Master Thesis - 7CC40 - Study load: 40 EC

Analyzing the Influence of Risk and Uncertainty in Transportation Mode Choice Involving Shared Micro-Mobility

February 2025 - September 2025
Year of Graduation: 2025 - 2026
Master's program: Construction Management and Engineering

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Eindhoven September 8, 2025

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Summary

Shared micro-mobility, such as shared e-bikes and shared e-mopeds, have the potential to solve current challenges urban mobility faces concerning the first- and last-mile of transportation. The flexible, on-demand, and short-term nature of shared micro-mobility fits the requirements for realizing first- and last-mile mobility. However, in many cities, actual usage patterns remain low. This limits the realization of the benefits of shared micro-mobility, which are both economical and sustainable. It is therefore important to understand how uptake in shared micro-mobility can be achieved. Aspects of shared micro-mobility that potentially prevent people from usage are the risks and uncertainties associated with the mode. Some examples are the availability of vehicles, which is especially uncertain in systems where vehicles can be parked anywhere in a service area, and uncertainty in the maintenance level of the vehicle. This results in various time- and safety-related risks, which people are not always willing to take.

To better understand decision-making behavior in situations involving uncertainty, Cumulative Prospect Theory (CPT) could be applied. This is a behavioral framework that recognizes that people react differently to situations that involve uncertainties and risks. In CPT, people do not see outcomes objectively, but rather place them as gains or losses compared to a reference point. These gains and losses are often treated differently, caused by a level of loss aversion. Next to this, CPT recognizes that people often distort probabilities, leading to underweighting high probabilities, and overweighting smaller probabilities. These elements influence how people see alternatives and thus make decisions. Research looking into the influence of the elements of uncertainty and risk in shared micro-mobility is scarce, showing a gap in literature. This research aims to fill this gap by applying CPT to understand the influence of risk and uncertainty in mode choice for shared micro-mobility, combining this with broadening the understanding of the importance of different attributes on decision-making for shared micro-mobility.

After a literature review, the price of a trip, the access time (the time it takes to walk to a shared e-moped), the maintenance level, and the remaining range of a shared e-moped have been chosen as attributes to be analyzed. Uncertainty is involved in both the access time and maintenance level-attributes, while using reference points to measure the cost, access time, and maintenance level-attributes as gains and losses. This research is operationalized by constructing an unlabeled stated-choice experiment. Each respondent is faced with 9 choice sets, each containing 2 alternative hypothetical trips with a shared e-moped. Each e-moped has a unique profile, consisting of the aforementioned attributes and levels of uncertainty. In each choice task, the respondent chooses the preferred alternative. The experiment was part of a larger survey that asked for travel patterns, experience with shared e-mopeds, and socio-demographics such as age and gender.

Data collection for this research was performed in the city of Enschede, in the East of the Netherlands. This survey was distributed through, among other channels, social media, field work in Enschede, and personal contacts. This resulted in a total of 280 responses, of which 21 were removed in data cleaning due to non-serious participation, invalid answers, or too high durations.

Choices were modeled using a utility function that included the elements of CPT and the aforementioned attributes. Choice probabilities were then estimated from the results of the survey using a multinomial logit model. Using Maximum Likelihood Estimation in Python, parameter and coefficient estimates were determined. These estimates were then interpreted to understand the importance of the different attributes, as well as the extent to which phenomena such as loss aversion and probability distortion play a role.

From the results, it became clear that respondents show little to no loss aversion in their choices. Losses were thus valued approximately the same as gains. Regarding probability distortion, probabilities related to gains were heavily distorted, causing underestimation of high- and medium-level probabilities. These phenomena have an impact on the importance of each of the attributes. By comparing the contributions of each of the attributes to utility at different attribute values, the importance of these attributes could be compared and the trade-offs respondents make regarding the different attributes could be analyzed.

