibility and extending the reach of train stations. This integration is particularly effective when travellers can avoid transfers during their train journey, as many are willing to cycle longer distances to reach a station that offers a direct route to their destination. This preference highlights the importance of a seamless travel experience, where the convenience of a transfer-free journey outweighs the extra effort of a longer initial bicycle ride.

Another study van Mil, 2020 emphasises the importance of first and last-mile transport as critical components in the effectiveness of public transportation systems, noting that these connections are often considered the weakest link in transit chains. It explores traveller preferences between traditional and emerging modes of transport, such as private cars, buses, bicycles, shared vehicles, and on-demand ride services. While many travellers currently rely on conventional options like buses and bicycles, there is a noticeable interest in newer options like shared and on-demand services. To understand these preferences, the study identifies six key factors that influence mode choice:

- **Traveler Characteristics:** This includes socio-demographic factors like age, gender, and income, which can significantly shape an individual's transport preferences.
- **Psychological Factors:** Attitudes, perceptions, lifestyle, and habits play a role in transport decisions, affecting how travellers perceive different modes of transport.
- T**rip-Specific Characteristics:** Elements like the distance of the first/last mile, trip purpose (such as commuting or leisure), and even weather conditions are crucial in determining mode choice.
- **Transport Mode Characteristics:** Factors such as travel time, cost, comfort, and convenience of different transport options are critical in shaping travellers' decisions.
- **Built Environment:** This includes the design, density, and diversity of the areas surrounding the trip's origin or destination, such as the availability of bike paths, sidewalks, and parking facilities.
- **Main Stage Factors:** These relate to the characteristics of the primary segment of a multimodal journey, like the type and quality of the leading transit service (e.g., train speed and frequency), which can impact the choice of first and last-mile transport modes.

These factors collectively shape travellers' decisions regarding their preferred means of transport for their journeys' first and last segments.

In addition, research in the Netherlands into including the e-scooter in the shared mobility setting for last-mile travel by van Kuijk et al., 2022 shows a positive attitude toward the e-scooter as a transportation option. The e-scooter and (electric-)bicycles tested better than other shared mobility options, like, for example, the shared e-moped scooter. The research further states that e-scooters target younger people (<26 years), which complies with the findings found in the papers about e-scooter usage in other countries. However, the research concluded that most public transport users prefer not to use shared mobility.

Besides reference papers, travel data analysis gives an in-depth and accurate overview of travel behaviour in the Netherlands. While literature studies provide a theoretical foundation and contextual understanding derived from previous research, integrating empirical travel data offers real-world insights and validates these theories. Travel data includes vehicle use, ownership, departure time, and public transport trip integration. Combining this information helps identify user patterns and the impact of socio-economic factors and predict future travel behaviours more reliably.
The travel data selection has been made on the ODiN data 2018 (CBS, 2018). The year 2018 is chosen because 2018 is the last full pre-COVID year. That means that the travel data is not restricted by any government safety regulations caused by COVID-19 or the traveller's fear of the risk of infection.

| Rank | Mode | Percentage |
|---|---|---|
| 1 | Walking | 43.2% |
| 2 | Cycling | 27.1% |
| 3 | Bus | 13.1 % |
| 4 | Car | 6.3% |
| 5 | Metro | 4.3 % |
| 6 | Tram | 4.2 % |

Table 3.1: Overview of the top 6 modes of connected trips to the main mode train (first and last mile)(CBS, 2018)

Table 3.1 shows the top 6 modes used for the first and last mile in the Netherlands for trips with the main mode train. What shows is that walking and cycling makeup 70% of trips. In addition, another 20% is made up of lower-level public transport like the metro, tram and bus. Going further into detail in only the ”active modes”, give the following table displayed in Table 3.2. Here, it shows that e-bikes and moped scooters are used to go to the train station, but in contrast to walking and cycling, this is only a small percentage.

| Rank | Mode | Percentage |
|---|---|---|
| 1 | Walking | 43.2% |
| 2 | Cycling | 27.1% |
| 3 | E-bike | 0.6 % |
| 4 | Moped | 0.4 % |

Table 3.2: Overview of the top 4 active modes of connected trips to the main mode train (first and last mile)(CBS, 2018)

The attitude towards (shared) e-scooters in the Netherlands seems positive. With the higher bicycle use in the Netherlands and bicycle culture, the stage seems perfect for a high usage number of e-scooters once they are legally introduced in the Netherlands.

In conclusion, understanding the existing first- and last-mile travel behaviours in the Netherlands is crucial before introducing new mobility solutions. Insights into current modes of transportation, user preferences, and commuter challenges help identify opportunities where these new solutions could add the most value, such as addressing long walking distances to transit hubs. Studies indicate a firm reliance on active modes like walking and cycling, comprising 70% of these trips, while smaller percentages use options like e-bikes and mopeds. Although these traditional modes dominate, younger users are keenly interested in innovative transportation options. Integrating empirical travel data further supports a deeper understanding of commuter habits and potential gaps that emerging transport options, such as e-scooters once they are legally introduced, could fill. Given the Netherlands' robust cycling culture, the environment appears conducive to adopting new solutions that could complement the existing transport landscape, provided they align with current travel preferences and infrastructure.

# 4
# Survey design

In this chapter, we delve into the intricate process of survey design, focusing on three key components: the choice experiment, travel behaviour, and socio-demographics. The centrepiece of the survey is the choice experiment, which constitutes the most substantial portion and is pivotal in understanding participants' decision-making processes. The survey explores travel behaviour to support the choice experiment, providing valuable insights into respondents' mobility patterns and preferences. Lastly, the survey collects socio-demographic factors to contextualise the findings within the broader demographic landscape. Each section is meticulously crafted to ensure comprehensive data collection and robust analysis, laying the groundwork for meaningful and actionable insights in chapter 5 and 6.

## 4.1. Choice experiment

Four main attributes are used to differentiate the choice scenarios for the build of the choice experiment. These four attributes are derived from the literature study.

### 4.1.1. Attributes

**Ticket price** As identified in analysing NS's different options for taking a vehicle onto the train mentioned under subsection 3.1.2 and comparing to other countries in section 3.2. There are two relevant options for the e-scooter. This can be as a carry-on mode without a ticket or as a regular bicycle in category B with a paid ticket. The bicycle ticket is 7.5 euros, which is currently set for bicycles. It seems excessive for a vehicle with the E-scooter's dimensions to uphold this high price for the E-scooter. Therefore, the survey will include lower, more accessible ticket pricing for the e-scooter in the 1 and 2 euros range. Including a ticket price might determine whether people will take their e-scooter onto the train. Therefore, the option of no cost is also included with the ticket cost levels.

**Parking time** As described in this research, the e-scooter is a carry-on mode that can be taken with one onto the train. The advantage of a carry-on is that one does not have to park their vehicle at the station. Therefore, parking time is added as an attribute to distinguish between the modes that must be parked and those that don't. Not every station is the same, and bigger stations have different parking garages. Various levels of parking time are added to the experiment. The levels are 3 min, 6 min and 9 min.

**Distance** The use in other countries showed a varied range of distances for which the e-scooter was used, as this data range was based on different cities throughout Europe. Distance is added to the attribute to asses how this translates to the Netherlands. The distances in the survey are based on the distance provided by these cities mentioned under section 3.2. The distances are set to 500, 1000 and 1500 meters. Per modes selected as alternatives, a mode-specific time for the mentioned distance will be presented to the participants. This time is based on vehicle speed characteristics and rounded to easily comprehensible numbers (e.g. 1 min, 1,5 min, 2 min).

### 4.1.2. Design of the experiment

Optimising the amount of information gathered from a limited number of observations is essential for designing the choice experiment. Therefore, a D-efficient design is created to achieve this goal by ensuring that the parameters of interest can be estimated with the highest precision possible with limited resources. This design allows for fewer choice tasks without sacrificing data quality.

The choice modelling tool Ngene (ChoiceMetrics, 2024) is used to create this D-efficient design, which employs advanced algorithms to optimise experimental designs. For the design of this research, the Fedorov algorithm (Kessels et al., 2004) within Ngene is used to iteratively select combinations of attributes and levels that maximise the determinant of the Fisher information matrix, ensuring the most informative design. Using initial priors for the parameters based on prior knowledge, Ngene optimised the design by minimising the determinant of the variance-covariance matrix, which directly enhances the precision of parameter estimates. This approach allowed for the creation of a highly efficient design, reducing the number of choice tasks while maintaining the robustness and quality of the data collected.

### 4.1.3. Choice sets - Familiarity

For the choice experiment, the choice is made to only present the participants with a choice set consisting of familiar modes. When individuals are limited in choosing between travel modes with which they are familiar. Their choices are more representative of their past travel behaviour. When conducting a choice experiment to introduce a new mode like the e-scooter, offering alternatives that participants are already familiar with is crucial for more realistic data. Ensuring the more realistic data leads to a more accurate and meaningful comparison, as participants can draw on their personal experiences and practical knowledge of the available options. Familiarity allows them to evaluate the advantages and disadvantages of their current modes of transport against e-scooters more effectively, leading to more reliable and relevant data on user preferences and potential adoption barriers for e-scooters. This approach enhances the experiment's validity and provides deeper insights into user behaviour and decision-making processes.
In the choice experiment, participants are always presented with three fixed options: the e-scooter, walking, and opting out. These three options form the base of the experiment. The e-scooter is the research subject, and walking is assumed to be always an option. The opting-out option is always included to prevent people from making trips they would not make in real life. This option will be written in the survey as; "I choose to make this trip differently". The remainder of the choice options within the choice set of the choice experiment are based, as mentioned in the paragraph above, on familiarity. For familiarity, ownership is taken as a sign of familiarity with the mode, reflecting one's travel possibilities when travelling to the train station. The remaining option for the choice set will be created out of the "Active modes" identified in section 3.3 as the most used active modes in the Netherlands (bicycle, e-bike, and Moped scooter). If a participant is familiar with one of these modes, the modes are added to the participant's choice set for the choice experiment.

### 4.1.4. Support question added to the survey

**Vehicle ownership** As mentioned in the subsection above, familiarity is tested based on vehicle ownership. For the vehicle ownership data, the participants were asked which modes they owned. They can choose from a list of the most used vehicles in the Netherlands based on the CBS, 2018 data. To limit confusion, participants can select any vehicle from this selection and are not limited to only the three identified active modes. In addition to the list, a participant can add as many types of vehicles they feel are missing.

**Current travel behaviour** In the later part of subsection 4.1.3, the limitation of not more than five choice options in a choice set is introduced. The situation that six choice options are possible only occurs when a participant owns all three of the modes: bicycle, e-bike and moped scooter. A selection criteria is added based on their currently used mode to choose from these three modes. The presently used mode is added to the choice set. The second mode added to the choice set is based on the overall usage of the modes in the Netherlands. This order is based on most usage per mode as per CBS, 2018. This gives the order of Bicycles, E-bikes, and Moped scooters.

### 4.1.5. Allocation of the choice sets

As mentioned under subsection 4.1.3 is the choice set composition included in the choice experiment based on familiarity and an extra selection based on current use. The flow diagram of the allocation of the possible different choice sets is added in the figure below. Which shows a total of six different choice sets. A bigger version of Figure 4.1 can be found in Appendix B in section B.1. An example of a person who only owns a bicycle will be presented to explain the flow of this diagram further. In the support question on vehicle ownership, this person has entered that they own a bike; no other relevant active modes have been selected. The allocation algorithm starts at the top of the flow diagram. At the first session point, it recognises that the person owns a bicycle and moves along the green line. At the next decision point, the algorithm recognises that the participant did not select an e-bike and moves further along the red line. For the next decision point, the algorithm again sees that this participant does not own the mode in question, the moped scooter and assigns this participant to the "Bike Only" choice set along the red line. For this example, the answer to the question of current preferred use is not used; this is only used when all three of the relevant modes are owned (see the successive green lines).

In addition, one can also view the workings of the diagram in situations where no mode is owned. For this scenario, the choice has been made to include the bicycle within the choice set. This decision is based on the assumption that those people have at least some experience with the bike since they live in the Netherlands. This assumption can not be made for the other modes, hence the allocation to the bike-only choice set. A similar system can be noted with the question about the usual mode of transport. Here, when the answer of current use is neither, the diagram allocates to the e-bike and bike choice set. This is based on the numbers of current use in CBS, 2018 where bicycles and e-bikes are used more often than mopeds. Therefore, the chance of using one of these modes is increased compared to the moped scooter.

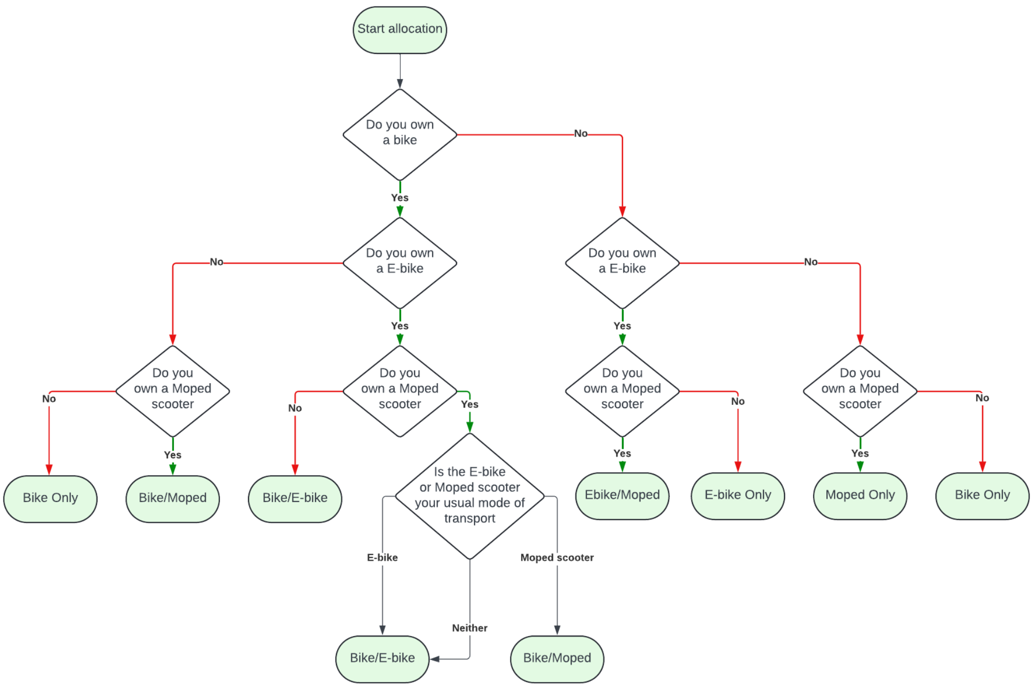



Figure 4.1: Allocation flow of the different choice sets available

### 4.1.6. The layout of the experiment

As described in the subsections above, the choice experiment is built up from six different scenarios balanced with the help of Ngene. Within this subsection, the visual layout of the experiment for these six scenarios is presented for all possible choice sets at once. This means all modes included over all the six possible choice sets are present per choice scenario. However, only the relevant ones will appear to the participants while conducting the survey. For reference, one can advise Appendix C for the scenarios per choice set in Dutch.

A minimalistic design is chosen to visually represent the modes included in the choice sets. This ensures that the modes are presented without bias. With this design choice, every participant can envision the modes in their own way. Modes supported by an electric motor are designed with a lightning bolt representing electric power. The moped scooter is not specified as electric or combustion-powered, so no specific fuel type is connected to this mode. The minimalistic design of the modes is shown in the five figures below.

Figure 4.2: Visual walking

Figure 4.3: Visual bicycle

Figure 4.4: Visual e-scooter

Figure 4.5: Visual e-bike

Figure 4.6: Visual moped-scooter

These five figures, plus a text descriptive option for opting out of the choice, are the inputs to create the six scenarios envisioned via Ngene. All the figures are enriched with information on travel time: the e-scooter with the carry-on cost and non-carry-on modes with parking time. The train's in-vehicle time is incorporated into the question above the choice options.

This results in the following six scenarios. At the start of each scenario, the text description provided within the survey is displayed. Here, the participants are asked to choose and provided with the train's in-vehicle time.

**Scenario 1:** *For this scenario, the distance to the train station is 500 meters, and the train trip lasts 15 minutes. How would you travel towards the train station if you had the following options?*


Figure 4.7: Visual walking sc1

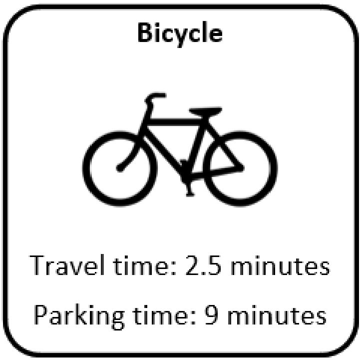



Figure 4.8: Visual bicycle sc1


Figure 4.9: Visual e-scooter sc1


Figure 4.10: Visual e-bike sc1

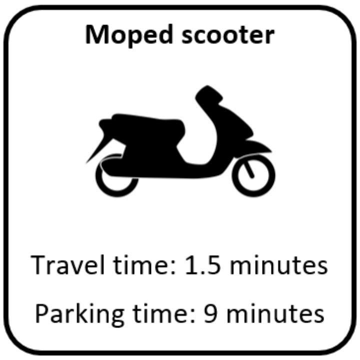



Figure 4.11: Visual moped-scooter sc1


Figure 4.12: Visual Opt-out

**Scenario 2:** *For this scenario, the distance to the train station is 1500 meters, and the train trip lasts 15 minutes. How would you travel towards the train station if you had the following options?*


Figure 4.13: Visual walking sc2


Figure 4.14: Visual bicycle sc2


Figure 4.15: Visual e-scooter sc2


Figure 4.16: Visual e-bike sc2

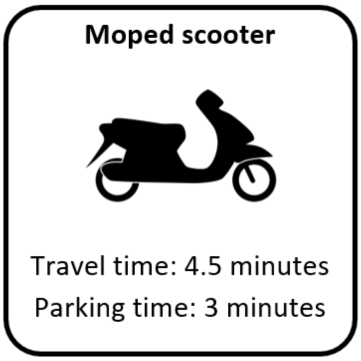



Figure 4.17: Visual moped-scooter sc2


Figure 4.18: Visual Opt-out

**Scenario 3:** *For this scenario, the distance to the train station is 1000 meters, and the train trip lasts 45 minutes. How would you travel towards the train station if you had the following options?*


Figure 4.19: Visual walking sc3


Figure 4.20: Visual bicycle sc3


Figure 4.21: Visual e-scooter sc3


Figure 4.22: Visual e-bike sc3

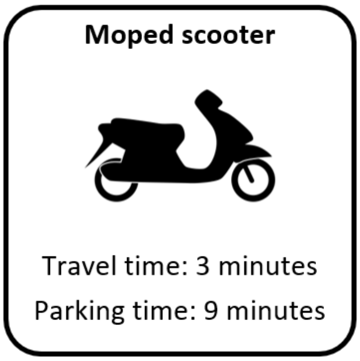



Figure 4.23: Visual moped-scooter sc3


Figure 4.24: Visual Opt-out

**Scenario 4:** *For this scenario, the distance to the train station is 1500 meters, and the train trip lasts 45 minutes. How would you travel towards the train station if you had the following options?*


Figure 4.25: Visual walking sc4

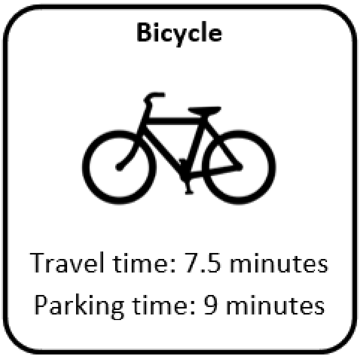



Figure 4.26: Visual bicycle sc4


Figure 4.27: Visual e-scooter sc4


Figure 4.28: Visual e-bike sc4

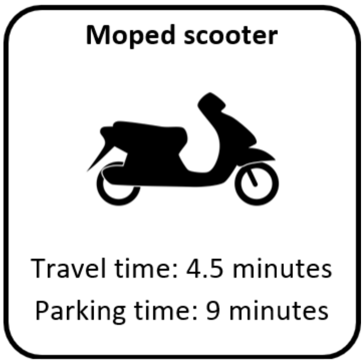



Figure 4.29: Visual moped-scooter sc4


Figure 4.30: Visual Opt-out

**Scenario 5:** *For this scenario, the distance to the train station is 1500 meters, and the train trip lasts 15 minutes. How would you travel towards the train station if you had the following options?*


Figure 4.31: Visual walking sc5


Figure 4.32: Visual bicycle sc5


Figure 4.33: Visual e-scooter sc5


Figure 4.34: Visual e-bike sc5

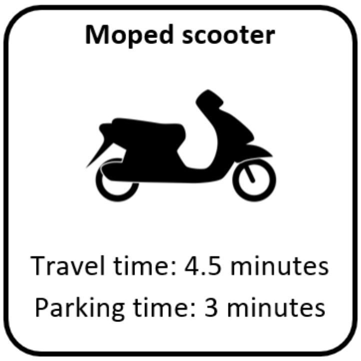



Figure 4.35: Visual moped-scooter sc5


Figure 4.36: Visual Opt-out

**Scenario 6:** *For this scenario, the distance to the train station is 500 meters, and the train trip lasts 45 minutes. How would you travel towards the train station if you had the following options?*


Figure 4.37: Visual walking sc6


Figure 4.38: Visual bicycle sc6


Figure 4.39: Visual e-scooter sc6


Figure 4.40: Visual e-bike sc6

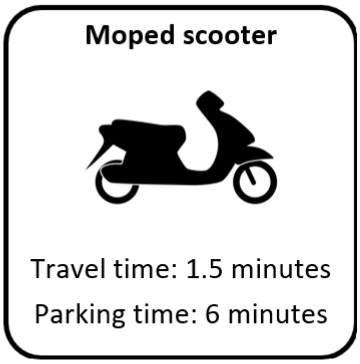



Figure 4.41: Visual moped-scooter sc6


Figure 4.42: Visual Opt-out

## 4.2. Experience with the e-scooter

### 4.2.1. Present experience and knowledge of the e-scooter

The articles selected during the literature study in chapter 3 on e-scooter travel in other countries stated that owners or frequent users of e-scooters were more prone to use e-scooters again. Since e-scooters are not yet legal in the Netherlands, the question of ownership is not as practical in the Netherlands as in the previously mentioned studies. Therefore, this survey uses a distinction in experience based on knowledge and actual driving experience with the e-scooter. This split is created as merely knowing what an e-scooter is and having real driving experience with one represents different levels of familiarity and understanding. Knowing what an e-scooter is refers to a basic knowledge of the device, its functions, and its general role in transportation. In contrast, real driving experience involves firsthand interaction, such as navigating the streets, understanding how the scooter handles, dealing with traffic, and recognising potential safety concerns. This experiential knowledge often leads to a more nuanced perspective on the advantages and limitations of e-scooters. By distinguishing between these two types of familiarity with the e-scooter, a better assessment of choice and attitude towards the e-scooter can be made during the data analysis phase.

The questions on knowledge and experience are added as binary yes or no questions. After these two questions, the survey participants all get a brief explanation of what the e-scooter entails within this experiment. This way, all the participants have the essential information to make an educated decision on the choice of e-scooters in the experiment, even if they stated in the question about knowledge that they do not possess knowledge of e-scooters.

### 4.2.2. Information on the e-scooter in the survey

To ensure every survey participant has at least the minimum knowledge of the e-scooter while participating in the choice experiment. The participants receive a small informative text on the e-scooter and the choice experiment. A picture of the e-scooter is attached for clarity.

The text included in the survey:
*The following six questions will all consist of a choice scenario. In these scenarios, one will be asked to choose a trip toward a train station. In these scenarios, you will choose between your familiar travel modes and the e-scooter as an extra option.*

For clarification, below is the definition of the e-scooter as envisioned in this survey.

- The e-scooter is private property
- The e-scooter is a foldable model, which one can take with them onto the train.

A picture of how such an e-scooter would look is added below as an example.

Figure 4.43: E-scooter model (Kostsov, 123RF.com, n.d.)

## 4.3. Inclusion of socio-demographics

The literature reviewed in chapter 3 frequently notes that e-scooters are primarily targeted toward young adults under 26. Additionally, several studies suggest that males are more likely to use e-scooters compared to females, albeit to a lesser extent. A minor trend is also observed among lower-income groups, although this demographic is often associated with students, given the strong correlation between income and age. To explore whether these patterns are reflected in this research, the survey includes specific questions designed to classify respondents based on socio-demographic characteristics such as age, gender, and income level.

For the socio-demographic information about age. The ages of the participants are grouped into groups of 10 years. This is done in the same way as the age groups used in (CBS, 2018). This entails creating groups starting from 25 and splitting every ten years. For example, 25-34, 35-44, 45-54, etc. The only group which does not follow the format of the ten years is the 18-24 group. Here, age 18 is used as a lower boundary for the age group. Ages lower than 18 are not taken into account for this research. This is in line with the data management rules concerning the data of minors within the research as discussed with the HREC of the TU Delft (TU Delft, 2024).

The gender question in the research gives the participants five options for answering the question. The first two options are the two binary genders, females and males. The third option is non-binary, and the fourth option is ”other”. For this answer, they can add the gender they identify with, but this is not mandatory, as they can leave the text box blank. In addition to the option to specify your gender, participants are also free to refrain from answering the gender question.
Although the question allows participants to enter their preferred gender, these specific gender types will not be used in the research analysis. This is done as previous research like CBS, 2018 or Fearnley et al., 2020 don’t specify past males and females. Comparing these other genders to those researches would not yield any insight since they were not included in these past researches.

The income categories for the income question are divided into three groups: less than €2,000 (low income), €2,000–€4,000 (middle income), and more than €4,000 (high income). This classification is intended to capture the relationship between income levels and e-scooter usage, as suggested by the reference papers.