Comparing the cost and access time-attributes, it was found that, under different levels of uncertainty, people would rather save money by spending additional time walking to a shared e-moped than spending money to save time, showing that the price of a trip is more important than the distance to a shared e-moped. As the certainty of availability decreases, access time gets more important. Looking at the maintenance level of a vehicle, people show risk-avoiding behavior. While a vehicle can be in either one of three states (excellent, average, and poor), each with a certain probability, having a higher probability of a 'Poor' vehicle decreases utility more heavily than increasing the chance at an 'Excellent' vehicle has a positive effect on the willingness to use. For example, increasing the chance at an 'Excellent' vehicle with 10% by decreasing the chance at a 'Poor' vehicle with the same amount results in a potential price increase of €0,37 (keeping the 'Average' state probability constant), while an equivalent change the other way around should result in a €0,89 reduction in price. Maintaining vehicles above the 'Poor' maintenance level is thus very important. Looking at the remaining range of a vehicle, it is important to keep the battery charge of a vehicle above 50%. While people would be willing to pay €0,83 extra for an e-moped with a 50% charge compared to a 20% charge, this is only €0,36 for an 80% charge compared to a 50% charge.

The importance of each of the attributes differs per socio-demographic group. It was found that people who have experience using a shared e-mopeds show less sensitivity to the cost of the trip. This is likely caused by the changed perception of the value of shared e-mopeds because of using the vehicles. Also, people who commute quite often, 3 to 4 times a week, are less sensitive to the price of the trip compared to those who do not commute often, which is likely related to the fact that transportation costs are already a part of their budget, where this is not the case for those who do not commute often. Regarding the remaining range of vehicles, people who have 3 to 4 leisure trips each week find having a fully charged vehicle less important, while also reacting less negatively to vehicles with a low charge. This is likely caused by the adaptability in their transport pattern. People who travel for leisure daily have more sophisticated travel patterns, showing greater reliance on their usual way of transport and thus increased importance on fully charged vehicle.

Concluding, this research has found the importance of cost, access time, maintenance level, and the remaining range of a vehicle regarding the choice to use shared e-mopeds considering risk and uncertainty through the framework of CPT. This involved the inclusion of phenomena such as loss aversion, reference dependence, and probability distortion in decision-making. This research has broadened the understanding of factors that play a role in transportation mode choice for shared micro-mobility, while providing practitioners with insights that can be used to create an environment that stimulates usage. Future research directions could include, among others, the addition of different attributes, labeled experiment designs to investigate mode switching behavior, and the development of simulation models to be able to see the impacts of certain situations or policy changes in real life. Limitations to this research should be taken into account in interpretation, such as the limited generalizability due to sample distribution and assumptions underlying the multinomial logit model that has been used.

Samenvatting

Deelmicromobiliteit, zoals elektrische deelfietsen of deelscooters, zijn potentiële oplossingen voor de uitdagingen binnen de stedelijke mobiliteit op het gebied van de eerste en de laatste kilometer. De flexibiliteit, korte gebruiksduur, en mogelijkheid op aanvraag gebruik te maken van de dienst zijn redenen waarom deelmicromobiliteit een goede oplossing voor de eerste en laatste kilometer kan zijn. Echter is het gebruik in veel steden nog te laag. Dit zorgt ervoor dat de economische en duurzame voordelen van deelmicromobiliteit niet (volledig) gerealiseerd worden. Het is daarom belangrijk om te begrijpen hoe het gebruik van deelmicromobiliteit gestimuleerd kan worden. Twee van de redenen die potentiële gebruikers weerhoudt van het gebruik van de vervoerswijze zijn de risico's en onzekerheden die het gebruik met zich meebrengt. Voorbeelden hiervan zijn de beschikbaarheid van voertuigen, vooral in systemen waarbij voertuigen vrij in een servicegebied kunnen worden geparkeerd, en de onzekerheid in het onderhoudsniveau van een voertuig. Dit zorgt voor tijds- en veiligheids-gerelateerde risico's die potentiële gebruikers niet altijd durven te nemen.