# 5

# Descriptive statistics

This chapter assesses the collected data from the survey. It is split into three major parts. The first part focuses on data collection itself, including the response rate and duration of the survey. The second part concentrates on the characteristics of the participants. This section will highlight the make-up of the sample and the demographic spread. The third and final section summarises the choice experiment and zooms in subgroups within the sample used for the next chapter's model estimation.

## 5.1. Collection and duration of the survey

The data collection has been conducted effectively for two weeks in December 2023. Within these two weeks, the survey was distributed in English and Dutch within the Netherlands via LinkedIn, internal communication channels of various companies, and closed groups of a differentiating nature to ensure a more diverse sample.

The yield of the data collection is 175 participants. Of these 175, 157 have finished 90 per cent or more of the survey. More than 90 per cent means that they have at least finished both the current travel behaviour part and the choice experiment. Therefore, the data of these 157 participants is valid for use in further assessment. Of the remaining 157, one of the participants is under 18, as there is no specification on whether this participant is below or above 16 years old. Therefore, the data of this specific participant will not be included in further assessment. This action is to comply with European law (Conditions for children's consent to information society services, (Europees Parlement, 2016) ). Resulting in a total of 156 valid participants in the survey to use for data analysis

Of the selected 156, the median time for taking the survey is 299 seconds (4:59 minutes), and the mean is 2036 seconds. Within these calculated times, the participants conducting the experiment and doing something else simultaneously or pausing while filling in the experiment are still included within the mean. To better represent the duration of the experiment, the durations in which the time is twice the expected time calculated via the Qualtrics tool for the survey duration are filtered out. The computed time via the Qualtrics tool is 8 minutes, which results in a cut-off of 16 minutes. The new group without the outliers gives a median time of 291 seconds and a mean of 325 seconds. The histogram in Figure 5.1 shows the duration without the outliers via bins with a size of 50 seconds. The outliers exceeding 16 minutes, nine in total, give no reason to exclude them from the data analysis.

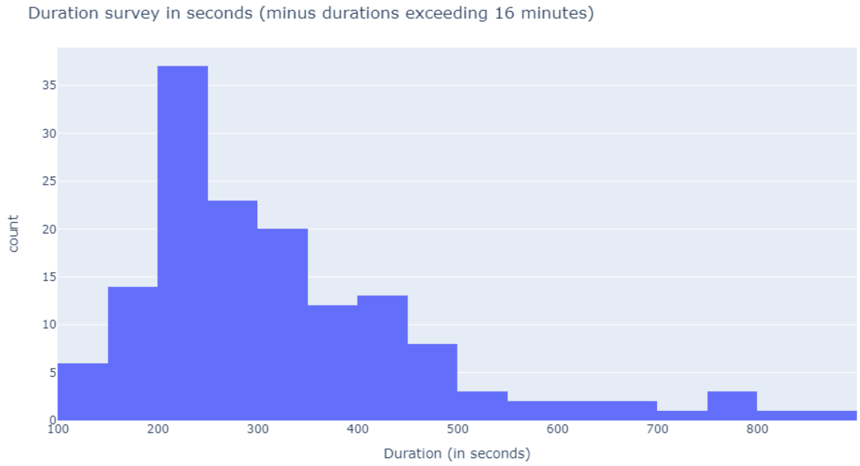



Figure 5.1: Time distribution participants of the survey

## 5.2. Sample decomposition

The analysis of the sample decomposition focuses on gender division. The gender division of the sample reveals a notable disparity between male and female respondents. Out of the total participants, 89 are males, constituting a significant portion of the sample. In comparison, there are 65 females, making up a smaller yet substantial segment of the respondents. This gender distribution highlights a predominance of male participation, which may influence the survey's overall findings. While the sample includes one non-binary individual and one prefers not to say who did not specify their gender, the primary focus remains on the male and female categories due to their more significant representation. Understanding this gender split is crucial for interpreting gender-related patterns and trends within the survey data, ensuring that any gender-based insights are grounded in the demographic reality of the sample. In Figure 5.2, the gender division in the sample is shown. For the Gender division of the participants, the male/female numbers are M, N=89 (57%); F, N=65 (42%). Compared to the sample of the Netherlands (CBS, 2022), where the division in the Netherlands between males and females is around 50/50. With a Chi-square test for homogeneity and one degree of freedom (binary) boundary condition for $\alpha = 0.05$ as defined in Equation 5.1 and 5.2. This results in a chi-square value of 3.72 for this sample of males and females, indicating that the sample is Representative for gender in the Netherlands.

$$\chi^2 = \sum (O/E)^2/E \tag{5.1}$$

$$\chi^2 < 3.84 \tag{5.2}$$

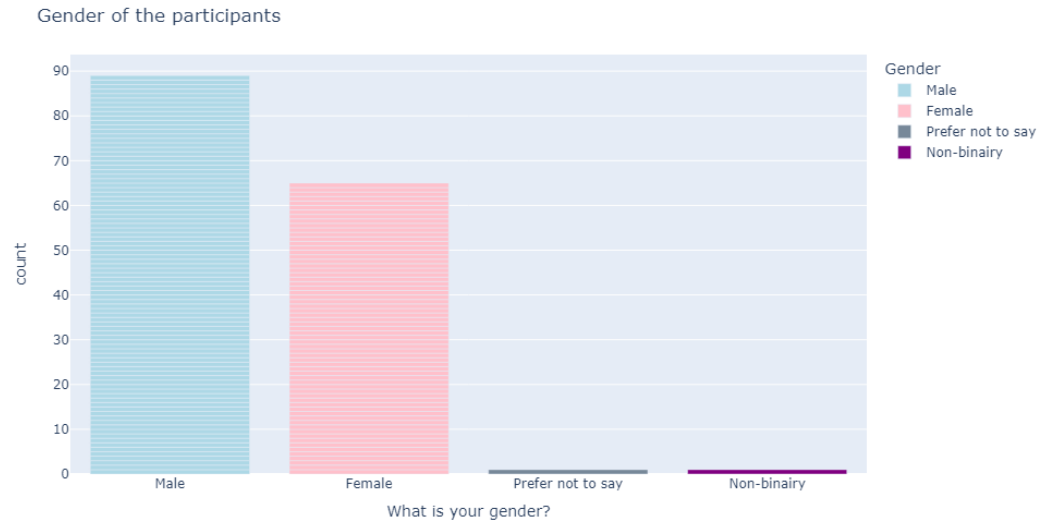



Figure 5.2: Gender of the participants

In Figure 5.3, the absolute numbers in vehicle ownership are shown. As expected in the Netherlands, there is a high percentage of 92.9 % in bicycle ownership. This percentage and the percentages for the other modes are given in Table 5.1. Notable is 1.1% for the males when it comes to e-scooter ownership. Indicating that although the e-scooter is not yet street-legal, a person already owns one.

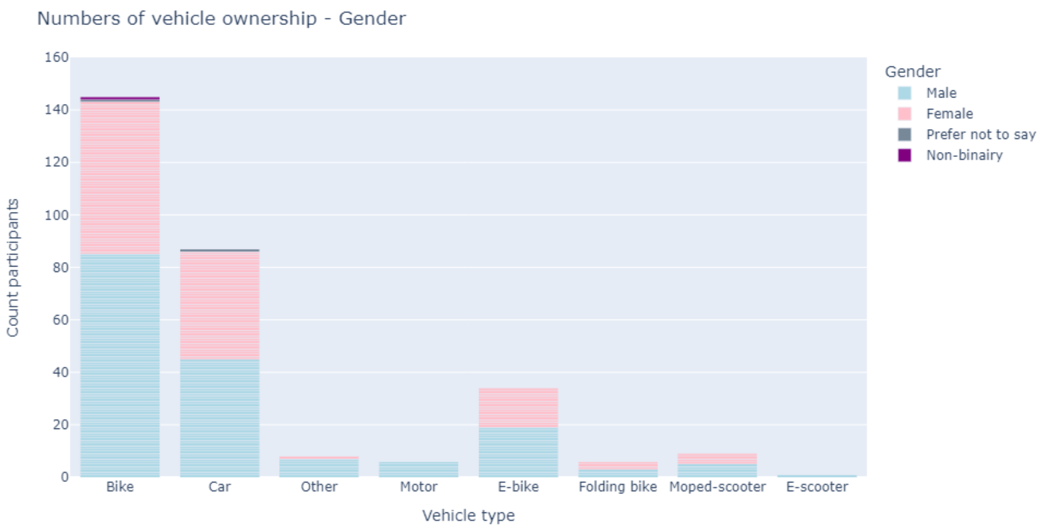



Figure 5.3: Numbers of vehicle ownership per gender

| Mode | Total N=156 | Males N=89 | Females N=65 |
|---|---|---|---|
| Bike | 92.9% | 95.5% | 89.2% |
| Car | 55.8% | 50.6% | 63.1% |
| Motor | 3.2% | 5.6% | 0.0% |
| E-bike | 21.8% | 21.3% | 23.1% |
| Folding bike | 3.8% | 3.4% | 4.6% |
| Moped-scooter | 5.8% | 5.6% | 6.2% |
| E-scooter | 0.6% | 1.1% | 0.0% |

Table 5.1: Vehicle ownership in percentages

## 5.3. The choice experiment

This section provides an in-depth analysis of the choice experiment conducted in the survey, with two primary areas of focus. The first subsection delves into the number of times particular choice sets are presented to participants, segmented by their vehicle ownership. This is followed by exploring the absolute number of choices for modes made across these sets, offering insights into patterns and preferences for the modes included in the experiment. The second subsection shifts focus to the overall scenario structure of the choice experiment. It provides a broader perspective by examining the scenarios one by one over the whole set of choice sets rather than focusing on individual choice sets, thereby allowing a more holistic understanding of the experiment outcome.

### 5.3.1. Statistics on choice set allocation and choices

There were a total of 6 choice sets available for the allocation of the choice experiment. Of these six choice sets, two are never allocated. This concerns the choice sets, ”Moped-scooter Only” and ”E-bike and Moped”. For the four choice sets that were allocated, the division is displayed in Table 5.2

| Choice set | Times allocated | Percentage allocated |
|---|---|---|
| Bike Only | 116 | 74.4% |
| E-bike Only | 8 | 5.1% |
| Bike and E-bike | 24 | 15.4% |
| Bike and Moped | 8 | 5.1% |

Table 5.2: Overview of the allocating of the choice set (Only allocated choice sets included)

Not every alternative is chosen equally for the options in the choice set. In Table 5.3, the options included in the choice sets are displayed with the percentage they are chosen. Here, the distinction is made between selected in total and chosen when available. All six choice scenarios are compressed into one overview in this table. In Appendix D, each choice scenario’s overview of the choice percentage per alternative is displayed separately.

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 936 | 330 | 35.26% | 35.26% |
| Cycling | 888 | 377 | 40.28% | 42.45% |
| E-scooter | 936 | 155 | 16.56% | 16.56% |
| E-bike | 192 | 36 | 3.85% | 18.75% |
| Moped-scooter | 48 | 7 | 0.75% | 14.58% |
| Opt-out | 936 | 31 | 3.31% | 3.31% |

Table 5.3: Choice percentage per alternative of the choice sets

Table 5.3 shows that the percentage chosen when available for the moped scooter and e-bike has around the same levels as e-scooters. Yet e-scooters are more often available. A more in-depth look at the scenarios in Appendix D shows a more significant difference. Where e-scooters and e-bikes always seem to retain a sure user base, the moped scooter has two scenarios where the moped scooter is not chosen. This contrasts with two other scenarios where the moped scooter clears the e-scooter in percentage chosen when available. This effect, where participants seemingly have a different choice pattern compared to people without moped scooters, will be further investigated within the model study in section 6.4

In the upcoming six figures, there will be a visual display of the choices per choice scenario. This gives a quick overview of which modes were popular choices per scenario.

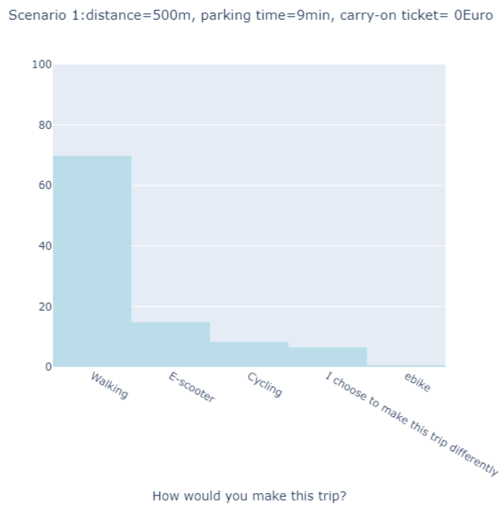



Figure 5.4: Choices for scenario 1

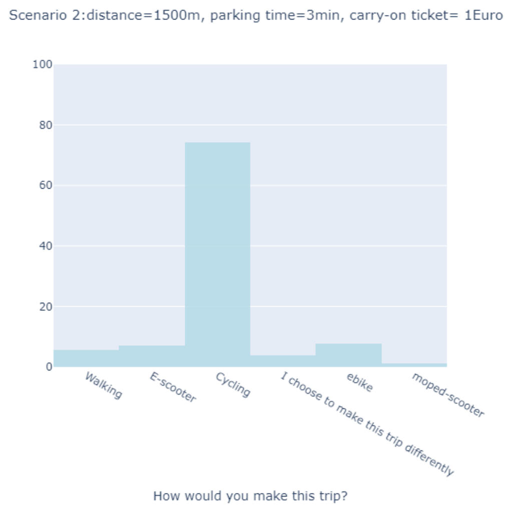



Figure 5.5: Choices for scenario 2

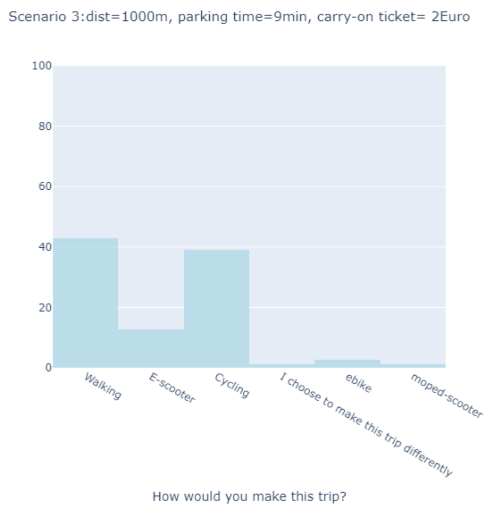



Figure 5.6: Choices for scenario 3

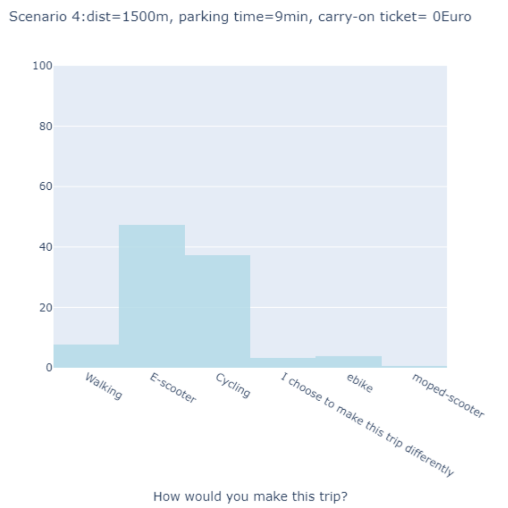



Figure 5.7: Choices for scenario 4

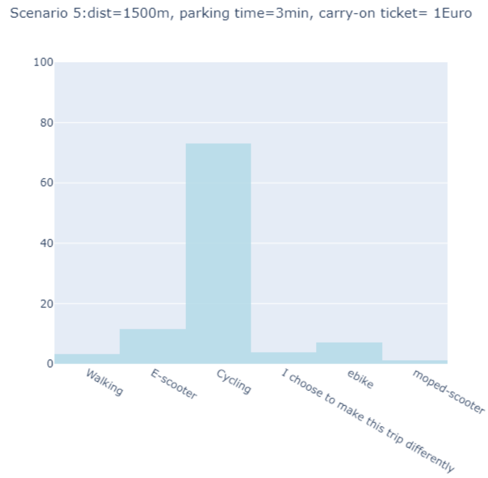



Figure 5.8: Choices for scenario 5

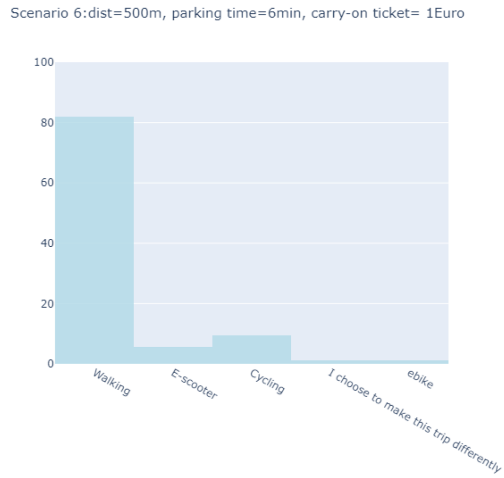



Figure 5.9: Choices for scenario 6

In conclusion, the choice experiment results highlight a clear preference for walking in short-distance scenarios of 500 meters, where walking emerged as the dominant option. However, this preference shifts as the distance increases to 1000 and 1500 meters. For these longer distances, the decision between cycling and using an e-scooter is heavily influenced by the costs of bringing an e-scooter onto the train and the parking time required to park the bicycle at the train station. Notably, the convenience and time saved by bringing the e-scooter on board becomes a critical factor in the decision-making process, underlining the impact of practical trade-offs between cost and time when selecting a mode of transport for the first mile to the train station. This can especially be seen in scenario 4, where the number of e-scooters is high. This goes back down once the cost of the tickets is introduced see scenario 3. The model study will address these emerging links between cost and time-saving in the next chapter.

### 5.3.2. Results and socio-demograhics

The figures included below are demographic groups split plotted over the six scenarios. This displayed the mode choice in the experiment per subgroup. From these figures, a selection will be used in the model to accommodate for socio-demographic influences.

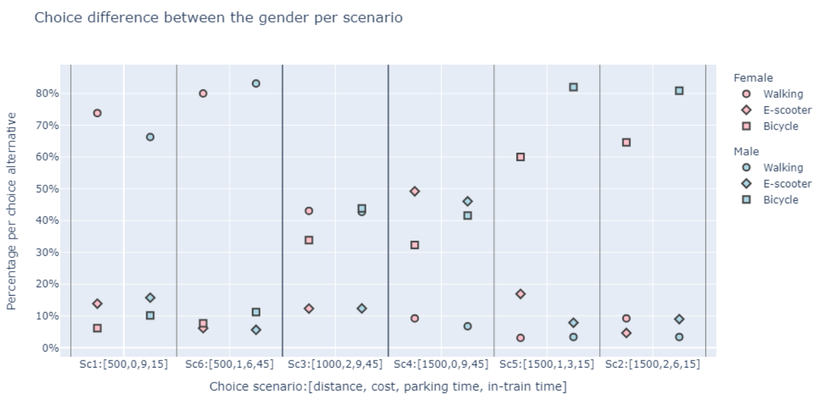



Figure 5.10: Choice behaviour for the subgroup of Gender

What shows for the gender division in Figure 5.10 is that for the long-distance scenarios in the two most right scenarios, cycling is higher for both long-distance scenarios for males compared to females. Therefore will the choices regarding distance made by males for bicycles be further assessed during the model study.

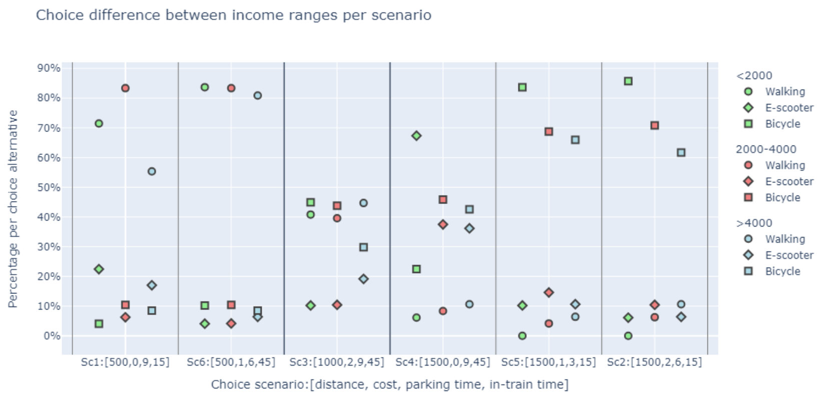



Figure 5.11: Choice behaviour for the subgroup of Income

What shows from Figure 5.11 is the deviation in scenarios 1 and 3. These are both scenarios where the ticket cost is 0. For these scenarios, a higher percentage of low-income participants chose the e-scooter. This behaviour will be further assessed during the model study. In addition to the cost, the overall preference for e-scooters for this subgroup will be tested as this group was marked by the literature study that this group prefers the e-scooter.

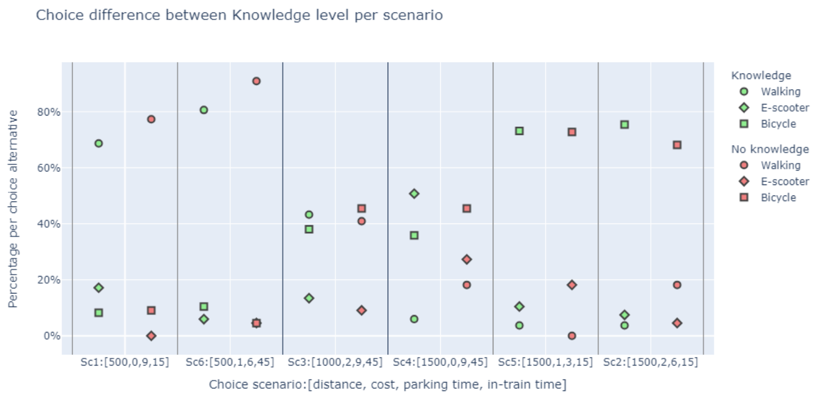



Figure 5.12: Choice behaviour for the subgroup of Knowledge

In Figure 5.12, the behaviour of choice for the e-scooter does not always follow the same expected changes as with another subgroup in different categories. For example, look at the right two scenarios. The cost and parking varies between the two scenarios, but the choice percentage remains relatively equal. For another subgroup, there is a more rational change between these scenarios. Therefore, the model study will test the knowledge level on cost and parking time in the next chapter.

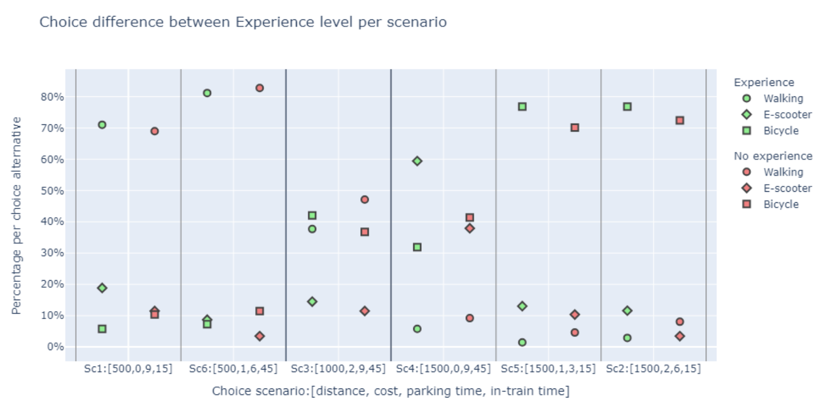



Figure 5.13: Choice behaviour for the subgroup of experience

What is indicated by Figure 5.13 is a higher overall choice for the e-scooter for the group with experience. This difference in choice behaviour will be further assessed in the model study.

From the figures, the following list of influencing subgroups is composed. The list is included in Table 5.4. These influencing factors will be tested in phase two of the model study.

| **Socio-Demographic** | Subgroup | linked attribute |
|---|---|---|
| Gender | Males | Bicycle travel time |
| Income | <2000 | E-scooter |
| Income | <2000 | Cost |
| Age | 56-65 | E-scooter |
| Education | Senior | Bike |
| Knowledge | No Knowledge | Cost |
| Knowledge | No Knowledge | Cost |
| Experience | With Experience | E-scooter |

Table 5.4: Socio-demographic influencing factors

# 6

# Model estimation

This chapter estimates a choice model, utilising a step-by-step approach to incorporate key decision-making factors. The goal is to develop a model that explains and predicts individual choices based on the survey choice data. The first step involves constructing a base model grounded in the choice attributes associated with the choice data. These attributes include the options available to participants, the costs of taking an e-scooter onto the train, the parking and travel time of each mode option, and the in-vehicle train travel time included within the survey design. Next, the model is enhanced by incorporating socio-demographic variables derived from the descriptive statistics conducted in chapter 5. This step adds a more nuanced understanding of how different demographic groups—such as gender, age, income, or education—affect choice behaviour. In the final step, the model is refined by applying conditional logit conditions. These added choice parameters account for whether particular choices were available to the participants at the time of decision and consider the participant's current mode of travel. This addition aims to include the actual choice made by the participant and align with the participant's established preferences. By following this systematic approach, the chapter aims to produce a comprehensive model that accurately reflects the choice behaviour of the participants across various influencing factors, providing a robust and reliable tool for the simulation of chapter 7

## 6.1. Estimation process

As mentioned in the introduction of this chapter, the first step of the model estimation is to create a base model. The type of model used is a Multinomial logit (MNL) model. The choice or MNL is based on the multi-categories of the choice scenarios (e.g. walking, cycling, e-scooter). The process for estimating the MNL is done based on the forward stepwise method. This method will individually test the attributes associated with the choice experiment with a single attribute model. These models are then ranked based on performance. The highest-ranked model will be used to continue the estimation. One by one, the other attributes are added to the best-performing model based on their ranking. When a new attribute is added to the model, it will be assessed whether it performs better than the old model. If this is no longer the case, the old model is the best for the dataset.

The second step for the model estimation is to check whether the participants' socio-demographics significantly influence their choice behaviour. For this step, the identified socio-demographic groups that showed different behaviours according to the analysis of the descriptive statistic chapter are used in the same forward stepwise method as the base model.

The last step of the model estimation includes the conditional influences associated with the participants. For this step, the approach differs from the previous two. All conditional attributes are added to the model simultaneously, and non-relevant attributes are removed one at a time. This step is done for both the vehicle ownership and the current preference. Socio-demographic groups may be deemed relevant in the model before the conditional attributes are added, but they will not be considered as relevant after adding the conditional attribute. The model will be adjusted for these socio-demographics, and the non-relevant socio-demographics will be removed.

## 6.2. Base MNL

### 6.2.1. Setup base model

As mentioned under section 6.1, the first step of creating the base model estimation is using the attributes of the choice scenarios. For the base model, the four attributes from the survey are assessed based on their performance as a single attribute model. For each of these four attributes, a singular model is estimated where only that attribute is added to the most primal model shown in Equation 6.1 and 6.2.

$$U_i = ASC_i \tag{6.1}$$

$$U_{opt-out} = 0 \tag{6.2}$$

| | |
|---|---|
| $Ui$ | Utility for mode i |
| $ASC_i$ | Alternative specific coefficient for mode i |
| $U_{Opt-out}$ | Utility for Opt-out alternative |
| $i$ | Modes:[Walking, Cycling, E-scooter, E-bike, Moped scooter] |

Equation 6.3 till 6.16 show the changed utility function per attribute per mode.

- Travel time

$$U_{Walking} = ASC_{Walking} + \beta_{TravelTime} * TravelTime_{Walking} \tag{6.3}$$

$$U_{Cycling} = ASC_{Cycling} + \beta_{TravelTime} * TravelTime_{Cycling} \tag{6.4}$$

$$U_{E-scooter} = ASC_{E-scooter} + \beta_{TravelTime} * TravelTime_{e-scooter} \tag{6.5}$$

$$U_{E-bike} = ASC_{E-bike} + \beta_{TravelTime} * TravelTime_{e-bike} \tag{6.6}$$

$$U_{Moped} = ASC_{Moped} + \beta_{TravelTime} * TravelTime_{Moped} \tag{6.7}$$

- Parking time

$$U_{Cycling} = ASC_{Cycling} + \beta_{ParkingTime} * ParkingTime \tag{6.8}$$

$$U_{E-bike} = ASC_{E-bike} + \beta_{ParkingTime} * ParkingTime \tag{6.9}$$

$$U_{Moped} = ASC_{Moped} + \beta_{ParkingTime} * ParkingTime \tag{6.10}$$

- Travel cost

$$U_{E-scooter} = ASC_{E-scooter} + \beta_{TravelCost} * TravelCost \tag{6.11}$$

- In-vehicle time train

$$U_{Walking} = ASC_{Walking} + \beta_{InVehicleTT} * InVehicleTT \tag{6.12}$$

$$U_{Cycling} = ASC_{Cycling} + \beta_{InVehicleTT} * InVehicleTT \tag{6.13}$$

$$U_{E-scooter} = ASC_{E-scooter} + \beta_{InVehicleTT} * InVehicleTT \tag{6.14}$$

$$U_{E-bike} = ASC_{E-bike} + \beta_{InVehicleTT} * InVehicleTT \tag{6.15}$$

$$U_{Moped} = ASC_{Moped} + \beta_{InVehicleTT} * InVehicleTT \tag{6.16}$$

Table 6.1: Attributes and levels included in the utility functions

| **Name** | Description | Levels |
|---|---|---|
| $TravelTime_{Walking}$ | Travel time Walking | [6,12,18] |
| $TravelTime_{Cycling}$ | Travel time Cycling | [2.5,5,7.5] |
| $TravelTime_{E-scooter}$ | Travel time e-scooter | [2,4,6] |
| $TravelTime_{E-bike}$ | Travel time e-bike | [2,6,9] |
| $TravelTime_{Moped}$ | Travel time Moped scooter | [1.5,3,4.5] |
| $ParkingTime$ | Parking time | [3,6,9] |
| $TravelCost$ | Cost to take e-scooter onto the train | [0,1,2] |
| $InVehicleTT$ | In vehicles travel time | [15, 30] |

After each model is run, the second step is to rank the attributes as a single attribute model based on performance. This is a process that ensures a thorough evaluation of each attribute. The models are ranked based on their adjusted Rho square values. Rhos square is the most commonly used method to rank choice models. It compares the performance of the single attribute models against a model defined by Equation 6.1 and 6.2, a model with only attribute-specific constants, LL(0). The adjusted Rho squared compensates for the extra parameters added to the single attribute models compared to the LL(0) model. Table 6.2 shows the ranked single attribute models. In the section of Appendix E, the full model estimation of every single attribute model can be found.

Table 6.2: Ranking of the single attribute models

| Rank | Attribute | $\rho^2 equalshares$ |
|---|---|---|
| 1 | Travel time general | 0.3059 |
| 2 | Parking time | 0.2281 |
| 3 | Travel cost | 0.179 |
| 4 | In-vehicle time train | 0.167 |

Third, a forward stepwise strategy is used to create the base model. As described under section 6.1, this method adds the second-best model to the first; this combined model is run and assessed against the previous best model, in this case, the best single attribute model. If the new model is better, it is the new best model. If not, the best single attribute model is the best for the data. If the new model is the best, the third-best single attribute model is added to the new best model. Again, the now new model is tested against the previous best model.

According to the ranking based on the performance of the single attribute models, the attributes are added stepwise to the best-performing model. This is the travel time single attribute model. The stepwise process results in a final base model with a rho square of 0.3545. The utility function in the final model is displayed in Equation 6.17 till 6.21. Not all four choice experiment attributes are present in this utility function. The train's in-vehicle time was added in the last step of the base model. However, it was shown not to be significant, making the base model with only travel time, parking time, and travel cost the best model for data. The model with the in-vehicle time in the train can be found for reference in Appendix E. The results of the best base model are displayed in Table 6.3 and 6.4.

$$U_{Walking} = ASC_{Walking} + \beta_{TravelTime} * TravelTime_{Walking} \tag{6.17}$$

$$U_{Cycling} = ASC_{Cycling} + \beta_{TravelTime} * TravelTime_{Cycling} + \beta_{ParkingTime} * ParkingTime \tag{6.18}$$

$$U_{E-scooter} = ASC_{E-scooter} + \beta_{TravelTime} * TravelTime_{E-scooter} + \beta_{TravelCost} * TravelCost \tag{6.19}$$

$$U_{E-bike} = ASC_{E-bike} + \beta_{TravelTime} * TravelTime_{E-bike} + \beta_{ParkingTime} * ParkingTime \tag{6.20}$$

$$U_{Moped} = ASC_{Moped} + \beta_{TravelTime} * TravelTime_{Moped} + \beta_{ParkingTime} * ParkingTime \tag{6.21}$$

Table 6.3: Ouput final base model - Indicators

| Indicator | Value |
|---|---|
| LL(0), equal shares | -1340.42 |
| LL(C), observed shares | -1120.76 |
| LL (final) | -857.25 |
| Rho-squared, equal shares | 0.3545 |
| Rho-squared, observed shares | 0.2324 |
| AIC | 1730.5 |
| BIC | 1769.24 |

Table 6.4: Ouput final base model - estimates

| Attribute | Estimate | P-value |
|---|---|---|
| $\beta_{TravelCost}$ | -0.7039 | $1.198e-10$ |
| $\beta_{ParkingTime}$ | -0.2215 | 0.000 |
| $\beta_{TravelTime}$ | -0.4420 | 0.000 |
| $ASC_{E-scooter}$ | 4.5397 | 0.000 |
| $ASC_{Bike}$ | 6.8146 | 0.000 |
| $ASC_{Walking}$ | 8.1266 | 0.000 |
| $ASC_{E-bike}$ | 5.3929 | 0.000 |
| $ASC_{Mopedscooter}$ | 4.7703 | $6.009e-10$ |

All attributes in Table 6.4 are as expected. The alternative specific constants are all positive. This indicates that all modes contribute to making trips instead of opting out. The attributes connected to the choice experiment, TravelCost, ParkingTime and TravelTime, negatively impact the choices. This is as expected as these attributes are all connected to resources, time, and money. Further, the values indicate that walking is preferred for short distances. For longer distances, the other modes catch up with the negative travel time Beta as the walking travel time grows steeper than the other modes. Additionally, the effect of cost to the e-scooter is visible with the utils value of -0.7039, penalising the total utility of the e-scooter

## 6.3. Socio-demographics

The socio-demographics asked of the participants in the survey are assessed in subsection 5.3.2. This assessment creates a list of socio-demographics connected to attributes included in the choice experiment. From this list, models are run where the identified socio-demographic groups in this list are added singularly to the base MNL formulated in section 6.2. These models are ranked based on their performance and whether they improve to the base MNL. Based on this ranking, the socio-demographics that enhance the base MNL are added to the base model using the same stepwise process that was used to formulate the base MNL. The added code to the utility function per socio-demographic is listed below in the equations. In these equations, BaseModel represents the string the utility function of the base model used in Equation 6.17 till 6.21.

- Experience

$$U_{E-scooter} = BaseModel_{E-scooter} + \beta_{Experience} * Experience \tag{6.22}$$

- Income (1)

$$U_{E-scooter} = BaseModel_{E-scooter} + \beta_{Income_1} * Income< 2000 \tag{6.23}$$

- Age

$$U_{E-scooter} = BaseModel_{E-scooter} + \beta_{Age} * Age56-65 \tag{6.24}$$

- Gender

$$U_{Bicycle} = BaseModel_{Bicycle} + \beta_{Males} * Gender * TravelTime_{Cycling} \tag{6.25}$$

- Education

$$U_{Bicycle} = BaseModel_{Bicycle} + \beta_{Education} * Education_{Senior} \tag{6.26}$$

- Income (2)

$$U_{E-scooter} = BaseModel_{E-scooter} + \beta_{Income_2} * Income< 2000 * Travelcost \tag{6.27}$$

- Knowledge (1)

$$U_{E-scooter} = BaseModel_{E-scooter} + \beta_{Knowledge_1} * Knowledge * Travelcost \tag{6.28}$$

- Knowledge (2)

$$U_{Bicycle} = BaseModel_{Bicycle} + \beta_{Knowledge_2} * Knowledge * ParkingTime \quad (6.29)$$
$$U_{E-bike} = BaseModel_{E-bike} + \beta_{Knowledge_2} * Knowledge * ParkingTime \quad (6.30)$$
$$U_{Moped} = BaseModel_{Moped} + \beta_{Knowledge_2} * Knowledge * ParkingTime \quad (6.31)$$

Table 6.5: Ranking socio-demographic and attribute combinations

| **Rank** | **Socio-demographic** | **subgroup** | attribute | $\rho^2$ | Improvement compared to base |
|---|---|---|---|---|---|
| 1 | Experience | With experience | E-scooter | 0.3589 | 0.0044 |
| 2 | Income | <2000 | E-scooter | 0.3582 | 0.0037 |
| 3 | Age | 56-65 | E-scooter | 0.3582 | 0.0037 |
| 4 | Gender | Males | Bicycle travel time | 0.3581 | 0.0036 |
| 5 | Education | Senior | Bike | 0.356 | 0.0015 |
| - | Income | <2000 | cost | 0.3541 | No |
| - | Knowledge | No Knowledge | cost | .3538 | No |
| - | Knowledge | No Knowledge | Parking time | .3538 | No |

The first two steps after the base + Experience model are focused on the same attribute: the alternative specific for e-scooters. Both steps improve the model to .3605 but do not reach significant levels for the added socio-demographic Beta (Income or Age group). The remaining two steps, gender and education, improve the model and remain significant. It must be noted that both Gender:males, and Education:Seniors, are going towards the non-significant mark of $\alpha = 0.05$. The final model with socio-demographic is added in Table 6.6 and 6.7. The utility function for this model are displayed in Equation 6.32 till 6.36

$$U_{Walking} = ASC_{Walking} + \beta_{TravelTime} * TravelTime_{Walking} \quad (6.32)$$
$$U_{Cycling} = ASC_{Cycling} + \beta_{TravelTime} * TravelTime_{Cycling} + \beta_{ParkingTime} * ParkingTime + \beta_{Males} * Gender * TravelTime_{Cycling} + \beta_{Education} * Education_{Senior} \quad (6.33)$$
$$U_{E-scooter} = ASC_{E-scooter} + \beta_{TravelTime} * TravelTime_{E-scooter} + \beta_{TravelCost} * TravelCost + \beta_{Experience} * Experience \quad (6.34)$$
$$U_{E-bike} = ASC_{E-bike} + \beta_{TravelTime} * TravelTime_{E-bike} + \beta_{ParkingTime} * ParkingTime \quad (6.35)$$
$$U_{Moped} = ASC_{Moped} + \beta_{TravelTime} * TravelTime_{Moped} + \beta_{ParkingTime} * ParkingTime \quad (6.36)$$

Table 6.6: Ouput final socio-demographic model - indicators

| **Indicator** | **Value** |
|---|---|
| LL(0), equal shares | -1340.42 |
| LL(C), observed shares | -1120.76 |
| LL (final) | -841.66 |
| Rho-squared, equal shares | 0.3639 |
| Rho-squared, observed shares | 0.2437 |
| AIC | 1705.31 |
| BIC | 1758.57 |

Table 6.7: Ouput final socio-demographic model - estimates

| Attribute | Unit | Estimate | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.7348 | $1.198e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.2187 | 0.000 |
| $\beta_{TravelTime}$ | Utils/min | -0.4332 | 0.000 |
| $ASC_{E-scooter}$ | Utils | 4.1518 | 0.000 |
| $ASC_{Bike}$ | Utils | 6.4950 | 0.000 |
| $ASC_{Walking}$ | Utils | 7.9650 | 0.000 |
| $ASC_{E-bike}$ | Utils | 5.3242 | 0.000 |
| $ASC_{Mopedscooter}$ | Utils | 4.5161 | $6.009e-10$ |
| $\beta_{Experience}$ | Utils | 0.7376 | 0.0051 |
| $\beta_{Males}$ | Utils/min | 0.0733 | 0.0228 |
| $\beta_{Education}$ | Utils | -0.7221 | 0.0304 |

The addition of socio-demographics has caused an increase in the Beta for travel costs and a slight decrease in parking time and travel time. The increase in the travel cost can be linked to adding the knowledge attribute since both are only present for the utility function of the e-scooter. In this utility function, the $ASC_{E-scooter}$ has also decreased due to the added $Beta_{Experience}$ now that this group does not influence the average ASC for the e-scooter.
On the contrary, does the new $\beta_{Education}$ not lead to an increase in $ASC_{Bike}$ as $Beta_{Males}$ has a greater pull toward a decrease for $ASC_{Bike}$ as the males attribute is present with more participants than the senior eduction attribute.

## 6.4. Conditional logit (CL)

The third model estimation phase involves integrating a conditional logit model into the pre-existing Multinomial Logit (MNL) model, as previously outlined in the methodology. The decision to employ a conditional logit model is grounded in the set-up of the choice experiment. Specifically, participants received a choice set tailored to their personal vehicle ownership, leading to variations in the choice sets across participants. This model adaptation allows us to determine whether the range of transportation options available to an individual influences their decision to opt for or against an e-scooter.

Another variant of the conditional logit model will also analyse participants' current usage patterns to identify whether certain user groups are more inclined to stick to their old ways or more prone to switch to e-scooter use than others.

### 6.4.1. Ownership

The first model for conditional logit is based on vehicle ownership. Here, the vehicle ownership will be used as a conditional. This means that, for example, the "Bike Only" variant can be combined with the "E-bike Only" and the "Bike & E-bike variant". The conditional terms for this example are displayed in Equation 6.37, 6.38 and 6.39

$$Bike\_only :\_Y_{bike} = 1, Y_{E-bike} = 0 \tag{6.37}$$
$$E - Bike\_only :\_Y_{bike} = 0, Y_{E-bike} = 1 \tag{6.38}$$
$$Bike\_\&\_E - bike :\_Y_{bike} = 1, Y_{E-bike} = 1 \tag{6.39}$$

The following string is added to the base model's existing non-opt-out and non-own utility functions to include these availability conditions in the utility functions. For the mop d scooter, this means that the following utility functions are affected

$$U_{Walking} = BaseModel_{Walking} + \beta AV_{Moped-Scooter} * Y_{Moped\_Scooter} \tag{6.40}$$
$$U_{E-scooter} = BaseModel_{E-scooter} + \beta AV_{Moped-Scooter} * Y_{Moped\_Scooter} \tag{6.41}$$
$$U_{Bicycle} = BaseModel_{Bycicle} + \beta AV_{Moped-Scooter} * Y_{Moped\_Scooter} \tag{6.42}$$
$$U_{E-bike} = BaseModel_{E-bike} + \beta AV_{Moped-Scooter} * Y_{Moped\_Scooter} \tag{6.43}$$

For the analysis, not every mode is considered an availability condition. Walking and the e-scooter are not used since these two modes are 100 % available for all choice scenarios. For the three remaining modes, availability is either 1 or 0. The total availability percentages of the three modes are displayed in Table 6.8

| condition | Percentage available |
|---|---|
| $Y_{bike}$ | 94.9% |
| $Y_{E-bike}$ | 20.5% |
| $Y_{MopedScooter}$ | 5.1% |

Table 6.8: Availibilty percentage different modes from the choice experiment

The model was initially run incorporating all three availability conditions to test the impact of different availability conditions on the utility function, as specified in Equation 6.40. However, this approach resulted in a non-viable model due to an excessively high percentage of bike availability. Consequently, the model was rerun, excluding the $Y_{bike}$ variable, producing viable output. Despite this adjustment, the influence of e-bike availability proved insignificant, leading to the removal of the $Y_{E-bike}$ variable from the utility function. This revision left the utility function comprising $Beta_{AVmopedscooter} * Y_{MopedScooter}$. By including these refined availability conditions in the base Multinomial Logit (MNL) to develop the Conditional Logit (CL) model, the influence of Moped scooter ownership is established for further analysis. Table 6.12 and 6.13 show the indicators and estimation for the base model with $Y_{MopedScooter}$ included.

Table 6.9: Ouput Conditional model - Indicators

| Indicator | Value |
|---|---|
| LL(0), equal shares | -1340.42 |
| LL(C), observed shares | -1120.76 |
| LL (final) | -841.66 |
| Rho-squared, equal shares | 0.3639 |
| Rho-squared, observed shares | 0.2437 |
| AIC | 1705.31 |
| BIC | 1758.57 |

Table 6.10: Ouput conditional User model - estimates

| Attribute | Unit | Estimate | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.703 | $4.112e-11$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.234 | 0 |
| $\beta_{TravelTime}$ | Utils/min | -0.454 | 0 |
| $ASC_{E-scooter}$ | Utils | 4.612 | 0.000 |
| $ASC_{Bike}$ | Utils | 6.520 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.216 | 0.000 |
| $ASC_{E-bike}$ | Utils | 4.308 | $1.609e-09$ |
| $ASC_{Mopedscooter}$ | Utils | 3.054 | $6.874e-10$ |
| $Y_{Mopedscooter}$ | Utils | -2.172 | 2.063e-05 |

What can be established from the negative utility of $Y_{MopedScooter}$ is that the ownership of a moped scooter negatively influences the choice for other modes. In other words, moped scooter owners will likely stick to the moped scooter when they have one available.

### 6.4.2. Current use

Besides the ownership of the active modes, the current use of these modes is also analysed as a condition. To be applicable as a user. The survey participants must have indicated that they would use the mode either as a direct mode to work or as the first mile when the train/metro/tram/bus is the primary mode. This results in the following user percentage in Table 6.11

| condition | Percentage available |
|---|---|
| $Y_{UserBike}$ | 55.8% |
| $Y_{UserWalking}$ | 9.0 % |
| $Y_{UserE-bike}$ | 6.4% |
| $Y_{UserMoped}$ | 1.9% |

Table 6.11: User percentage different from current travel behaviour

The Table indicates a deficient user percentage for the moped scooters. This translates to 3 users out of the 156 participants. This group is too small to be used for further analysis and will, therefore, not be used for the conditional logit model. The other three, bike, walking, and e-bike, will be used as input for the second conditional logit model. Firstly, the current use will be combined with the base model. A user condition is added as a separate factor for the associated alternative. In Equation 6.44, the added string for the example of bike use is displaced.

$$U_{bike} = ... + \beta_{UserBike} * Y_{UserBike} \tag{6.44}$$

Adding the remaining three user conditions to the MNL model. Results in the outputs in Table 6.12 and 6.13. All three added user conditions are significant and yield a positive effect on the utility of a mode. This implies that people who use a specific mode in their regular travel have a higher chance of choosing this mode again.

Table 6.12: Ouput Conditional model - indicators

| Indicator | Value |
|---|---|
| LL(0), equal shares | -1340.42 |
| LL(C), observed shares | -1120.76 |
| LL (final) | -841.66 |
| Rho-squared, equal shares | 0.3639 |
| Rho-squared, observed shares | 0.2437 |
| AIC | 1705.31 |
| BIC | 1758.57 |

Table 6.13: Ouput conditional User model - estimates

| Attribute | Unit | Estimate | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.703 | $4.112e-11$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.234 | 0.000 |
| $\beta_{TravelTime}$ | Utils/min | -0.454 | 0.000 |
| $ASC_{E-scooter}$ | Utils | 4.612 | 0.000 |
| $ASC_{Bike}$ | Utils | 6.520 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.216 | 0.000 |
| $ASC_{E-bike}$ | Utils | 4.308 | $1.609e-09$ |
| $ASC_{Mopedscooter}$ | Utils | 4.729 | $6.874e-10$ |
| $Y_{UseWalking}$ | Utils | 0.781 | 0.006 |
| $Y_{Use-bike}$ | Utils | 0.726 | 0.002 |
| $Y_{UseE-bike}$ | Utils | 2.471 | $1.400e-04$ |

## 6.5. Combining and concluding the model estimation

A combined model was executed in the final analysis stage, incorporating the identified socio-demographic factors and the two conditional logit models. After evaluating each attribute's performance and significance within this combined model, a streamlined version was executed by excluding statistically insignificant attributes. Notably, the 'education' attribute was removed due to its p-value of approximately 0.065, indicating insignificance. The tables below present the final model configuration without the education attribute. For comparison, the model version that includes the now-excluded 'education' attribute can be referenced in Appendix E.

Table 6.14: Ouput of the final model with conditional of Use and the sociodemographics model - Indicators

| Indicator | Value |
|---|---|
| LL(0), equal shares | -1340.42 |
| LL(C), observed shares | -1120.76 |
| LL (final) | -807.11 |
| Rho-squared, equal shares | 0.3874 |
| Rho-squared, observed shares | 0.2718 |
| AIC | 1642.22 |
| BIC | 1710 |

Table 6.15: Ouput of the final model with conditional of Use and the sociodemographics model - estimates

| Attribute | Unit | Estimate | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.733 | $4.112e-11$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.229 | 0.000 |
| $\beta_{TravelTime}$ | Utils/min | -0.447 | 0.000 |
| $ASC_{E-scooter}$ | Utils | 4.443 | 0.000 |
| $ASC_{Bike}$ | Utils | 6.360 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.296 | 0.000 |
| $ASC_{E-bike}$ | Utils | 4.505 | $1.924e-09$ |
| $ASC_{Mopedscooter}$ | Utils | 3.095 | $1.906e-07$ |
| $\beta_{Experience}$ | Utils | 0.757 | 0.005 |
| $\beta_{Males}$ | Utils/min | 0.070 | 0.029 |
| $Y_{Moped}$ | Utils | -2.010 | $4.117e-05$ |
| $Y_{UseWalking}$ | Utils | 0.782 | 0.006 |
| $Y_{Use-bike}$ | Utils | 0.757 | 0.002 |
| $Y_{UseE-bike}$ | Utils | 2.317 | $3.910e-04$ |

To conclude the final model. The estimates can be split into four categories. The first is the alternative specific constants (ASC) for e-scooters, bikes, walking, e-bikes and moped scooters (ranging from 3.095 to 8.296), suggesting a strong baseline preference for these modes compared to not making the trip at all.

The second group consist of the attributes connected to resources. For this model estimation, these are cost and time. All three base time and cost attributes are negative, meaning the more you need to use them for a particular trip, the less favourable this trip becomes. The fourth attribute connected to the resources, the gender-specific Beta for travel time with the bike, is positive. This indicates that it is less of a problem for males to bike further than for females. The third group is a singular attribute, the attribute for experience. The possible value for Beta associated with the experience of an e-scooter shows the higher likelihood of people using one to use it again. This positive attribute also indicates hidden potential for greater e-scooter use once people get familiar with it. Lastly, the conditional influence of past usage. The variables representing the usage of walking, bikes, and e-bikes show significant positive effects (from 0.757 to 2.317). This indicates that prior usage of a transport mode positively influences its future selection, likely due to comfort, habit formation, or satisfaction with previous experiences.

## 6.6. Validation of the model

The 80:20 rule, often called the Pareto Principle, validates the model. 80 % of the data is allocated for training and 20 % for testing. This approach helps ensure that the model is trained on a substantial portion of the data to capture patterns while retaining a smaller portion to evaluate the model's performance. This split balances model learning and validation, preventing overfitting to the training data and allowing for a more reliable assessment of how the model will perform for real-world applications.

The 80:20 rule is performed ten times with random 80:20 data splits. The first two validation estimates are displayed in the Table F.1 and F.2to show how the estimates vary or resemble the estimates of the primary model. The remaining 8 validation models can be found in Appendix F.

Table 6.16: Ouput of the validation models with a random 80 per cent of the data - Validation 1

| Attribute | Unit | estimates of validation 1 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.769 | $4.461e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.217 | $2.343e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.409 | 0.000 |
| $ASC_{E-scooter}$ | Utils | 4.104 | $5.773e-15$ |
| $ASC_{Bike}$ | Utils | 5.758 | 0.000 |
| $ASC_{Walking}$ | Utils | 7.579 | 0.000 |
| $ASC_{E-bike}$ | Utils | 3.735 | $3.347e-06$ |
| $ASC_{Mopedscooter}$ | Utils | 2.857 | $1.500e-06$ |
| $\beta_{Experience}$ | Utils | 0.738 | 0.010 |
| $\beta_{Males}$ | Utils/min | 0.068 | 0.042 |
| $Y_{Moped}$ | Utils | -1.779 | $2.664e-04$ |
| $Y_{UseWalking}$ | Utils | 0.688 | 0.022 |
| $Y_{Use-bike}$ | Utils | 0.790 | 0.003 |
| $Y_{UseE-bike}$ | Utils | 2.930 | $3.84410e-05$ |

Table 6.17: Ouput of the validation models with a random 80 per cent of the data - Validation 2

| Attribute | Unit | estimates of validation 2 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.690 | $4.461e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.236 | $2.343e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.445 | 0.000 |
| $ASC_{E-scooter}$ | Utils | 4.303 | $5.773e-15$ |
| $ASC_{Bike}$ | Utils | 6.257 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.060 | 0.000 |
| $ASC_{E-bike}$ | Utils | 4.765 | $3.347e-06$ |
| $ASC_{Mopedscooter}$ | Utils | 3.294 | $6.444e-08$ |
| $\beta_{Experience}$ | Utils | 0.800 | 0.007 |
| $\beta_{Males}$ | Utils/min | 0.063 | 0.051 |
| $Y_{Moped}$ | Utils | -1.860 | $8.087e-04$ |
| $Y_{UseWalking}$ | Utils | 1.083 | 0.004 |
| $Y_{Use-bike}$ | Utils | 0.732 | 0.008 |
| $Y_{UseE-bike}$ | Utils | 1.980 | 0.002 |

In nine of the ten validation models, all estimated attributes remain consistent with the values observed in the primary model. This indicates stability and robustness across the models, as the key parameters show minimal variation. The alignment of these estimates suggests that the relationships and effects captured in the primary model hold across the validation tests, further confirming the reliability of the initial findings. However, not all nine validation models could estimate a complete set of significant attribute values. As mentioned in the paragraph above, these attributes did show values around the same level as the primary model but did not have a low enough p-value. This can be caused by the smaller sample (80% of the total) used for the validation.

As described, it was one of the ten models unable to estimate attribute values in correspondence with the primary model. This is due to the low number of moped-scooter users in the sample. From the slim selection of the moped-scooter users in this 80%, no users chose the moped scooter in the choice scenarios, causing the model crash on the standard errors of the estimated attributes. This indicates that the model is vulnerable to misinterpreting the behaviour of moped-scooter users. For this specific group, it would be advised to repeat the experiment and increase the number of respondents to increase the change in moped-scooter users with the data, leading to a better-represented model for moped-scooter users. The values of the other estimated attributes align with the validation models that can calculate the standard errors.

To conclude the validation, the estimated validation models show that the primary model represents all modes except the moped scooter. However, the estimates of the moped scooter will be used in the simulation going forward. Not simulating the moped scooter user would result in a greater error than simulating the moped scooter with the estimates of the primary model, as moped scooter users do exist in the data.

The second validation step is the test against the remaining 20 per cent. Only the nine validation models that could estimate standard errors are used here. The key finding from this analysis is that the predicted values generated by the models on the validation sets fall within a 5% margin compared to the predictions for the test sets. This consistency between the two datasets indicates that the model generalises well and is capable of making reliable predictions even when applied to unseen data.

The 5% margin suggests that the model's outputs are stable, implying that overfitting has been effectively managed. If a model were overfitting, we would expect a significant difference between the validation and test predictions, as the model would perform well on the training data but poorly on new, unseen data. However, this close alignment between the validation and test set predictions indicates that the model is not overly tailored to the training data. Instead, it can generalise its learned patterns and relationships to new data points with high accuracy.

This result is crucial for real-world applications, demonstrating the model's robustness. The 5% deviation falls within an acceptable range for many practical uses, such as financial forecasting, medical diagnostics, or demand predictions, where slight variations are often tolerable. It suggests that the predictions made during model validation can be relied upon as a close approximation of how the model will perform in real-world scenarios, offering confidence that its decisions will remain consistent when deployed.

# 7 Simulation

This chapter consists of a simulation based on the estimated parameters of chapter 6. For this simulation, the travel data from ODiN 2018 is converted into the subgroups estimated within the choice models. The sizes of these subgroups represent a percentage of the population. section 7.1 details how this process of combining the subgroups and the model estimates is done. section 7.2 shows how the model estimates affect the choice between modes for different distances in combination with different costs and parking times. section 7.3 uses the simulation and goes into further detail on how this simulation can used in practice.

## 7.1. Matching subgroups

As described in this chapter's introduction, the simulation uses the ODiN 2018 travellers data to simulate a user percentage for e-scooters for train travellers. This means that this simulation only simulates a trip to a train station. The percentage within this simulation only represents trips to the train station. For this simulation setup, the model study's opt-out rate can be discarded as this simulation only focuses on trips made, not trips not made or made differently. This process does not use the entire ODiN 2018 database; instead, it focuses only on the trips associated with train travel and for which the users' age is above 18. Table 7.1 shows the filtration steps to create the sub-sample of ODiN 2018 used for the simulation. Under the header column name, the column name associated with the ODIN database is presented. The condition under the last header depicts the condition to which this column in the ODIN that base is filtered.

| Column name | column desciption | filter |
|---|---|---|
| Hvm | main means of transport | train only |
| Leeftijd | Age | >18 |

Table 7.1: Filters used to create subsample ODiN 2018

The next step in the simulation setup is to create the subgroups identified in chapter 6. Table 7.2 shows the filtration steps for making these subgroups. For the model estimate experience with the e-scooter, no link with the ODiN data can be made. As a result, the simulation will be done twice in section 7.2 for both experienced and inexperienced users.

| Column name | column desciption | filter |
|---|---|---|
| OPID | Unique id of OP | Unique only |
| Geslacht | What is the Gender op OP | Male or not |
| RitNmr | Unique id per trip | Unique only |
| Rvm | What mode is used for a leg | Walking, Bicycle, Moped, E-bike or Other |
| HHEFiets | Does OP own an E-bike/ever use it | Yes or No |
| OpSnor, OpBrom | Does OP own a moped scooter | Yes or No |

Table 7.2: Filters used to create subgroups for the simulation

The filters created 26 subgroups. Of these, 24 are affected by current use, ownership, and gender; the last two groups are only affected by gender. The percentage of the subsample they represent is calculated for all 26 subgroups. The simulation uses this percentage to estimate the influence of every subgroup on the total. The 26 subgroups and their respective percentage are displayed in Appendix G. The last step for the simulation setup is calculating the user percentage per subgroup. This step takes the model estimated in Chapter 7. It calculates a user percentage for every mode within the model based on the utility of the relevant attributes for the subgroups. Combined with the percentage the subgroups represent, this forms the user percentage for the entire subsample. In Equation 7.1, an example of the mode e-scooter is displayed. The equation calculates the user percentage over all the subgroups. The user percentage is calculated using the same principle for the other modes.

$$UPE = \sum_{i=1}^{26} (UPE_i * SGP_i) \tag{7.1}$$

| | |
|---|---|
| $UPE$ | User percentage E-scooter |
| $UPE_i$ | User percentage E-scooter for subgroup i |
| $SGP_i$ | percentage subgroup i of the subsample |

## 7.2. The simulation

The simulation has three different stages. The first stage creates a base simulation. The base means that the cost of taking an e-scooter is zero, and the parking time is a minimum value of 3 minutes. The second stage shows the effect of varying the identified influencers' cost and parking time on the choice of the e-scooter. The third and final stage takes the extreme e-scooter use or disuse of stage 2 and simulates the other modes around the e-scooter use.

### 7.2.1. Base simulation

The base simulation takes the model estimates with a cost attribute of zero and a parking time attribute of 3 minutes, the lowest available in the experiment. The model estimates and attributes simulate the user percentage for all the identified subgroups and their percentual presence in ODiN 2018. The subgroups and their percentual presence combined give an overall user percentage for the used sub-sample from ODiN. As mentioned under section 7.1, the user percentage is only for the groups that use the train—resulting in a situation where people who don't take the train are not included in the percentages and are out of the scope of this simulation. Figure 7.1 and 7.2 show the percentages for the three most chosen modes, walking, cycling, and e-scooter, ranging between 0.5 to 2.5 kilometres. The two figures differ in terms of experience level with the e-scooter. The split complies with the non-existing information about the e-scooter experience in the Netherlands. The difference between the figures indicates the difference in choice behaviour between people with and without experience with the e-scooter.

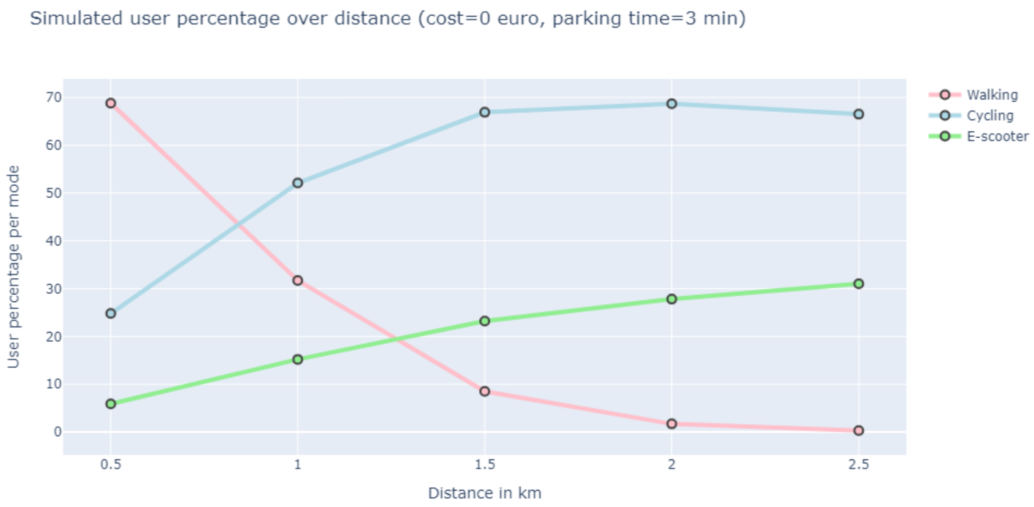



Figure 7.1: Base simulation without e-scooter experience for walking, cycling and e-scooters


Figure 7.2: Base simulation with e-scooter experience for walking, cycling and e-scooters

The difference between the two figures shows an overall higher mode share in e-scooters and a steep growth in user percentage for the experienced group compared to their non-experienced counterparts. For the lower distances, this is at the expense of walking and for the longer distances, this is at the expense of cycling. The contrast in the closeness of the lines of e-scooter and cycling clearly shows the effect of experience. For the inexperienced simulation, the line of cycling is roughly 30 per cent higher than the line of the e-scooter. For the experienced simulation, the lines are closer and almost intersect at the 2.5 km point. Figure 7.3 further shows the e-scooter user percentage contrast for experience, plotting both lines within the same graph.

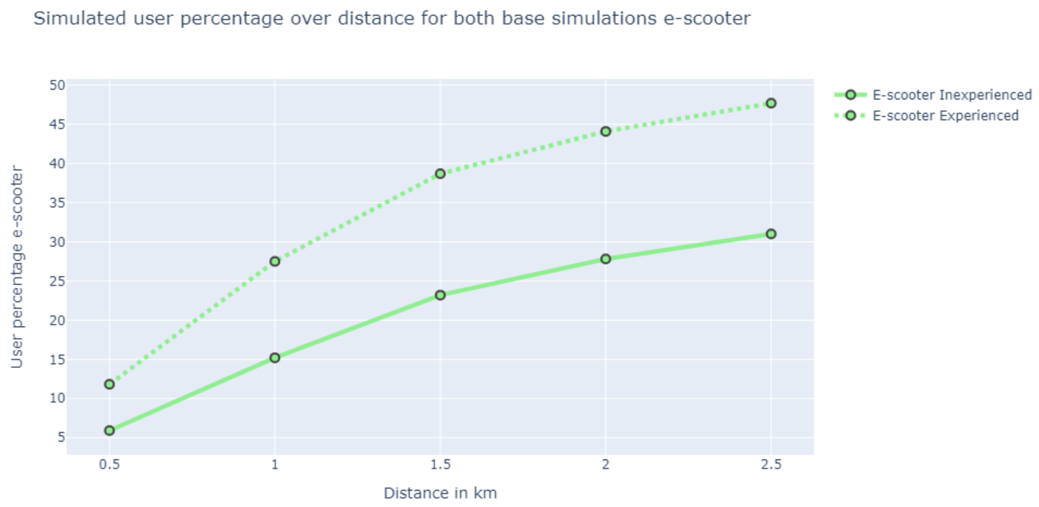



Figure 7.3: Base mode share simulation for both inexperienced and experienced

The two lines in Figure 7.3 show the e-scooter user percentage for the two groups. The experienced group ends up at the 2.5 km mark with a rate of 45 per cent. This is high for a new mode not yet introduced in the Netherlands. Especially when compared to the bicycle rate at 2.5 in Figure 7.2 when it is almost at par, it is expected that a bias in the research has caused this high percentage. More on bias within this study can be found within the discussion in section 8.2.

### 7.2.2. E-scooter variation

To better understand the potential mode share of the e-scooter, the base simulation will be repeated with alterations. The new simulations are variations on the base simulation with different cost and parking time values. Figure 7.4 and 7.5 show the effects of these alterations for both experienced and inexperienced. The highest mode share of the e-scooter per simulation for inexperienced (at the 2.5 km mark) varies between 18.3 and 61.5 per cent. For experienced, this varies between 31.5 and 76.5 per cent. It must be noted here that the higher parking time does not affect the modes of walking and taking the e-scooter, as for both of these modes, parking is irrelevant, either by not including a vehicle or being a carry-on vehicle. The added parking time for these modes has a positive effect in the form of time saved by not having to park. Hence, the increase in e-scooter use corresponds with the rise in parking time.

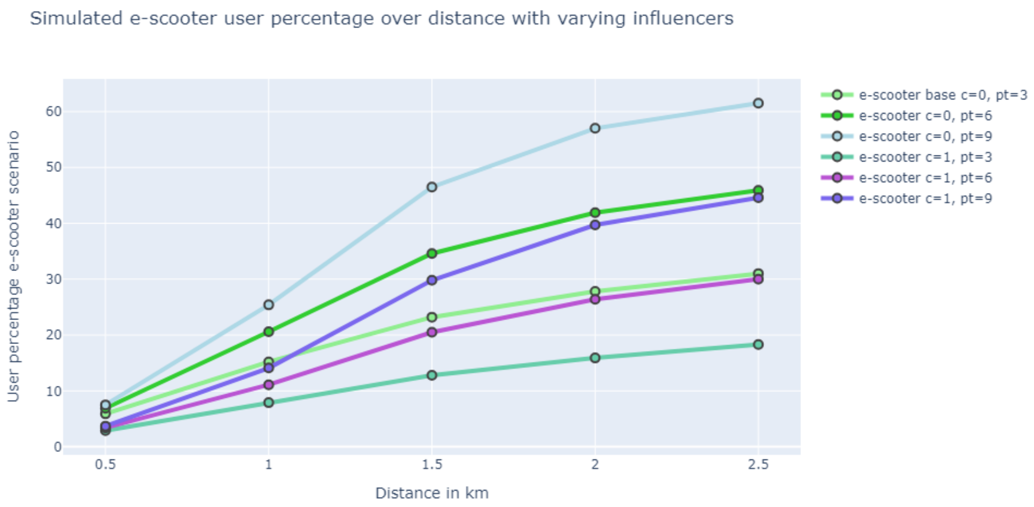



Figure 7.4: E-scooter variation inexperienced

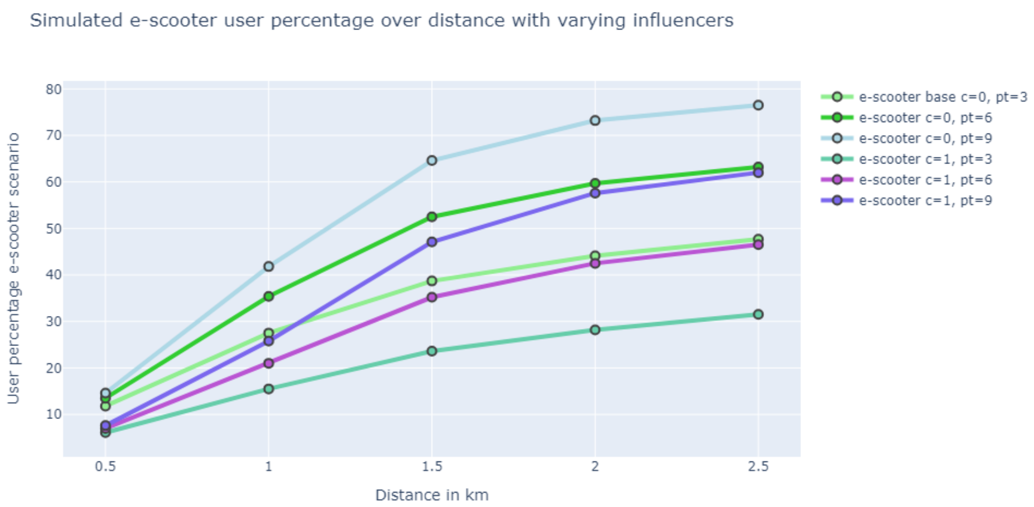



Figure 7.5: E-scooter variations experienced

As mentioned at the end of the previous section, the negative correlation of the cost factor decreases the number of times the e-scooter is used. As mentioned in the paragraph above, the saved parking time increases the use of e-scooters, resulting in the ideal scenario where there is a lot of parking time saved and no cost for carrying the e-scooter onboard the train. And the non-ideal scenario for high cost and low number of parking time-saving.

### 7.2.3. Extreme scenario's

As a result of the simulation of the e-scooter choice percentage in subsection 7.2.2, two scenarios from the plotted lines in Figure 7.4 and 7.5 stand out as extreme scenarios. These two scenarios briefly mentioned at the end of subsection 7.2.2 are the one where the cost is zero and the parking time is 9 minutes (parking relatively far away from the platforms) and the one with the highest price for carry-on and easily accessible parking distance (3 minutes). Figure 7.6 and 7.7 display both scenarios with the associated modes of walking and cycling for the participant's group with no experience with the e-scooter.

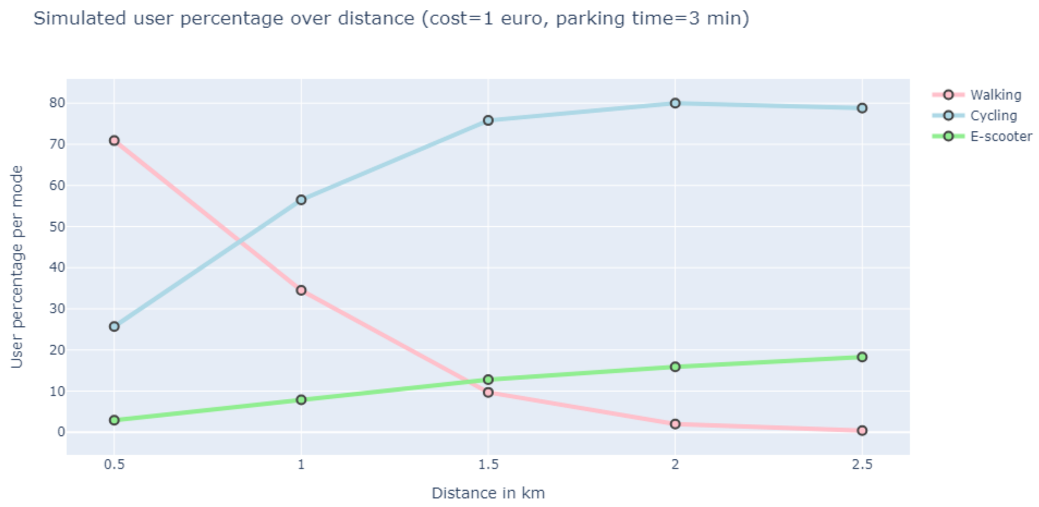



Figure 7.6: Extreme "Low" scenario for participants with no experience

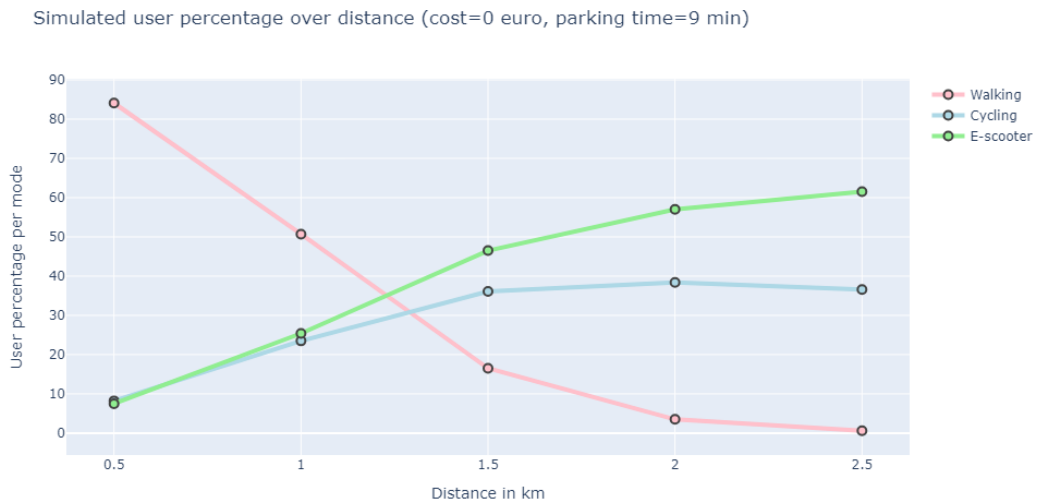



Figure 7.7: Extreme "High" scenario for participants with no experience

The two figures illustrate how user preferences for walking, cycling, and e-scooter use change over varying distances, based on the choice model estimates combined with the representative sample of Dutch train travellers. The simulation compares an "Extreme Low" scenario, with a cost of 1 euro and a parking time of 3 minutes, to an "Extreme High" scenario, where no fee is involved, and parking time is extended to 9 minutes. Across both scenarios, distance plays a crucial role in shaping transportation choices. Walking is preferred at shorter distances (around 0.5 km) but quickly loses favour as distances increase, with users turning to other modes. In the "Extreme Low" scenario, cycling rapidly becomes the dominant choice beyond short distances, while e-scooters see a moderate increase in use. However, in the "Extreme High" scenario, where e-scooters are free and don't have the adverse effects of longer parking times, they become significantly more attractive, particularly for distances beyond 1.5 km, surpassing both walking and cycling.

Overall, the simulation highlights that user preferences are highly sensitive to economic factors like cost and the convenience of not having to park. While cycling consistently remains a viable option across distances, its appeal diminishes when the cost barrier for e-scooters is removed. In contrast, e-scooters, which become more appealing when their use is economically advantageous, dominate the longer-distance choices in the ”Extreme High” scenario. These results underscore how variations in pricing and convenience can shift user behaviour, with e-scooters emerging as an exceptionally competitive option when such factors are favourable.

## 7.3. Use in practice

Privately owned e-scooters can be a crucial mobility tool in city areas poorly served by traditional public transportation systems. These areas often suffer from ”last mile” connectivity issues, where the distance between public transport stops and a resident’s home or destination is too far to walk comfortably. E-scooters can bridge this gap, providing a quick and convenient means to complete such journeys.

The simulated data shows that the participants of this research intend to use e-scooters in situations like that. Although this data has a high overprediction, it does show potential.

# 8 Conclusion and Discussion

## 8.1. Conclusion

The findings of this research indicate promising potential for the adoption and integration of e-scooters in the Netherlands. In the remainder of this chapter, the research questions will be addressed one by one and explained how this promising potential is built up.

The **first** sub-question aimed at the spatial and technical conditions for introducing the e-scooter in the Netherlands. It shows mixed results in terms of promising integration. On the technical side, a good framework now allows for controlled admission of e-scooters onto the public roads. However, for the spatial conditions in trains, integrating e-scooters into train travel in the Netherlands requires clearer and more tailored regulations to ensure a smooth transition. The current NS guidelines classify e-scooters as luggage. Still, their larger dimensions often create uncertainty for users, who may be denied access if their devices exceed the size limits for hand luggage. This ambiguity hinders the seamless adoption of e-scooters as part of multimodal travel. Looking at European policies, it becomes evident that there is no single solution for incorporating e-scooters into train systems. Other countries have adopted varying approaches shaped by local needs and constraints. For instance, Austria allows folded e-scooters as hand luggage without extra charges, while in Denmark, a bicycle ticket is required, and Germany's rules vary by region. These diverse strategies highlight that a one-size-fits-all solution does not exist, making it essential for the Netherlands to develop its tailored approach. Updating the NS's three-category system to include e-scooters or creating a new category could provide the clarity and flexibility needed to support their use in train travel. By doing so, the Netherlands can establish a framework that aligns with its unique needs rather than attempting to adopt the varied policies seen across Europe directly.

The **second** sub-question focussing on the use of e-scooter in other countries gives insight into how the e-scooter can function in the Netherlands. Firstly, the socio-demographic profile of e-scooter users is a crucial factor. Studies from Vienna, Germany, and Austin, TX, consistently indicate that young to middle-aged males, often with higher education levels, are likelier to adopt e-scooters. Moreover, familiarity with the e-scooter mode, such as through ownership, increases the likelihood of using shared e-scooters. Understanding these demographic trends will help target e-scooter initiatives in the Netherlands effectively, ensuring they cater to likely user groups.

Secondly, the data on trip characteristics provides crucial benchmarks for planning. A comprehensive analysis of 40 European cities reveals that the median e-scooter trip distances range between 0.91 km and 1.79 km, with trip durations spanning from 5.67 minutes to 13.77 minutes. Further research from Oostendorp and Hardinghaus, 2023 supports these findings, indicating a median trip duration of around 8 minutes for shared e-scooters and up to 18 minutes for private ones. These insights can guide infrastructure development, such as dedicated e-scooter lanes and parking areas tailored to typical trip lengths and durations.

Additionally, the interaction between e-scooters and public transport is a critical consideration. According to Oostendorp and Hardinghaus, 2023, 23.6% of shared e-scooter users utilise them as a feeder mode to public transport, while this figure drops to 14.5% for private e-scooters. Notably, around

60% of private e-scooter users reported reduced use of public transport since acquiring an e-scooter. This pattern of e-scooters both complementing and competing with public transport is further highlighted by Aarhaug et al., 2023, where 20% of e-scooter trips were linked to public transport, yet 35.9% of users stated they would have used public transport if e-scooters were not available. These findings emphasise the need to balance fostering multimodal connectivity and mitigating potential competition with public transport services.

By leveraging these insights, the Netherlands can create a well-informed approach to introducing e-scooters, ensuring they contribute positively to urban mobility while minimising challenges. The combination of targeted user engagement, infrastructure planning, and balanced integration with public transport will be crucial for successfully adopting e-scooters in the Dutch urban landscape.

The **third** sub-question regarding the current state of first-mile travel. It concludes that understanding the existing first- and last-mile travel behaviours in the Netherlands is crucial before introducing new mobility solutions. Insights into current modes of transportation, user preferences, and commuter challenges help identify opportunities where these new solutions could add the most value, such as addressing long walking distances to transit hubs. Studies indicate a strong reliance on active modes like walking and cycling, comprising 70% of these trips, while smaller percentages use options like e-bikes and mopeds. Although these traditional modes dominate, younger users are interested in innovative transportation options. Integrating empirical travel data further supports a deeper understanding of commuter habits and potential gaps that emerging transport options, such as e-scooters once they are legally introduced, could fill. Given the Netherlands' robust cycling culture, the environment appears conducive to adopting new solutions that could complement the existing transport landscape, provided they align with current travel preferences and infrastructure.

The **Fourth** sub-question related to the survey and the model study investigated this potential by executing and analysing the stated choice experiment. Initially, within the descriptive statistics of this research, it was observed that several key socio-demographic factors mentioned for sub-question two were not reflected in the survey data. Factors such as education, age, and gender influenced choice within the experiment, although their effects were not directly related to e-scooter usage but more towards other modes within the experiment. However, the participants' previous experience with e-scooters did stand out. This finding aligns with the literature, which showed that individuals who have used e-scooters or have one are more likely to continue using them. However, not all of these socio-demographics did emerge as prominent characteristics in this dataset. The notable exception was the low-income group, which initially appeared to be significant in the descriptive statistics data analysis but was later found to be insignificant during model estimation. This suggests that, although broader socio-demographic trends might be present in this dataset, they were not significant enough with the current sample to be confirmed within the model study. A larger sample than used in this research might lead to significant values for these trends in future research.

A choice model was estimated to better understand the survey data. The final model reveals a cohesive story about travel behaviour and preferences, categorised into four key insights that shape people's choices.

First, the model highlights a baseline preference for certain modes of transport through the alternative specific constants (ASC) for e-scooters, bikes, walking, e-bikes, and moped scooters, with values ranging from 3.095 to 8.296. These values suggest that people are generally more inclined to choose these options over not travelling, underscoring their attractiveness and role in meeting mobility needs.

Next, the influence of resource-related factors—cost and time—emerges as a crucial consideration in travel decisions. As expected, higher time and price make a trip less desirable, reflecting the natural tendency to avoid longer or more expensive journeys. However, the model also reveals a gender-specific nuance: the positive effect of travel time for biking among males suggests that they are less deterred by longer biking distances than females, indicating variations in how time is perceived across different groups.

Experience with a transport mode is another influential factor, as seen in the positive effect of having used an e-scooter before. Those who previously used an e-scooter are likelier to choose it again, suggesting familiarity breeds comfort and confidence. This finding hints at the potential for increased e-scooter adoption as more people become accustomed to this mode of transport.

Lastly, the role of past behaviour in shaping future choices ties the model's story together. The significant positive impact of previous usage of walking, biking, and e-biking (with effects ranging from 0.757 to 2.317) shows that once a mode becomes part of a person's routine, it tends to remain a preferred choice. This likely stems from comfort, habit formation, and satisfaction with past experiences.

Together, these insights weave a narrative of how people choose their travel modes, balancing inherent preferences, practical considerations like cost and time, the impact of prior experiences, and the habits they form over time. This understanding provides a valuable foundation for developing transportation strategies that align with travellers' needs and behaviours.

The **fifth** and **final** sub-question on how the estimated attributes translate to the Dutch train travelling population. The simulation that supports this question shows that people are willing to use the e-scooter. For both the experienced and inexperienced group, the e-scooter outperformed the e-bike and the scooter. For the group with experience, the e-scooters even outperformed the bicycle in extreme scenarios. However, these results must be taken with a grain of salt. During the experiment, everyone had access to the e-scooter. This is not the case in real life, as people still need to buy the e-scooter. Reflecting on the impact of monetary values on the choice of participants, it begs whether these people are willing to buy an e-scooter when seeing how the ticket price for carrying an e-scooter onto the train already influences their choice for choosing the e-scooter. However, the number of times the e-scooter was chosen can not be disregarded based on the influence of ticket pricing alone. Even in the least favourable scenario, the "low scenario for the inexperienced group", the choice for the e-scooter is simulated between 1̃0 to 20 per cent for the distance range between 1 to 2.5 km. For the 0.5 distance, this is less due to the walking dominance at this distance. This shows that if people possess an e-scooter, they are willing to use the e-scooter even if the conditions are not optimal (Including ticket price). For the scenarios where the price is not included, the "High scenario" for both experience level groups, the e-scooter reaches even higher and outperforms the bicycle. Although this is based on stated preference and assumed ownership of the e-scooter, this outcome indicates a hidden demand for introducing e-scooters with enough base to develop and plan for their arrival in the Netherlands.

## 8.2. Discussion

The discussion examines the research findings and limitations on adding private e-scooters to the multimodal chain. It delves into the implications of sporadic e-scooter exposure among participants, which may inflate expectations of their utility in daily commuting. Challenges in data alignment highlight the difficulty of replicating real-world conditions in simulations, mainly when key details are absent. Critical assumptions regarding universal access to e-scooters are examined for their potential to skew perceptions of market readiness.

Further analysis reveals the importance of larger sample sizes to ensure diverse subgroup representation and capture subtle behavioural trends. Additionally, the study addresses potential misconceptions arising from the experimental design, particularly among older participants, which could affect the validity of the findings. And finally, how external regulatory changes and methodological decisions impact the interpretation and applicability of the research.

**Understanding Experience: The Challenge of Unrealistic Projections** The research reveals a notable disparity in simulation outcomes, with a 20% difference between participants familiar with e-scooters and those not. Crucially, much of this familiarity derives from occasional use, typically during vacations or infrequent instances in the Netherlands, where regular street use of e-scooters remains illegal. This sporadic exposure paints an incomplete picture of daily e-scooter usage, potentially skewing the data towards an overly optimistic view of user satisfaction. This unrealistic basis for comparison may lead to over-predictions about how e-scooters would perform in everyday settings, emphasising the need for a more grounded and cautious interpretation of the simulation results to avoid misleading conclusions about their practicality and user satisfaction in regular use scenarios.

**Simulation Details: Subgroup Formation** During the simulation, subgroups were meticulously formed from the ODiN data to align with the model estimates derived from choice modelling. However, achieving a perfect match with the model estimates was impossible. For instance, the ODiN data lacked specific details such as individual bicycle or e-bike ownership; it only provided information on household ownership and the frequency of e-bike usage. Targeted assumptions and tailored solutions were employed to address these gaps and facilitate an effective match between the real-world data and the model's parameters. This approach ensured that the simulation remained as accurate and representative as possible despite the data limitations. However, this still creates a possibility for a mismatch and an under or over-estimation of specific mode shares depending on which direction the mismatch goes.

**Assumed Ownership and Economic Factors:** The study assumed that all participants had ready access to an e-scooter, effectively bypassing real-world considerations such as the economic feasibility and personal desire to own an e-scooter. This foundational assumption fails to address critical barriers. Notably, the cost of acquiring an e-scooter and the individual's financial capacity and motivation to purchase it once e-scooters become legally available. Given these oversights, the data collected could paint an overly optimistic picture of e-scooter adoption and usage. Therefore, the responses may not accurately represent genuine consumer behaviour but an idealised vision where e-scooters are universally accessible and desirable. This disconnect could skew policymakers' and manufacturers' understanding of the market, potentially leading to strategies and production levels that do not align with actual consumer demand and economic realities.

**Sample Size Considerations** When evaluating socio-demographic subgroups within the dataset, it is evident that not all groups are represented equally or with sufficient numbers to draw reliable conclusions about their behaviours. An increase in the sample size is necessary to assess the various subgroups comprehensively. A larger sample size would ensure that more subgroups achieve statistical significance, thereby enhancing the ability to capture and measure behaviours that current models may fail to detect. This improvement in sample representation can lead to more robust and generalisable findings.

**Misunderstanding: the first choice scenario.** The data reveals instances of potential misunderstanding among the older age group during a choice experiment. This group chose to opt out in the first scenario rather than in the sixth, despite the sixth being objectively less favourable. The attributes in scenario 6, which negatively influence the choice of modes, were more pronounced than in scenario 1. Given that scenario one is the initial scenario presented and completed by participants, the high opt-out rate likely stemmed from a lack of clarity about the experiment's requirements rather than a deliberate choice. This inconsistency between the scenarios suggests a misunderstanding rather than an actual preference. This issue, if not addressed, could significantly impact the reliability and validity of our research findings. To mitigate such problems in future studies, it could be beneficial to introduce a preliminary 'training' scenario.

**Variability in Distances and Its Impact on Study Validity** In this study, the distances between participants' homes and the train station were varied, with set intervals of 500, 1000, and 1500 meters. This design choice, while helpful in understanding the impact of distance on travel preferences, introduces a significant variable that may not align with the participants' real-world experiences. Typically, commuters travel a fixed distance to their nearest station daily, establishing a consistent reference frame for evaluating travel choices. The introduction of variable distances in the study has its potential pitfalls. It could skew the responses. Participants might react differently to hypothetical scenarios than in commuting situations, leading to answers that do not accurately reflect their preferences or behaviours. This discrepancy can exceptionally affect the validity of the study's conclusions, as the data might reflect the participants' adaptability to change rather than their established commuting preferences.

**External Influences on Research Assumptions** This research methodology assumes that an e-scooter can be transported on a train like a folding bike. However, this premise is challenged by recent announcements from the NS, which indicate a policy shift towards prohibiting the transport of vehicles that do not conform to bike, e-bike, or folding bike categories. Defining transport rules without considering the actual dimensions and storage capabilities of e-scooters could lead to flawed policies. Unlike traditional bikes, e-scooters are compact enough to easily store under a train seat, occupying less space than a standard bicycle. Therefore, policy decisions should be informed by the practical aspects of e-scooter storage and usage rather than strict categorisations that may not reflect their functional benefits. This approach would ensure that transportation policies are adaptable, inclusive and grounded in the realities of modern commuting needs.

**Bias for the subject of the research** The subject of a research study can significantly influence the outcomes observed, particularly regarding participant responses. When examining e-scooter use in research, various factors can contribute to a higher expected percentage of e-scooter usage among participants. Three aspects of this phenomenon have been identified.

- Selection bias:
  Research focusing on e-scooter usage might inadvertently attract participants who are already inclined towards using such modes of transportation. People who own, frequently use, or have a positive attitude towards e-scooters are likelier to participate in studies investigating this subject. This pre-selection bias can lead to overestimating the general popularity and acceptance of e-scooters as a transportation mode.

- Behavioral Confirmation:
  Participants aware of the research's focus on e-scooters might subconsciously alter their behaviour to align with what they perceive as the researchers' expectations. This phenomenon, known as the Hawthorne effect, suggests that individuals may increase their usage of e-scooters during the study period, skewing the results towards a higher apparent preference for e-scooters.

- Social Desirability Bias:
  In studies that address environmentally friendly or innovative transportation solutions like e-scooters, participants might over report their usage because they want to be seen as ecologically conscious or tech-savvy. This social desirability bias can result in data reflecting a higher usage rate than everyday life outside the research context.

**Older data set: ODiN 2018 vs 2023** Add the start of the research period in early 2023. The ODiN 2018 data was opted for as a reference for travel data in the Netherlands. At that moment, this was the only available ODiN data set unaffected by COVID-19. During this research, a new ODiN data set, ODiN 2023, was published (resp. 04-07-2024). The first COVID-19 "free" year after the pandemic. This data set would have better fit the current travel behaviour and increased the research outcome's realism. Current trends in travel behaviour, such as the growth in e-bike ownership since the pandemic, are not included in the 2018 data set but would have been present in its 2023 counterpart.

# 9 Recommendation

This section outlines several critical recommendations based on the conclusions and discussion points presented in the previous chapter. Each recommendation is accompanied by a detailed explanation of its rationale and proposed implementation. These recommendations aim to address the limitations identified in the current study and provide a roadmap for future research and policy development. By adopting these suggestions, future studies can yield more comprehensive and actionable insights, ultimately contributing to the effective integration of e-scooters into urban transportation systems.

**Expanding Sample Size for Greater Representation:** The initial research produced promising results but was limited by a relatively small sample size, which could not fully capture the diversity of the population. Future research should involve a more extensive and diverse sample to enhance the validity and generalisability of the findings. This broader participant base should include significant representation from various demographic groups, such as different ages, income levels, and geographic locations, as well as other factors like gender, occupation, and education level. By incorporating a more comprehensive cross-section of society, the study can provide deeper insights into the patterns and behaviours associated with e-scooter usage, ultimately informing more inclusive and effective transportation policies.

In particular, moped-scooter users represent a segment that warrants closer examination. Though they were present in the initial study, the sample size for this group was too limited to yield statistically significant conclusions. Including a substantial number of moped-scooter users in future research would allow for a more nuanced understanding of their travel behaviours and motivations.

**Including E-Scooter Price in Future Studies:** The current study did not consider the impact of the e-scooter's price on user behaviour despite recognising its potential significance. Understanding price sensitivity and how different price points influence the decision to use e-scooters is crucial. Future research should integrate the cost of purchasing an e-scooter into its scenarios to address this gap. This information would be invaluable for policymakers to anticipate market demand and develop appropriate regulations and incentives. It can also help manufacturers and retailers optimise pricing strategies to encourage wider adoption.

**Assessing Realistic Travel Distances:** In the initial experiment, participants made choices based on hypothetical travel distances to train stations. To increase the realism and applicability of the findings, future studies should ask participants to report their travel distances and make decisions accordingly. This approach would provide a more accurate representation of travel behaviour and preferences. By understanding how real-world travel distances influence transportation choices, researchers can better predict how e-scooters might be integrated into existing transit systems. This data would be crucial for designing efficient and user-friendly multimodal transportation networks.

**Conducting Interviews with Transportation Providers:** While the current research focuses on the demand side of e-scooter usage, incorporating the perspectives of transportation providers like NS

(Dutch Railways) and HTM (The Hague's public transport operator) can offer a more holistic view. Interviews with these stakeholders can reveal practical considerations and potential challenges from the supply side, such as infrastructure requirements, operational logistics, and safety concerns. This supply-side analysis would complement the demand-side findings, providing a comprehensive understanding of how e-scooters can be effectively integrated into the public transportation ecosystem. Insights gained from transport providers can guide the development of supportive policies, infrastructure investments, and collaborative initiatives to ensure a seamless and efficient transportation system.

**ODiN 2023** As addressed during the discussion, ODiN presented a newer dataset, ODiN 2023, during the running of this research. For future research, a similar process can be conducted with more recent data that better captures the effect of current mobility trends.

Addressing these five areas will allow future research to build on the initial findings and provide more detailed, realistic, and actionable insights into the potential integration and impact of e-scooters in urban transportation systems. These insights will inform policy decisions and guide practical initiatives to improve urban mobility.

# Bibliography


Aarhaug, J., Fearnley, N., & Johnsson, E. (2023). E-scooters and public transport – complement or competition? *Research in Transportation Economics*, *98*. https://doi.org/10.1016/j.retrec.2023.101279

Baek, K., Lee, H., Chung, J.-H., & Kim, J. (2021). Electric scooter sharing: How do people value it as a last-mile transportation mode? *Transportation Research Part D: Transport and Environment*, *90*, 102642. https://doi.org/10.1016/j.trd.2020.102642

CBS. (2018). *Rijkswaterstaat (rws) (2018): Onderzoek onderweg in nederland - odin 2018. dans.* https://doi.org/10.17026/dans-xn4-q9ks

CBS. (2022). Hoeveel mannen en vrouwen wonen in nederland? https://www.cbs.nl/nl-nl/visualisaties/dashboard-bevolking/mannen-en-vrouwen#:~:text=Op%201%20januari%202022%20telde,meerderheid%2C%20op%20hogere%20leeftijden%20vrouwen.

ChoiceMetrics. (2024). Ngene 1.4 user manual  reference guide. https://choice-metrics.com/

Degele, J., Gorr, A., Haas, K., Kormann, D., Krauss, S., Lipinski, P., Tenbih, M., Koppenhoefer, C., Fauser, J., & Hertweck, D. (2018). Identifying e-scooter sharing customer segments using clustering. *2018 IEEE International Conference on Engineering, Technology and Innovation, ICE/ITMC 2018 - Proceedings*. https://doi.org/10.1109/ICE.2018.8436288

Dekker, H.-J. (2021). *Cycling pathways*. https://doi.org/10.5117/9789463728478

DOT. (2024a). Bicycle-ticket-and-bicycle-space-reservation. https://dinoffentligetransport.dk/en/find-tickets/single-tickets/bicycle-ticket-and-bicycle-space-reservation

DOT. (2024b). How to travel: Bicycles and scooter. https://dinoffentligetransport.dk/en/how-to-travel/bicycles-and-scooters

Eerstekamer.nl. (2023). Goedkeuringsprocedure toelating bijzondere bromfietsen op de weg en introductie kader lichte elektrische voertuigen. https://www.eerstekamer.nl/wetsvoorstel/36269_goedkeuringsprocedure

Europees Parlement, R. v. d. E. U. (2016). Verordening (eu) 2016/679 van het europees parlement en de raad van 27 april 2016 betreffende de bescherming van natuurlijke personen in verband met de verwerking van persoonsgegevens en betreffende het vrije verkeer van die gegevens en tot intrekking van richtlijn 95/46/eg (algemene verordening gegevensbescherming) (voor de eer relevante tekst). https://eur-lex.europa.eu/legal-content/NL/TXT/?uri=CELEX:32016R0679#d1e40-1-1

Fearnley, N., Berge, S. H., Johnsson, E., of Transport Economics (TOI), I., Administration, N. P. R., of Health, N. D., & of Norway, R. C. (2020). Shared e-scooters in oslo.

IenW. (2022). *Dutch framework for light electric vehicles (levs)*. Ministry of Infrastructure and Water Management. https://www.government.nl/documents/publications/2021/05/10/the-netherlands-and-light-electric-vehicles-levs#:~:text=The%20goal%20of%20the%20framework,and%20the%20new%20national%20framework.

Jiao, J., & Bai, S. (2020). Understanding the shared e-scooter travels in austin, tx. *ISPRS International Journal of Geo-Information*, *9*. https://doi.org/10.3390/ijgi9020135

Kessels, R., Goos, P., & Vandebroek, M. (2004). Comparing algorithms and criteria for designing bayesian conjoint choice experiments.

KiM. (2024). Cycling facts 2023. https://english.kimnet.nl/publications/publications/2024/01/10/cycling-facts-2023

Kostsov, 123RF.com. (n.d.). Electric scooter isolated on white background. eco transport. 3d rendering [[Online; accessed June, 2024]]. https://www.123rf.com/photo_117814173_electric-scooter-isolated-on-white-background-eco-transport-3d-rendering.html

Laa, B., & Leth, U. (2020). Survey of e-scooter users in vienna: Who they are and how they ride. *Journal of Transport Geography*, *89*, 102874. https://doi.org/10.1016/j.jtrangeo.2020.102874

Li, A., Zhao, P., Liu, X., Mansourian, A., Axhausen, K. W., & Qu, X. (2022). Comprehensive comparison of e-scooter sharing mobility: Evidence from 30 european cities. *Transportation Research Part D: Transport and Environment*, *105*. https://doi.org/10.1016/j.trd.2022.103229

NS. (2024a). Algemene voorwaarden voor het vervoer van reizigers en handbagage van de nederlandse spoorwegen (avr-ns). https://www.ns.nl/binaries/_ht_1719812817796/content/assets/ns-nl/voorwaarden/ns-algemene-voorwaarden-avr.pdf

NS. (2024b). Met trein en fiets op stap. https://www.ns.nl/reisinformatie/fiets-in-de-trein.html

Oostendorp, R., & Hardinghaus, M. (2023). Shared vs. private e-scooters: Same vehicle – different mode? empirical evidence on e-scooter usage in germany. *Transportation Research Procedia*, *72*, 2173–2180. https://doi.org/10.1016/J.TRPRO.2023.11.703

RDW. (2024). Wegwijzer bijzondere bromfietsen. https://www.rdw.nl/over-rdw/actueel/dossiers/bijzondere-bromfietsen

Slovenske zeleznice. (2024). Take your scooter on board. https://potniski.sz.si/en/useful-information/take-your-scooter-on-board/

Stam, B. (2021). Travellers' preferences towards existing and emerging means of first/last mile transport: A case study for the almere centrum railway station in the netherlands. https://doi.org/10.1186/s12544-021-00514-1

TFW. (2024). Can i take my e-scooter on a train. https://tfw.wales/help-and-contact/rail/faq/on-board/can-i-take-my-escooter-train

TU Delft. (2024). Human research ethics. https://www.tudelft.nl/over-tu-delft/strategie/integriteitsbeleid/human-research-ethics

van Kuijk, R. J., de Almeida Correia, G. H., van Oort, N., & van Arem, B. (2022). Preferences for first and last mile shared mobility between stops and activity locations: A case study of local public transport users in utrecht, the netherlands. *Transportation Research Part A: Policy and Practice*, *166*, 285–306. https://doi.org/10.1016/j.tra.2022.10.008

van Mil, J. F. P. (2020). Insights into factors affecting the combined bicycle□transit mode. https://doi.org/10.1007/s12469-020-00240-2

VRB. (2024). Bicycles, e-scooter, etc.: Last-mile mobility. everything you need to know about travelling with bicycles, e-scooters, pushchairs, etc. https://www.vrb-online.de/en/service/bicycles-e-scooters-etc

WestBahn. (2024). Taking your e-scooter on the train; what you need to know. https://westbahn.at/en/news/taking-your-e-scooter-on-the-train/

Yanatma, S. (2023). Cycling in europe: Which countries and cities are the most and least bicycle-friendly? https://www.euronews.com/next/2023/09/19/cycling-in-europe-which-countries-and-cities-are-the-most-and-least-bicycle-friendly

# A

# Dutch LEV framework

| | Category 1a | Category 1b | Category 2a | Category 2b |
|---|---|---|---|---|
| | EPAC* (carrier)bikes <75kg | All Light Electric Vehicles other than 1a < 55 kg | Cargo bikes | Carrier bikes for passengers |
| **Method of admission and supervision** | | | | |
| Method of admission | Self-certification | Approval | Approval | Approval |
| Surveillance method | Market | Manufacturer | Manufacturer | Manufacturer |
| Baseline | EU Machine Directive / EN 15194 | EU 168-2013 / Designating specialmopeds / EN 17128 / German norm + integrated risk assessment | EU 168-2013 / Designating special mopeds + integrated risk assessment | EU 168-2013 / Designating special mopeds + integrated risk assessment |
| **Admission requirements** | | | | |
| Maximum Measurements LxWxH | 2 wheels: 3 x 0,75 x 2 m / > 2 wheels: 3 x 1 x 2 m | 2 x 0,75 x 1,50 | 3 x 1 x 2 m | 3 x 1 x 2 m |
| Maximum construction speed | > 6 km / h and < 25 km/h | > 6 km / h and < 25 km/h | > 6 km / h and < 25 km/h | > 6 km / h and < 25 km/h |
| Max. mass | Max. kerb weight <75 kg, total max. mass: 250 kg | Max. kerb weight <55 kg, total max. mass: 140 kg | Max. kerb weight 270 kg or 425 kg for more wheels, total max. mass: 565 kg | Max. kerb weight 270 kg or 425 kg for more wheels, total max. mass: 565 kg |
| Performance | < 250 W | < 400 W | Pedal assistance: < 250W, No pedal assistance: <1250 W | Pedal assistance: < 250W, No pedal assistance: <1250 W |
| Number of persons | 1 driver, max. 3 passengers | 1 driver | 1 driver | 1 driver, max. 8 passengers |
| **Requirements for road usage** | | | | |
| License plate | No license plate | License plate | License plate | License plate |
| Insurance | third-party liability insurance | Motor Vehicle Liability Insurance Act | Motor Vehicle Liability Insurance Act | Motor Vehicle Liability Insurance Act |
| Helmet | No | No | No | No |
| Drivers license | No | No | AM | AM |
| Minimum age | No | 16 yrs | 18 yrs | 18 yrs |

* *Electrically Power Assisted Cycle*

Figure A.1: Schematic overview Dutch LEV framework (IenW, 2022)

# B

# Enlarged figures from the document

## B.1. Allocation of the choice sets

On the second page of this appendix, the allocation flow of the choice sets within the survey (Figure 4.1) is displayed with an enlargement factor of 1.67 compared to the original figure in chapter 4.

## B.2. Direct results of the choice experiment

From the third to the eighth page of this appendix, the direct results of the choice experiment as displayed in chapter 5 are shown with an enlargement factor of 2.

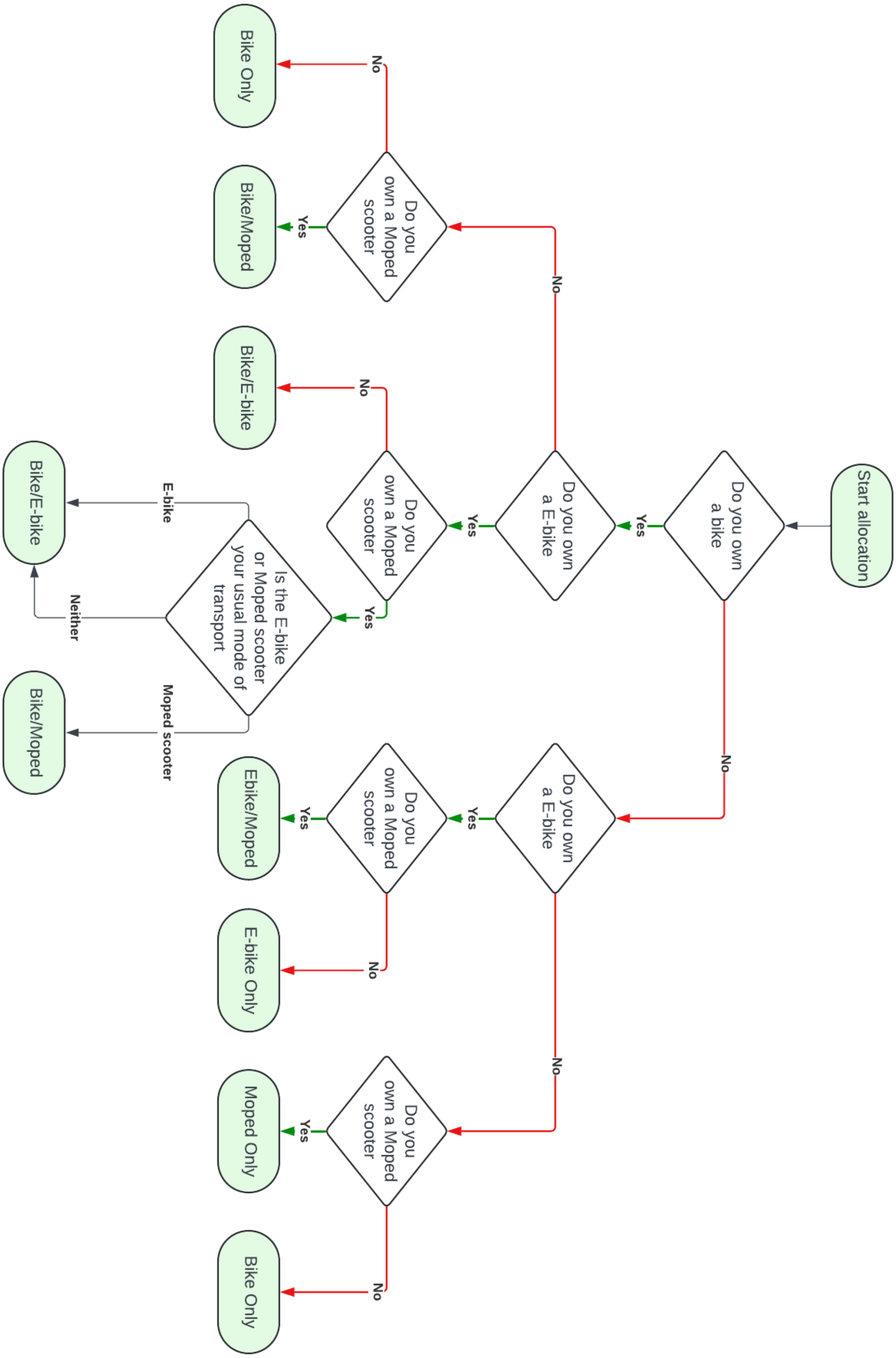



Figure B.1: 1.67x enlarged version of Figure 4.1

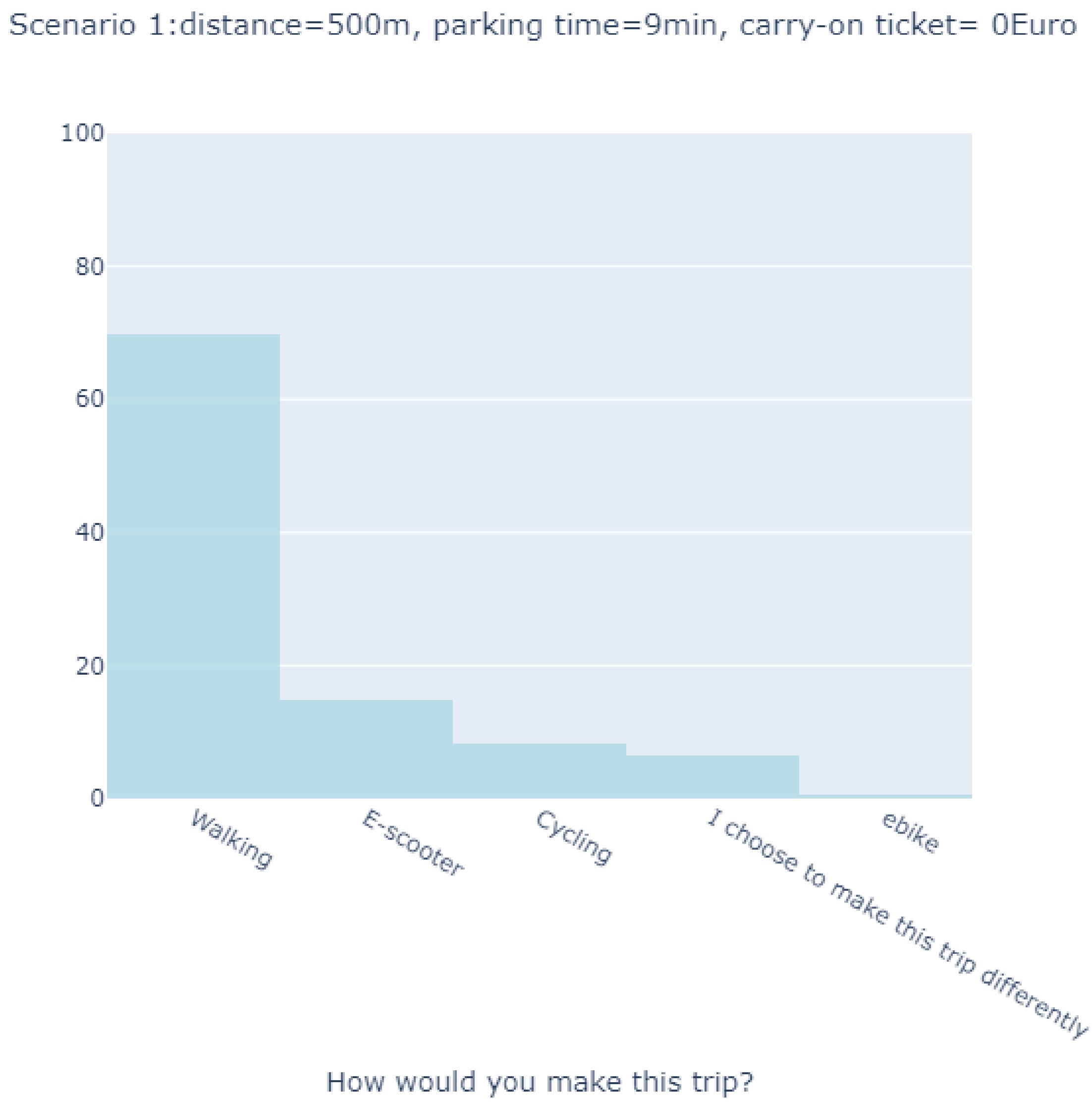



Figure B.2: Choices for scenario 1

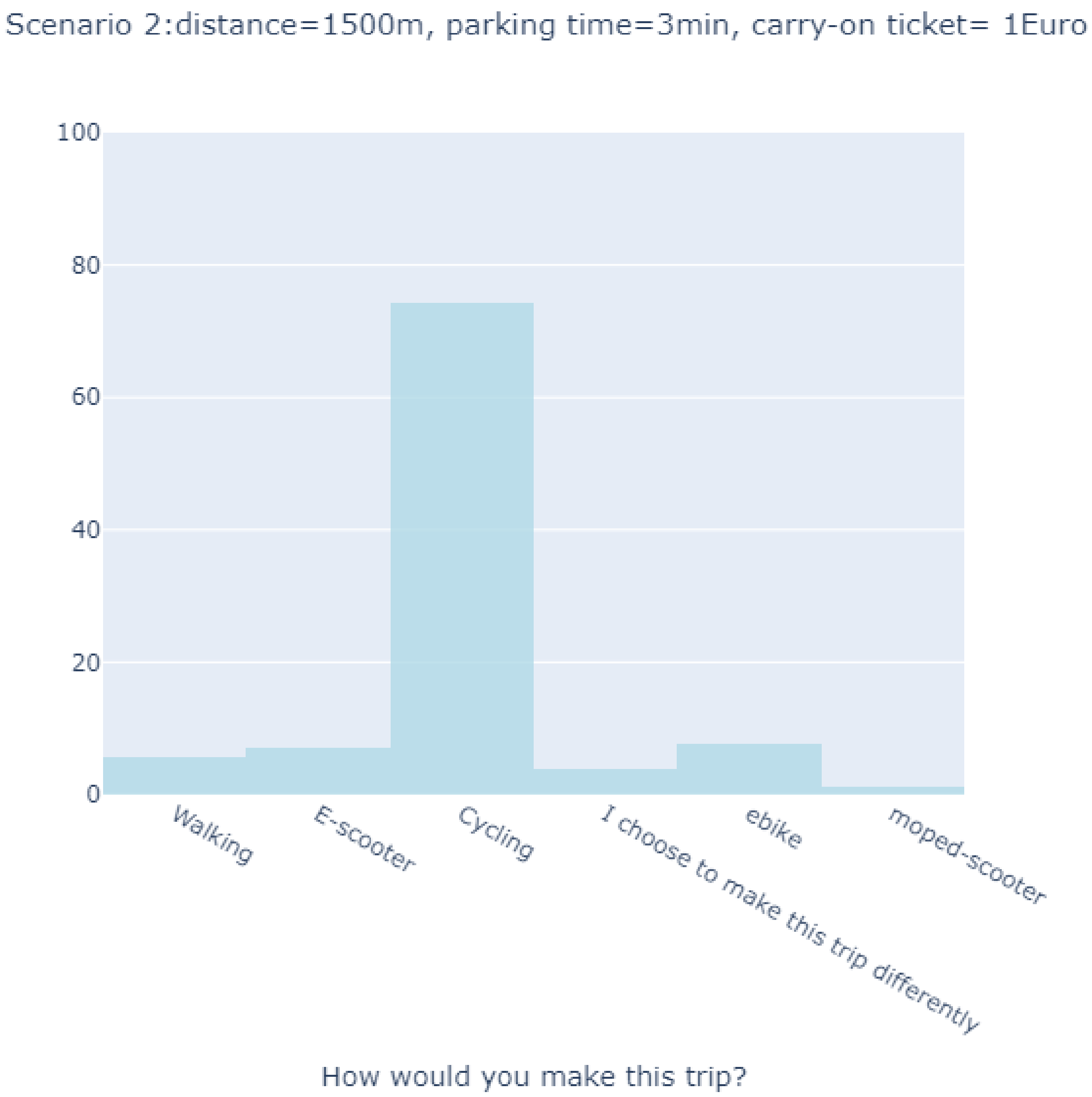



Figure B.3: Choices for scenario 2

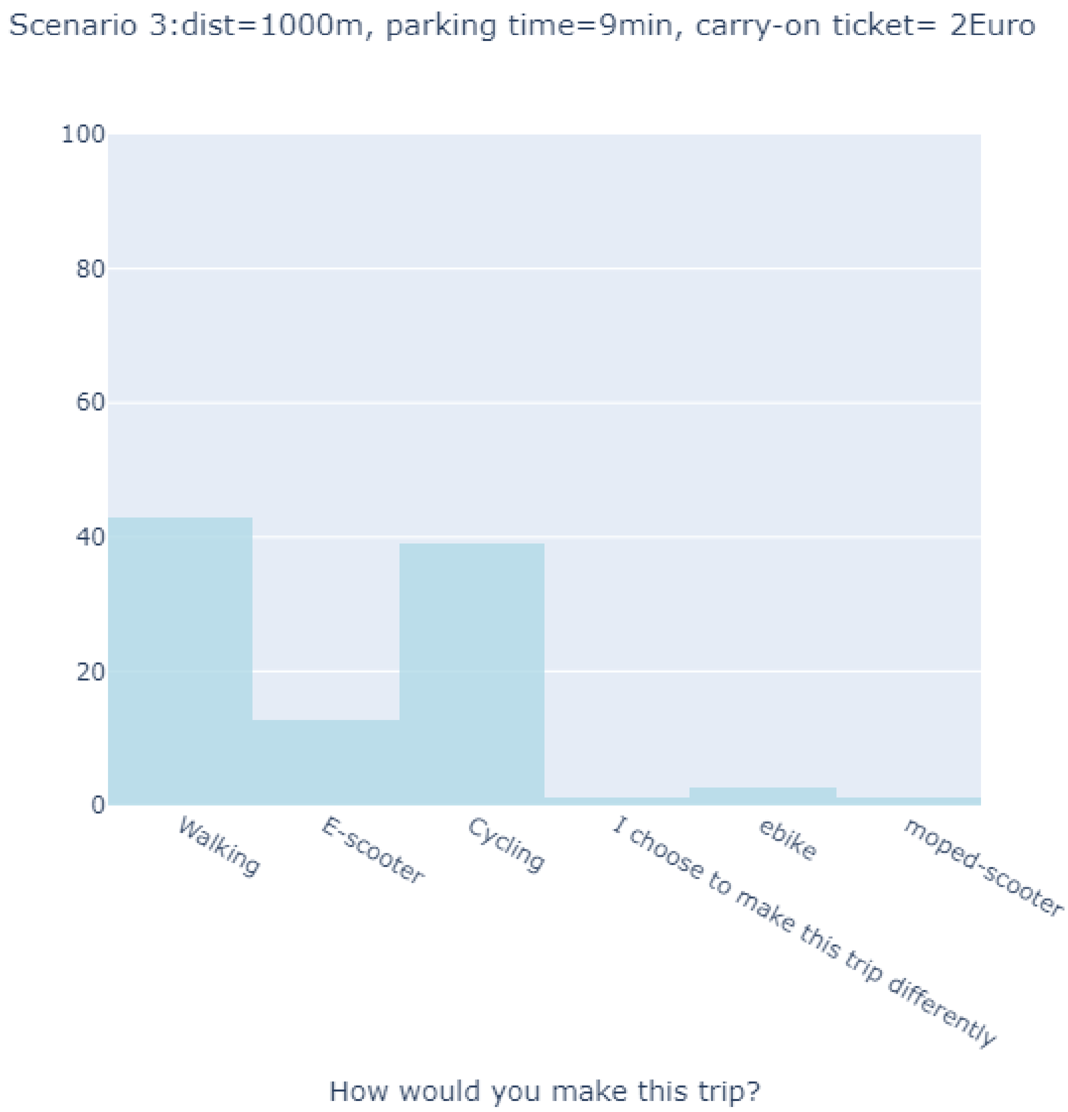



Figure B.4: Choices for scenario 3

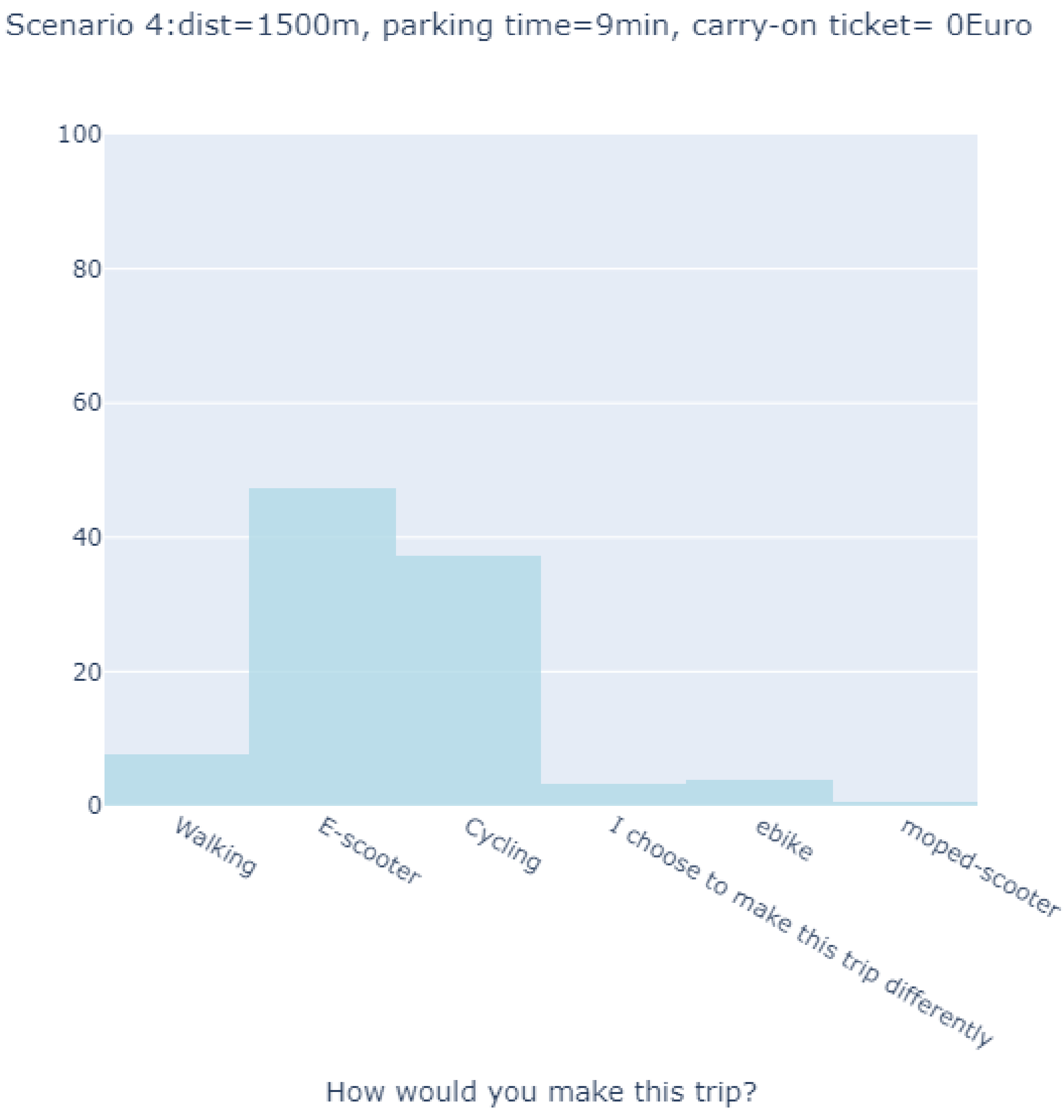



Figure B.5: Choices for scenario 4

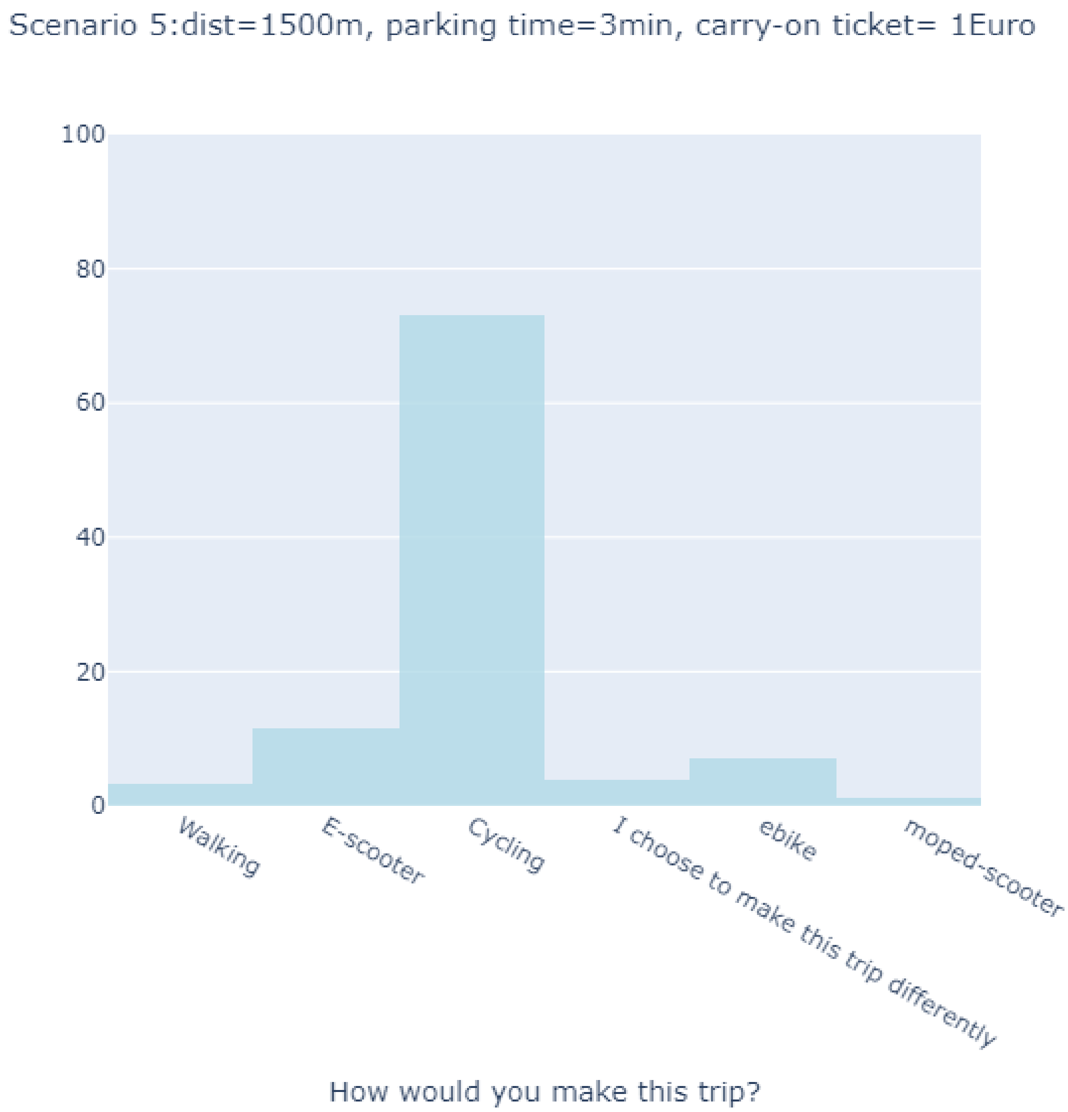



Figure B.6: Choices for scenario 5

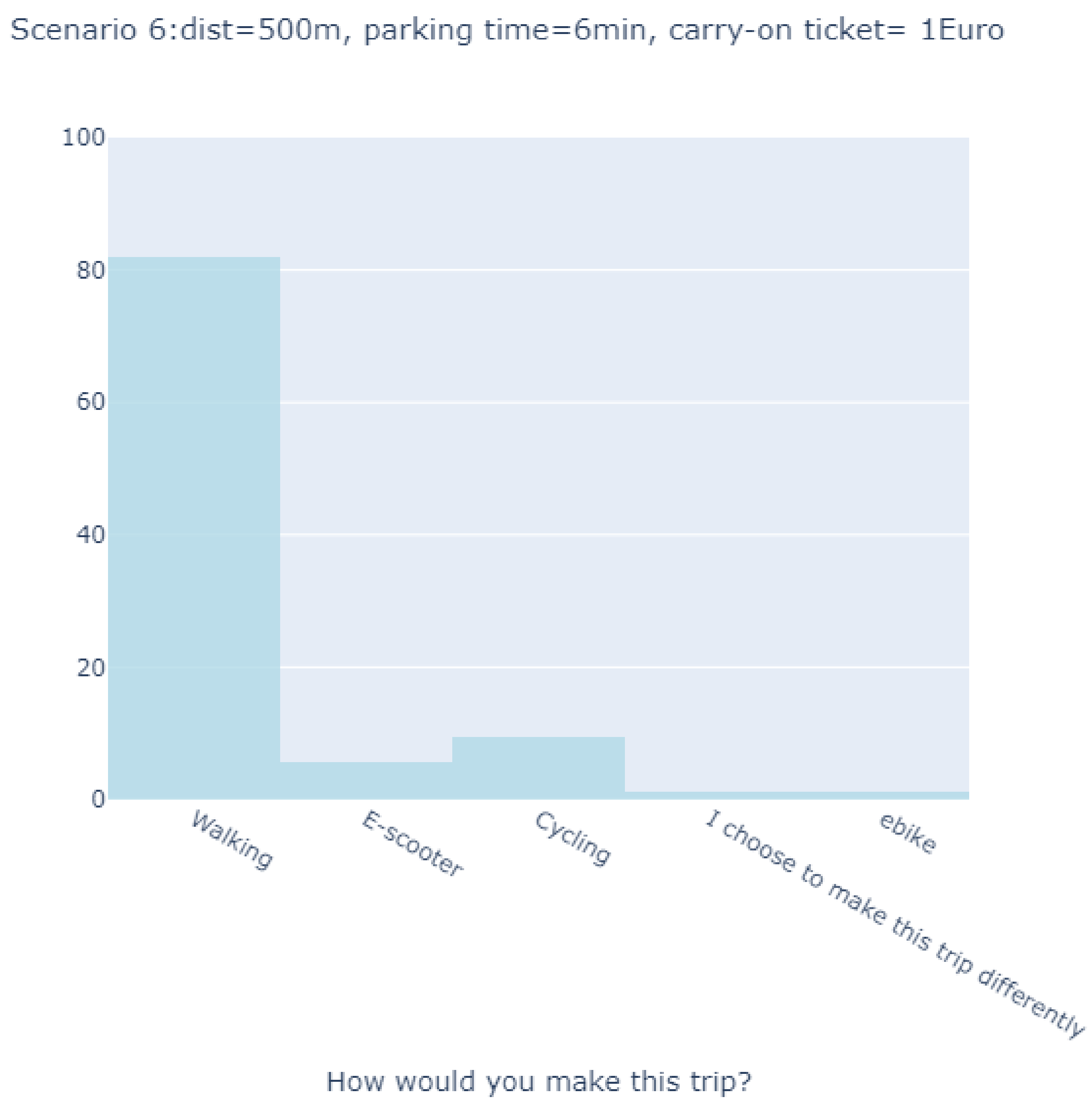



Figure B.7: Choices for scenario 6

# C The survey (NL)

This appendix contains the survey distributed to participants in this research study. The survey was designed to gather insights on the potential use of e-scooters in the Netherlands. It was sent out via LinkedIn and closed professional and non-professional groups. The questions were structured to be concise and easy to understand to collect quantitative and qualitative data on the critical areas of interest. Participants were assured that their responses would be confidential and used solely for this research.

The following pages include the complete survey in its original (Dutch) form, precisely as it was presented to the participants.

When assessing the embedded survey document. One can find more questions in the survey than are used during this research. Two of these questions are at the end of the embedded document, under the section effect questions. These two questions include interest that was sparked at the beginning of the research but was deemed not significantly present in reference research to be included in the choice experiment and, therefore, moved to separate questions. Later, the decision was made not to incorporate the questions in the research. As the survey print is in Dutch, the question description is added below.

**Crowding level** :
Carrying on a mode like the e-scooter onto the train would cause you to have extra luggage. In which of the situations below would it be acceptable for you to take such an extra piece of luggage with you onto the train

*You can select multiple options*

- ☐ Scenario 1: You have a seat on the train. You can place the e-scooter under your seat.
- ☐ Scenario 2: You have a seat on the train. You can place the e-scooter next to you on the ground.
- ☐ Scenario 3: It is busy on the train, but you have a seat. You have to keep the e-scooter between your legs.
- ☐ Scenario 4: It is busy on the train. You have to stand beside your e-scooter
- ☐ In none of the scenarios above, I would take an e-scooter or a comparable vehicle with me.

**Use of e-scooters in the absence of ...** :
The advantage of a carrying-on mode like the e-scooter will be enhanced for train travel if there are insufficient alternatives at the end station to continue the trip. In which of the below-mentioned scenarios would you consider using an e-scooter or other carry-on mode during a train trip?

*You can select multiple options*

*By the exclusion of:*

- ☐ Sequential public transport (e.g. Regional bus, tram)
- ☐ OV-bikes (Bicycles from the train operator)
- ☐ Shared bicycles
- ☐ Shared moped scooters
- ☐ Shared e-scooters (When they are introduced)
- ☐ Other []
- ☐ I would not reconsider using the e-scooter or any other similar carry-on mode
- ☐ The availability conditions of alternative transport do not influence my choice of the e-scooter

# The Dutch survey starts on the next page

Nederlands

## Intro

Beste deelnemer,

Je wordt uitgenodigd om deel te nemen aan een onderzoek genaamd "Mobiliteit onderzoek e-step als voor- en natransport voor treinreizen". Dit onderzoek wordt uitgevoerd door Wouter van der Veer, Student aan de TU Delft in samenwerking met RoyalHaskoningDHV. Het onderzoek is onderdeel van de Master thesis voor het afronden van de Msc Opleiding Transport & Planning aan de TU Delft.

Het doel van dit onderzoek is inzicht te krijgen in het mogelijke reis gedrag na de legalisering van e-steps in Nederland in betrekking tot voor en natransport voor de trein. Het merendeel van de vragen in het onderzoek richt zich voornamelijk op het voortransport, tussen thuis en het vertrek station. Het onderzoek neemt ongeveer **8 minuten** in beslag. Het onderzoek gebruikt de data voor berekeningen over de gebruiksbereidheid voor e-steps. Deze berekeningen worden gebruikt als ondersteuning van de eerder beschreven Master Thesis. De eindresultaten worden na afronding van het onderzoek en de thesis gepubliceerd. In het eerste deel van dit onderzoek word je gevraagd naar je huidige reisgedrag. Waarna je in het tweede deel van het onderzoek wordt gevraagd een reis keuze te maken in 6 hypothetische situaties.

Zoals bij elke online activiteit is het risico van een databreuk aanwezig. Door de data anoniem op te slaan en de data dus ook anoniem te verwerken minimaliseren wij de impact van deze geringe kans. De informatie die invult gebruiken wij enkel voor onderzoeksdoeleinden. Je deelname aan dit onderzoek is volledig vrijwillig, en u kunt zich elk moment zonder reden terugtrekken.

Alvast hartelijk bedankt voor het nemen van de tijd voor het invullen van deze survey.

Wouter van der Veer
W.R.vanderveer@student.tudelft.nl

Door volgende te klikken gaat u akkoord met het Opening Statement en gaat u door naar de survey.

**Travel behaviour**

## Reisgedrag

Welke voertuigen heb jij thuis tot de beschikking?

- ☐ Auto
- ☐ Motor
- ☐ Fiets
- ☐ E-bike
- ☐ Vouwfiets
- ☐ Scooter
- ☐ Electrische step
- ☐ [ ] Anders

Wat is jouw voornaamste reden om te reizen?

- ○ Woon-werk
- ○ Zakelijk
- ○ Studie
- ○ Vrije tijd

Voor de reden om te reizen: ${q://QID8/ChoiceGroup/SelectedChoices}, welk voertuig gebruikt je hier om te reizen?

- ○ Lopend

- Trein
- Metro
- Tram
- Bus

Hoe reis je naar het ${q://QID7/ChoiceGroup/SelectedChoices}station?

- Metro
- Tram
- Bus
- Lopen

Heb je in deze ${q://QID7/ChoiceGroup/SelectedChoices} reis een overstap?

- Ja
- Nee
- Soms wel, soms niet

Hoe vaak reis je gemiddeld per week met de trein?

- 5 of meer keer per week
- 3 of 4 keer per week

- 1 of 2 keer per week
- minder dan 1 keer

Weet je wat een e-step is en hoe deze werkt?

- Ja
- Nee

Heb je ooit een e-step gebruikt?

- Ja
- Nee

**Intro e-step**

De volgende 6 vragen bevatten elk een scenario. In deze scenario's word je gevraagd een keuze te maken voor een reis richting een treinstation. In deze scenario's maak je een keuze uit voor jou bekende vervoersmiddelen met de e-step als extra optie.

Ter verduidelijking hieronder een omschrijving van de e-step in dit onderzoek:

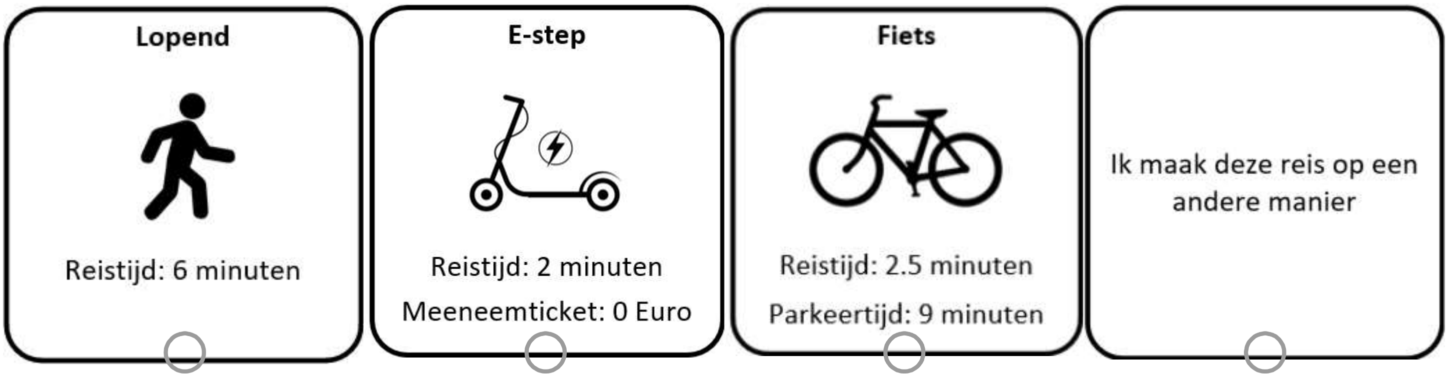
- Privé eigendom.

- Inklapbare modellen die je net als een vouwfiets mee kan nemen in de trein.

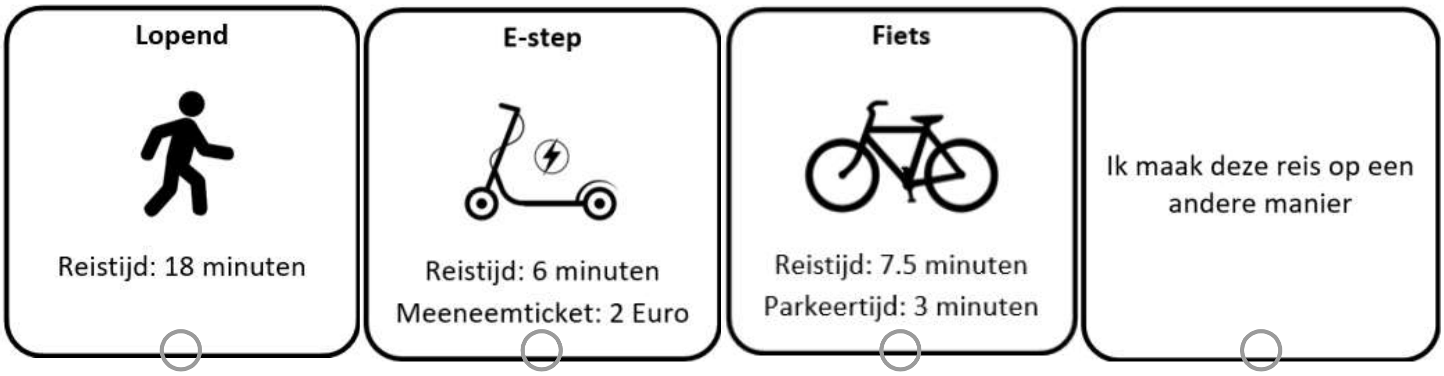
Hieronder een afbeelding van een voorbeeld van zo'n model.

**Choice experiment - fiets**

Voor deze situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?




Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?




Voor de volgende situatie is de afstand naar het treinstation 1000 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?



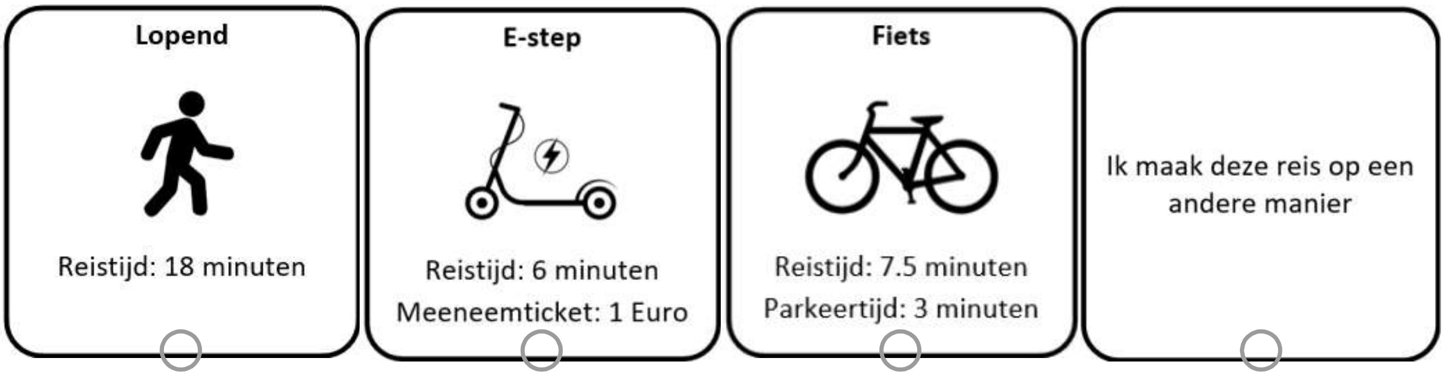


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

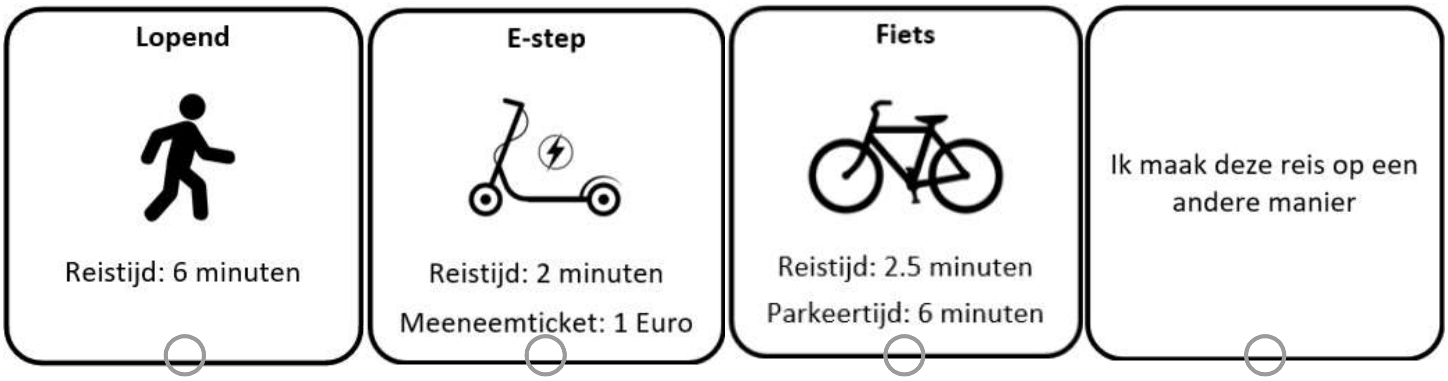




Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

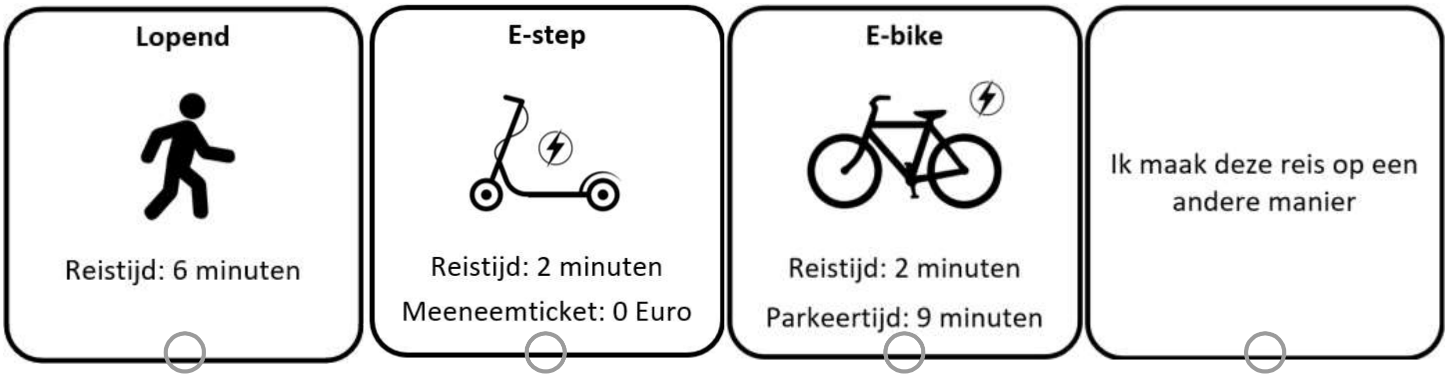



Voor de volgende situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

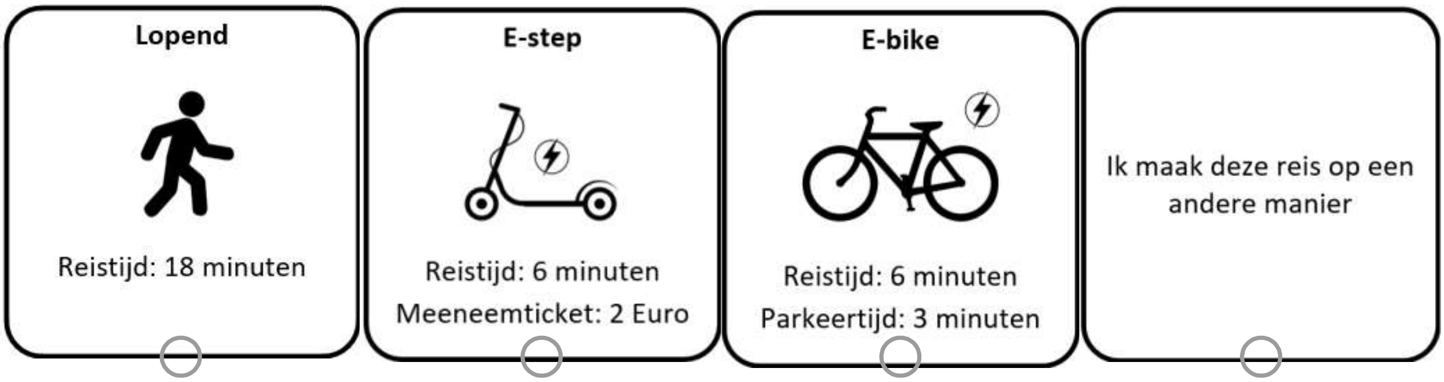



## Choice experiment - E-bike

Voor deze situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?



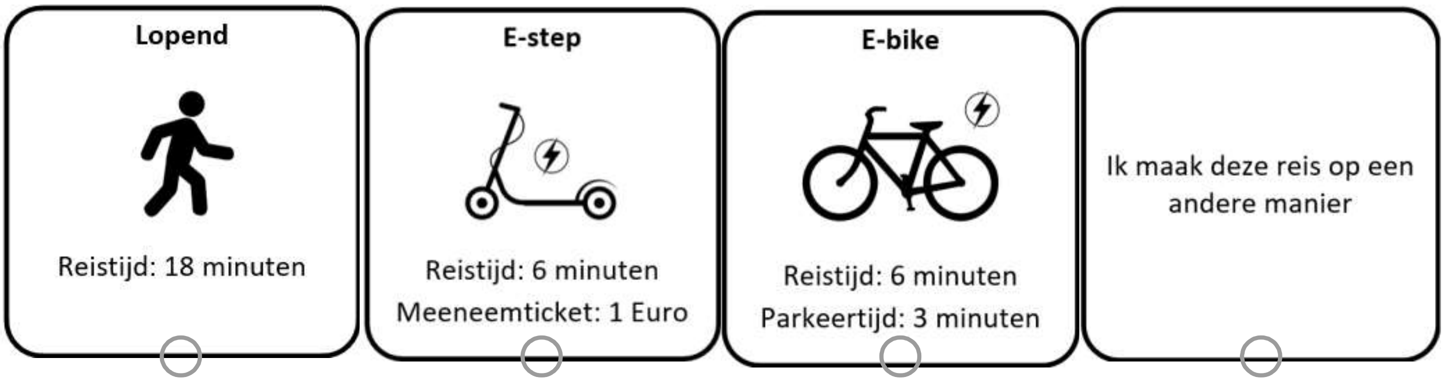

Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?



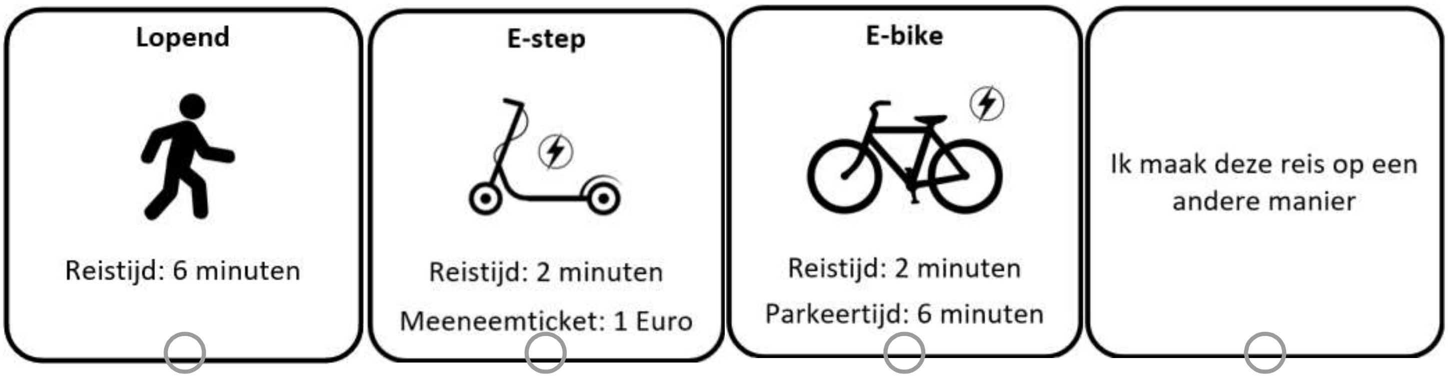

Voor de volgende situatie is de afstand naar het treinstation 1000 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?



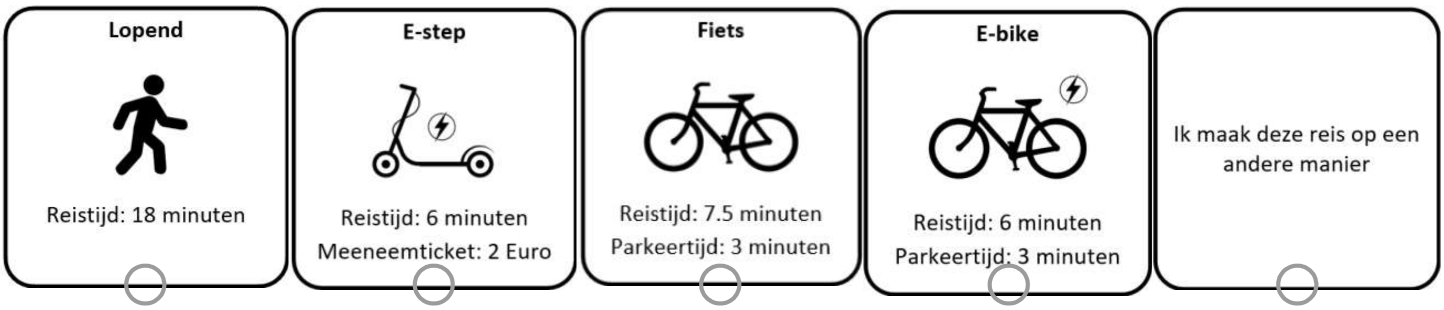

Voor de volgende situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?




## Choice experiment - Fiets & E-bike

Voor deze situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?




Voor de volgende situatie is de afstand naar het treinstation 1000 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


## Choice experiment - Scooter

Voor deze situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1000 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

**Lopend**

Reistijd: 18 minuten

**E-step**

Reistijd: 6 minuten
Meeneemticket: 0 Euro

**Scooter**

Reistijd: 4.5 minuten
Parkeertijd: 9 minuten

Ik maak deze reis op een andere manier

Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

**Lopend**

Reistijd: 18 minuten

**E-step**

Reistijd: 6 minuten
Meeneemticket: 1 Euro

**Scooter**

Reistijd: 4.5 minuten
Parkeertijd: 3 minuten

Ik maak deze reis op een andere manier

Voor de volgende situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


## Choice experiment - Fiets & Scooter

Voor deze situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1000 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


## Choice experiment - E-bike & Scooter

Voor deze situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


Voor de volgende situatie is de afstand naar het treinstation 1000 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

| Lopend | E-step | E-bike | Scooter | |
|---|---|---|---|---|
| Reistijd: 12 minuten | Reistijd: 4 minuten<br>Meeneemticket: 2 Euro | Reistijd: 4 minuten<br>Parkeertijd: 9 minuten | Reistijd: 3 minuten<br>Parkeertijd: 9 minuten | Ik maak deze reis op een andere manier |

Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

| Lopend | E-step | E-bike | Scooter | |
|---|---|---|---|---|
| Reistijd: 18 minuten | Reistijd: 6 minuten<br>Meeneemticket: 0 Euro | Reistijd: 6 minuten<br>Parkeertijd: 9 minuten | Reistijd: 4.5 minuten<br>Parkeertijd: 9 minuten | Ik maak deze reis op een andere manier |

Voor de volgende situatie is de afstand naar het treinstation 1500 meter en de treinreis duurt ongeveer 15 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?

| Lopend | E-step | E-bike | Scooter | |
|---|---|---|---|---|
| Reistijd: 18 minuten | Reistijd: 6 minuten<br>Meeneemticket: 1 Euro | Reistijd: 6 minuten<br>Parkeertijd: 3 minuten | Reistijd: 4.5 minuten<br>Parkeertijd: 3 minuten | Ik maak deze reis op een andere manier |

Voor de volgende situatie is de afstand naar het treinstation 500 meter en de treinreis duurt ongeveer 45 minuten. Hoe zou jij de reis naar het treinstation maken als je de keuze hebt uit de volgende opties?


**Socio-demographics**

# Over jezelf

wat is jouw geslacht?

- Man
- Vrouw
- Non-binair
- Zeg ik liever niet
- Anders

## Wat is jouw leeftijd?

- <18
- 18-25
- 26-35
- 36-45
- 46-55
- 56-65
- >66

## Wat is het jouw hoogst behaalde opleidingsniveau?

- Basis onderwijs
- VMBO, MBO (niveau 1)
- HAVO, VWO, MBO (niveau 2,3,4)
- HBO-, WO-Bachelor
- HBO-, WO-Master, Doctor
- [ ] Anders
- zeg ik liever niet

## Wat is jouw bruto maandelijks inkomen?

- <2000
- 2000-4000

- ○ >4000
- ○ zeg ik liever niet

## Effect question

De volgende twee vragen gaan over factoren die de keuze voor het gebruik van een e-step kunnen beïnvloeden. Geef bij beide vragen aan wat voor jou van toepassing zou zijn.

Het meenemen van een voertuig in de trein zoals de e-step zorgt ervoor dat je een extra stuk bagage bij je hebt. In welk van de onderstaande situaties zou het voor jou acceptabel zijn om zo een voertuig mee te nemen in de trein?

Je kunt meerdere opties selecteren.

- ☐ Situatie 1:
  Je heb een zitplaats.
  De e-step kan je onder je stoel kwijt
- ☐ Situatie 2:
  Je hebt een zitplaats,
  De e-step kan je naast je op de grond kwijt

- [ ] Situatie 3:
  Het is druk in de trein maar je hebt een zitplaats.
  De e-step moet je tussen je benen houden
- [ ] Situatie 4:
  Het is druk in de trein.
  Je moet met de e-step naast je staan
- [ ] Ik zou in geen van deze situaties een e-step of vergelijkbaar voertuig meenemen

Het voordeel van een meeneembaar voertuig zoals de e-step bij treinreizen wordt vergroot als er op de eindbestemming geen alternatieve vervoersmiddelen aanwezig zijn om de reis te vervolgen. Selecteer hieronder de situaties waarin je zou overwegen om een e-step of ander meeneembaar voertuig te gebruiken bij een trein reis.

Je kunt meerdere opties selecteren.

Bij het ontbreken van:

- [ ] Vervolg openbaar vervoer (bv. Regio bus en/of tram)
- [ ] OV-fiets
- [ ] Deel fiets
- [ ] Deel scooters
- [ ] Deel e-step (Wanneer deze geïntroduceerd worden)
- [ ] ____________ Anders

- [ ] Ik zou het niet overwegen een e-step of vergelijkbaar voertuig te gebruiken
- [ ] De aanwezigheid van alternatieve vervoersmiddelen zijn niet van invloed op mijn keuze voor de e-step

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# D

# Choice experiment: Choices per scenario

## D.1. Choice split for scenario 1

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 156 | 109 | 69.87 % | 69.87 % |
| Cycling | 148 | 13 | 8.33 % | 8.78 % |
| E-scooter | 156 | 23 | 14.74 % | 14.74 % |
| E-bike | 32 | 1 | 0.64 % | 0.64 % |
| Moped-scooter | 8 | 0 | 0 % | 0 % |
| Opt-out | 156 | 10 | 6.41 % | 6.41 % |

Table D.1: Choice percentage per alternative of the choice sets - Scenario 1

## D.2. Choice split for scenario 2

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 156 | 9 | 5.77 % | 5.77 % |
| Cycling | 148 | 116 | 74.36 % | 78.38 % |
| E-scooter | 156 | 11 | 7.05 % | 7.05 % |
| E-bike | 32 | 12 | 7.69 % | 37.50 % |
| Moped-scooter | 8 | 2 | 1.28 % | 25.00 % |
| Opt-out | 156 | 6 | 3.85 % | 3.85 % |

Table D.2: Choice percentage per alternative of the choice sets - Scenario 2

## D.3. Choice split for scenario 3

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 156 | 67 | 42.95 % | 42.95 % |
| Cycling | 148 | 61 | 39.10 % | 41.22 % |
| E-scooter | 156 | 20 | 12.82 % | 12.82 % |
| E-bike | 32 | 4 | 2.56 % | 12.50 % |
| Moped-scooter | 8 | 2 | 1.28 % | 25.00 % |
| Opt-out | 156 | 2 | 1.28 % | 1.28 % |

Table D.3: Choice percentage per alternative of the choice sets - Scenario 3

## D.4. Choice split for scenario 4

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 156 | 12 | 7.69 % | 7.69 % |
| Cycling | 148 | 58 | 37.18 % | 39.19 % |
| E-scooter | 156 | 74 | 47.44 % | 47.44 % |
| E-bike | 32 | 6 | 3.85 % | 18.75 % |
| Moped-scooter | 8 | 1 | 0.64 % | 12.5 % |
| Opt-out | 156 | 5 | 3.21 % | 3.21 % |

Table D.4: Choice percentage per alternative of the choice sets - Scenario 4

## D.5. Choice split for scenario 5

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 156 | 5 | 3.21 % | 3.21 % |
| Cycling | 148 | 114 | 73.08 % | 77.03 % |
| E-scooter | 156 | 18 | 11.54 % | 11.54 % |
| E-bike | 32 | 11 | 7.05 % | 34.38 % |
| Moped-scooter | 8 | 2 | 1.28 % | 25.00 % |
| Opt-out | 156 | 6 | 3.85 % | 3.85 % |

Table D.5: Choice percentage per alternative of the choice sets - Scenario 5

## D.6. Choice split for scenario 6

| Alternative | Times available | Times chosen | Percentage chosen | Percentage chosen when available |
|---|---|---|---|---|
| Walking | 156 | 128 | 82.05 % | 82.05 % |
| Cycling | 148 | 15 | 9.62 % | 10.14 % |
| E-scooter | 156 | 9 | 5.77 % | 5.77 % |
| E-bike | 32 | 2 | 1.28 % | 6.25 % |
| Moped-scooter | 8 | 0 | 0 % | 0 % |
| Opt-out | 156 | 2 | 1.28 % | 1.28 % |

Table D.6: Choice percentage per alternative of the choice sets - Scenario 6

# E

# Models

This appendix displays the relevant models supporting choices made while composing the intermediate and final models. The intermediate and final models can not be found in this appendix. These models are found within the chapter 6.

## E.1. single attribute models

A forward stepwise model was used to estimate the base MNL model. This section shows the single attribute models assessed during this step.

### E.1.1. Travel time

**Utility functions**

$$U_{Walking} = ASC_{Walking} + Beta_{TravelTime} * TravelTime_{Walking} \quad (E.1)$$

$$U_{E-scooter} = ASC_{E-scooter} + Beta_{TravelTime} * TravelTime_{E-scooter} \quad (E.2)$$

$$U_{Bicycle} = ASC_{Bicycle} + Beta_{TravelTime} * TravelTime_{Bicycle} \quad (E.3)$$

$$U_{E-bike} = ASC_{E-bike} + Beta_{TravelTime} * TravelTime_{E-bike} \quad (E.4)$$

$$U_{Moped} = ASC_{Moped} + Beta_{TravelTime} * TravelTime_{Moped} \quad (E.5)$$

$$U_{Opt-out} = 0 \quad (E.6)$$

| Indicator | Value |
|---|---|
| LL(start) | -1340.42 |
| LL at equal shares, LL(0) | -1340.42 |
| LL at observed shares, LL(C) | -1120.76 |
| LL(final) | -924.34 |
| Rho-squared vs equal shares | 0.3104 |
| Adj.Rho-squared vs equal shares | 0.3059 |
| Rho-squared vs observed shares | 0.1753 |
| Adj.Rho-squared vs observed shares | 0.1744 |
| AIC | 1860.69 |
| BIC | 1889.73 |

Table E.1: Caption

### E.1.2. Parking time

**Utility functions**

$$U_{Walking} = ASC_{Walking} \tag{E.7}$$
$$U_{E-scooter} = ASC_{E-scooter} \tag{E.8}$$
$$U_{Bicycle} = ASC_{Bicycle} + Beta_{ParkingTime} * ParkingTime_{Bicycle} \tag{E.9}$$
$$U_{E-bike} = ASC_{E-bike} + Beta_{ParkingTime} * ParkingTime_{E-bike} \tag{E.10}$$
$$U_{Moped} = ASC_{Moped} + Beta_{ParkingTime} * ParkingTime_{Moped} \tag{E.11}$$
$$U_{Opt-out} = 0 \tag{E.12}$$

| Indicator | Value |
|---|---|
| LL(start) | -1340.42 |
| LL at equal shares, LL(0) | -1340.42 |
| LL at observed shares, LL(C) | -1120.76 |
| LL(final) | -1028.63 |
| Rho-squared vs equal shares | 0.2326 |
| Adj.Rho-squared vs equal shares | 0.2281 |
| Rho-squared vs observed shares | 0.0822 |
| Adj.Rho-squared vs observed shares | 0.0813 |
| AIC | 2069.26 |
| BIC | 2098.31 |

Table E.2: Indicators Parking time

### E.1.3. Ticket cost

**Utility functions**

$$U_{Walking} = ASC_{Walking} \tag{E.13}$$
$$U_{E-scooter} = ASC_{E-scooter} + Beta_{TicketCost} * TicketCost_{E-scooter} \tag{E.14}$$
$$U_{Bicycle} = ASC_{Bicycle} \tag{E.15}$$
$$U_{E-bike} = ASC_{E-bike} \tag{E.16}$$
$$U_{Moped} = ASC_{Moped} \tag{E.17}$$
$$U_{Opt-out} = 0 \tag{E.18}$$

| Indicator | Value |
|---|---|
| LL(start) | -1340.42 |
| LL at equal shares, LL(0) | -1340.42 |
| LL at observed shares, LL(C) | -1120.76 |
| LL(final) | -1094.47 |
| Rho-squared vs equal shares | 0.1835 |
| Adj.Rho-squared vs equal shares | 0.179 |
| Rho-squared vs observed shares | 0.0235 |
| Adj.Rho-squared vs observed shares | 0.0226 |
| AIC | 2200.94 |
| BIC | 2229.99 |

Table E.3: Indicators ticket cost

### E.1.4. In-vehicle time

**Utility functions**

$$U_{Walking} = ASC_{Walking} + +Beta_{InVehicle} * InVehicleTime \tag{E.19}$$

$$U_{E-scooter} = ASC_{E-scooter} + Beta_{InVehicle} * InVehicleTime \tag{E.20}$$

$$U_{Bicycle} = ASC_{Bicycle} + Beta_{InVehicle} * InVehicleTime \tag{E.21}$$

$$U_{E-bike} = ASC_{E-bike} + Beta_{InVehicle} * InVehicleTime \tag{E.22}$$

$$U_{Moped} = ASC_{Moped} + Beta_{InVehicle} * InVehicleTime \tag{E.23}$$

$$U_{Opt-out} = 0 \tag{E.24}$$

| Indicator | Value |
|---|---|
| LL(start) | -1340.42 |
| LL at equal shares, LL(0) | -1340.42 |
| LL at observed shares, LL(C) | -1120.76 |
| LL(final) | -1110.52 |
| Rho-squared vs equal shares | 0.1715 |
| Adj.Rho-squared vs equal shares | 0.167 |
| Rho-squared vs observed shares | 0.0091 |
| Adj.Rho-squared vs observed shares | 0.0082 |
| AIC | 2233.04 |
| BIC | 2262.09 |

Table E.4: Indicators in-vehicle time

F

# Validation models

This appendix shows the ten validation models created by a random 80 per cent of the data. The validation models all use the same utility functions as the final model as defined in chapter 6

## Validation model 1

Table F.1: Ouput of the validation models with a random 80 per cent of the data - Validation 1

| Attribute | Unit | estimates of validation 1 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.769 | $4.461e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.217 | $2.343e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.409 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.104 | $5.773e-15$ |
| $ASC_{Bike}$ | Utils | 5.758 | 0.000 |
| $ASC_{Walking}$ | Utils | 7.579 | 0.000 |
| $ASC_{Ebike}$ | Utils | 3.735 | $3.347e-06$ |
| $ASC_{Mopedscooter}$ | Utils | 2.857 | $1.500e-06$ |
| $\beta_{Experience}$ | Utils | 0.738 | 0.010 |
| $\beta_{Males}$ | Utils/min | 0.068 | 0.042 |
| $Y_{Moped}$ | Utils | -1.779 | $2.664e-04$ |
| $Y_{UseWalking}$ | Utils | 0.688 | 0.022 |
| $Y_{UseBike}$ | Utils | 0.790 | 0.003 |
| $Y_{UseEbike}$ | Utils | 2.930 | $3.84410e-05$ |

## Validation model 2

Table F.2: Ouput of the validation models with a random 80 per cent of the data - Validation 2

| Attribute | Unit | estimates of validation 2 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.690 | $4.461e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.236 | $2.343e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.445 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.303 | $5.773e-15$ |
| $ASC_{Bike}$ | Utils | 6.257 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.060 | 0.000 |
| $ASC_{Ebike}$ | Utils | 4.765 | $3.347e-06$ |
| $ASC_{Mopedscooter}$ | Utils | 3.294 | $6.444e-08$ |
| $\beta_{Experience}$ | Utils | 0.800 | 0.007 |
| $\beta_{Males}$ | Utils/min | 0.063 | 0.051 |
| $Y_{Moped}$ | Utils | -1.860 | $8.087e-04$ |
| $Y_{UseWalking}$ | Utils | 1.083 | 0.004 |
| $Y_{UseBike}$ | Utils | 0.732 | 0.008 |
| $Y_{UseEbike}$ | Utils | 1.980 | 0.002 |

## Validation model 3

Table F.3: Ouput of the validation models with a random 80 per cent of the data - Validation 3

| Attribute | Unit | estimates of validation 3 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.735 | $7.466e-08$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.223 | $1.121e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.444 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.107 | $6.106e-13$ |
| $ASC_{Bike}$ | Utils | 6.284 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.126 | 0.000 |
| $ASC_{Ebike}$ | Utils | 4.194 | $8.525e-07$ |
| $ASC_{Mopedscooter}$ | Utils | 3.403 | $1.002e-08$ |
| $\beta_{Experience}$ | Utils | 0.909 | 0.004 |
| $\beta_{Males}$ | Utils/min | 0.054 | 0.078 |
| $Y_{Moped}$ | Utils | -1.851 | 0.003 |
| $Y_{UseWalking}$ | Utils | 0.827 | 0.002 |
| $Y_{UseBike}$ | Utils | 0.770 | 0.003 |
| $Y_{UseEbike}$ | Utils | 3.141 | $1.730e-05$ |

# Validation model 4

Table F.4: Ouput of the validation models with a random 80 per cent of the data - Validation 4

| **Attribute** | **Unit** | **estimates of validation 4** | **P-value** |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.643 | $3.321e-07$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.209 | $4.506e-12$ |
| $\beta_{TravelTime}$ | Utils/min | -0.467 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.878 | 0.000 |
| $ASC_{Bike}$ | Utils | 6.774 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.937 | 0.000 |
| $ASC_{Ebike}$ | Utils | 5.353 | $9.068e-12$ |
| $ASC_{Mopedscooter}$ | Utils | 2.917 | $5.891e-06$ |
| $\beta_{Experience}$ | Utils | 0.618 | 0.036 |
| $\beta_{Males}$ | Utils/min | 0.072 | 0.050 |
| $Y_{Moped}$ | Utils | -2.570 | $9.901e-07$ |
| $Y_{UseWalking}$ | Utils | 0.496 | 0.056 |
| $Y_{UseBike}$ | Utils | 0.808 | 0.003 |
| $Y_{UseEbike}$ | Utils | 1.815 | 0.006 |

# Validation model 5

Table F.5: Ouput of the validation models with a random 80 per cent of the data - Validation 5

| **Attribute** | **Unit** | **estimates of validation 5** | **P-value** |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.709 | $2.185e-09$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.212 | $2.569e-12$ |
| $\beta_{TravelTime}$ | Utils/min | -0.482 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.558 | $6.217e-15$ |
| $ASC_{Bike}$ | Utils | 6.377 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.882 | 0.000 |
| $ASC_{Ebike}$ | Utils | 4.734 | $8.598e-09$ |
| $ASC_{Mopedscooter}$ | Utils | 2.021 | 0.004 |
| $\beta_{Experience}$ | Utils | 0.933 | 0.003 |
| $\beta_{Males}$ | Utils/min | 0.045 | 0.113 |
| $Y_{Moped}$ | Utils | -2.058 | $1.074e-04$ |
| $Y_{UseWalking}$ | Utils | 0.417 | 0.100 |
| $Y_{UseBike}$ | Utils | 1.112 | $5.989e-05$ |
| $Y_{UseEbike}$ | Utils | 2.455 | $3.879e-04$ |

# Validation model 6

Table F.6: Ouput of the validation models with a random 80 per cent of the data - Validation 6

| Attribute | Unit | estimates of validation 6 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.751 | $1.754e-09$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.252 | $6.661e-16$ |
| $\beta_{TravelTime}$ | Utils/min | -0.445 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.276 | $1.632e-14$ |
| $ASC_{Bike}$ | Utils | 6.263 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.084 | 0.000 |
| $ASC_{Ebike}$ | Utils | 4.342 | $6.287e-07$ |
| $ASC_{Mopedscooter}$ | Utils | 3.358 | $3.913e-08$ |
| $\beta_{Experience}$ | Utils | 0.901 | 0.003 |
| $\beta_{Males}$ | Utils/min | 0.069 | 0.028 |
| $Y_{Moped}$ | Utils | -2.023 | $4.461e-04$ |
| $Y_{UseWalking}$ | Utils | 0.880 | 0.005 |
| $Y_{UseBike}$ | Utils | 1.023 | $1.650e-04$ |
| $Y_{UseEbike}$ | Utils | 2.310 | 0.001 |

# Validation model 7

Table F.7: Ouput of the validation models with a random 80 per cent of the data - Validation 7

| Attribute | Unit | estimates of validation 7 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.769 | $4.461e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.217 | $2.343e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.409 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.104 | $5.773e-15$ |
| $ASC_{Bike}$ | Utils | 5.758 | 0.000 |
| $ASC_{Walking}$ | Utils | 7.579 | 0.000 |
| $ASC_{Ebike}$ | Utils | 3.735 | $3.347e-06$ |
| $ASC_{Mopedscooter}$ | Utils | 2.857 | $1.500e-06$ |
| $\beta_{Experience}$ | Utils | 0.738 | 0.010 |
| $\beta_{Males}$ | Utils/min | 0.068 | 0.042 |
| $Y_{Moped}$ | Utils | -1.779 | $2.664e-04$ |
| $Y_{UseWalking}$ | Utils | 0.688 | 0.022 |
| $Y_{UseBike}$ | Utils | 0.790 | 0.003 |
| $Y_{UseEbike}$ | Utils | 2.930 | $3.84410e-05$ |

# Validation model 8

Table F.8: Ouput of the validation models with a random 80 per cent of the data - Validation 8

| Attribute | Unit | estimates of validation 8 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.752 | N/A |
| $\beta_{ParkingTime}$ | Utils/min | -0.204 | N/A |
| $\beta_{TravelTime}$ | Utils/min | -0.452 | N/A |
| $ASC_{Escooter}$ | Utils | 4.382 | N/A |
| $ASC_{Bike}$ | Utils | 6.120 | N/A |
| $ASC_{Walking}$ | Utils | 8.448 | N/A |
| $ASC_{Ebike}$ | Utils | 4.560 | N/A |
| $ASC_{Mopedscooter}$ | Utils | -260.585 | N/A |
| $\beta_{Experience}$ | Utils | 0.993 | N/A |
| $\beta_{Males}$ | Utils/min | 0.076 | N/A |
| $Y_{Moped}$ | Utils | -1.547 | N/A |
| $Y_{UseWalking}$ | Utils | 0.801 | N/A |
| $Y_{UseBike}$ | Utils | 0.988 | N/A |
| $Y_{UseEbike}$ | Utils | 2.194 | N/A |

# Validation model 9

Table F.9: Ouput of the validation models with a random 80 per cent of the data - Validation 9

| Attribute | Unit | estimates of validation 9 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.835 | $1.436e-10$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.217 | $8.037e-13$ |
| $\beta_{TravelTime}$ | Utils/min | -0.457 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.673 | $9.992e-16$ |
| $ASC_{Bike}$ | Utils | 6.358 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.446 | 0.000 |
| $ASC_{Ebike}$ | Utils | 4.279 | $1.198e-06$ |
| $ASC_{Mopedscooter}$ | Utils | 3.227 | $8.795e-08$ |
| $\beta_{Experience}$ | Utils | 0.661 | 0.022 |
| $\beta_{Males}$ | Utils/min | 0.085 | 0.026 |
| $Y_{Moped}$ | Utils | -2.130 | $1.181e-04$ |
| $Y_{UseWalking}$ | Utils | 0.792 | 0.009 |
| $Y_{UseBike}$ | Utils | 0.768 | 0.004 |
| $Y_{UseEbike}$ | Utils | 2.242 | 0.002 |

## Validation model 10

Table F.10: Ouput of the validation models with a random 80 per cent of the data - Validation 10

| Attribute | Unit | estimates of validation 10 | P-value |
|---|---|---|---|
| $\beta_{TravelCost}$ | Utils/Euro | -0.883 | $8.506e-11$ |
| $\beta_{ParkingTime}$ | Utils/min | -0.233 | $4.852e-14$ |
| $\beta_{TravelTime}$ | Utils/min | -0.487 | 0.000 |
| $ASC_{Escooter}$ | Utils | 4.882 | 0.000 |
| $ASC_{Bike}$ | Utils | 6.892 | 0.000 |
| $ASC_{Walking}$ | Utils | 8.711 | 0.000 |
| $ASC_{Ebike}$ | Utils | 4.967 | $7.382e-11$ |
| $ASC_{Mopedscooter}$ | Utils | 4.165 | $5.437e-12$ |
| $\beta_{Experience}$ | Utils | 0.549 | 0.053 |
| $\beta_{Males}$ | Utils/min | 0.054 | 0.085 |
| $Y_{Moped}$ | Utils | -2.832 | 0.005 |
| $Y_{UseWalking}$ | Utils | 1.027 | 0.001 |
| $Y_{UseBike}$ | Utils | 0.586 | 0.020 |
| $Y_{UseEbike}$ | Utils | 1.962 | 0.003 |

# G

# Simulation

## G.1. List of subgroups in the simulation

For the simulation, there are 26 subgroups based on the attributes of the final model estimated in chapter 6. Table G.1 list the 26 subgroups.

| Number | Gender | Current use | Specific vehicle ownership |
|---|---|---|---|
| 1 | Male | Walking | Moped & E-bike |
| 2 | Male | Walking | Moped |
| 3 | Male | Walking | E-bike |
| 4 | Male | Walking | - |
| 5 | Male | Cycling | Moped & E-bike |
| 6 | Male | Cycling | Moped |
| 7 | Male | Cycling | E-bike |
| 8 | Male | Cycling | - |
| 9 | Male | Ebike | Moped & E-bike |
| 10 | Male | Ebike | Moped |
| 11 | Male | Ebike | E-bike |
| 12 | Male | Ebike | - |
| 13 | Male | Other | - |
| 14 | Female | Walking | Moped & E-bike |
| 15 | Female | Walking | Moped |
| 16 | Female | Walking | E-bike |
| 17 | Female | Walking | - |
| 18 | Female | Cycling | Moped & E-bike |
| 19 | Female | Cycling | Moped |
| 20 | Female | Cycling | E-bike |
| 21 | Female | Cycling | - |
| 22 | Female | Ebike | Moped & E-bike |
| 23 | Female | Ebike | Moped |
| 24 | Female | Ebike | E-bike |
| 25 | Female | Ebike | - |
| 26 | Female | Other | - |

Table G.1: Subgroups of the simulation

## G.2. Representative percentage of the subgroups

The 26 defined subgroups represent a part of the population sample used from ODiN. The influence each subgroup has on the total sample is based on the percentage of the ODiN sample they represent. Table G.2 displays the percentage each subgroup represents. Not every subgroup in the model influences the simulation, and another significant number of subgroups only influence the model slightly. Subgroups that are not currently present in the sample are marked with grey.

| Number | N | Percentage of gender ($N/N_{Gender}$) | Percentage of total ($N/N_{total}$) |
|---|---|---|---|
| Male | 4720 | 100 | 51.33 |
| 1 | 2 | 0.04 | 0.02 |
| 2 | 67 | 1.42 | 0.73 |
| 3 | 150 | 3.18 | 1.63 |
| 4 | 1923 | 40.74 | 20.91 |
| 5 | 0 | - | - |
| 6 | 34 | 0.72 | 0.37 |
| 7 | 56 | 1.19 | 0.61 |
| 8 | 1234 | 26.14 | 13.42 |
| 9 | 0 | - | - |
| 10 | 3 | 0.06 | 0.03 |
| 11 | 23 | 0.49 | 0.25 |
| 12 | 4 | 0.08 | 0.04 |
| 13 | 1224 | 25.93 | 13.31 |
| Female | 4475 | 100 | 48.67 |
| 14 | 1 | 0.02 | 0.01 |
| 15 | 33 | 0.74 | 0.36 |
| 16 | 112 | 2.50 | 1.22 |
| 17 | 1713 | 38.28 | 18.63 |
| 18 | 1 | 0.02 | 0.01 |
| 19 | 6 | 0.13 | 0.07 |
| 20 | 45 | 1.01 | 0.49 |
| 21 | 5 | 24.94 | 12.14 |
| 22 | 1 | 0.02 | 0.01 |
| 23 | 0 | - | - |
| 24 | 20 | 0.45 | 0.22 |
| 25 | 5 | 0.11 | 0.05 |
| 26 | 1442 | 31.78 | 15.46 |

Table G.2: Representation of the subgroups in the used sample