Om de besluitvorming van potentiële gebruikers in situaties met onzekerheid beter te kunnen begrijpen kan de *Cumulative Prospect Theory* (CPT) worden toegepast. Dit is een gedragstheorie die erkent dat mensen anders reageren op situaties waarin onzekerheden en risico's zijn betrokken. Volgens CPT bekijken mensen uitkomsten niet objectief, maar plaatsen zij deze als een winst of verlies ten opzichte van een referentiepunt. Winsten en verliezen worden vaak anders behandeld door de invloed van verliesaversie. Daarnaast erkent CPT dat mensen kansen vertekenen, wat ervoor zorgt dat grote kansen worden onderschat en kleinere kansen worden overschat. Deze elementen hebben invloed op hoe mensen een alternatief zien en dus op hun keuzes. Onderzoek naar hoe risico en onzekerheid invloed hebben op de keuze voor deelmicromobiliteit is schaars, wat een gat in de literatuur aantoont. Dit onderzoek heeft als doel dit gat op te vullen door CPT toe te passen om te begrijpen hoe risico en onzekerheid invloed hebben op de keuze voor deelmicromobiliteit. Daarnaast heeft dit onderzoek als doel bij te dragen aan de verbreding van kennis over het belang van verschillende factoren in het keuzeproces voor deelmicrobiliteit.

Na een uitgebreid literatuuronderzoek zijn de prijs van een rit, de toegangstijd (de tijd om naar een voertuig toe te lopen), het onderhoudsniveau van een voertuig en het resterend bereik van het voertuig gekozen als factoren die worden geanalyseerd. Onzekerheid wordt betrokken in zowel de toegangstijd als het onderhoudsniveau. Referentiepunten worden gebruikt om de prijs, de toegangstijd, en het onderhoudsniveau als winsten of verliezen te kunnen beschouwen. Dit onderzoek wordt uitgevoerd door middel van een ongelabeld keuze-experiment. Iedere respondent krijgt 9 keuzesets, elk met 2 hypothetische trips met een deelscooter. Iedere deelscooter heeft een uniek profiel bestaande uit de hierboven genoemde factoren, rekening houdend met een mate van onzekerheid. Bij iedere keuze kiest de respondent de geprefereerde rit van de 2 alternatieven. Dit experiment was onderdeel van een grotere enquête met vragen over reispatronen, ervaring met deelscooters, en sociaal-demografische gegevens zoals leeftijd en geslacht.

Dataverzameling voor dit onderzoek vond plaats in Enschede. De enquête werd verspreid via onder andere sociale media, veldwerk in Enschede en persoonlijke contacten. Dit resulteerde in een totaal van 280 ingevulde enquêtes, waarvan er 21 zijn verwijderd tijdens het opschonen van de data door onserieuze deelname, invalide antwoorden of een te hoge tijdsduur.

Keuzes werden gemodeleerd door middel van een nutsfunctie die onderdelen van CPT en de eerdergenoemde factoren bevatte. De kans dat een alternatief werd gekozen werd vervolgens geschat door middel van een multinomiaal logit model. *Maximum Likelihood Estimation* door middel van Python werd gebruikt om de waardes van parameters en coefficienten te benaderen. Deze benaderingen

werden vervolgens geïnterpreteerd om het aandeel van de verschillende factoren en de invloed van verliesaversie en kansvervorming in de keuze voor deelmobiliteit te begrijpen.

Uit de resultaten werd duidelijk dat respondenten zeer weinig tot geen verliesaversie tonen in hun keuzes. Verliezen en winsten worden bijna hetzelfde behandeld. Kijkend naar kansvervorming worden kansen op winsten hevig vervormd, waardoor grote- en middelgrote kansen onderschat worden. Dit heeft invloed op het belang van iedere factor in het maken van keuzes. Door de bijdrage van iedere factor aan de waarde van de nutsfunctie te vergelijken kan het belang van ieder attribuut worden bekeken en de afwegingen die respondenten maken met betrekking tot de factoren worden geanalyseerd.

Bij het vergelijken van de prijs van een rit met de toegangstijd werd duidelijk dat, onder verschillende gradaties van onzekerheid, men liever geld bespaard door een extra afstand te lopen dan dat men tijd bespaard door meer voor een rit te betalen. Dit toont aan dat de prijs van een rit belangrijker is dan de afstand naar een deelscooter. Naar mate de onzekerheid groeit wordt de toegangstijd belangrijker. Kijkend naar de impact van het onderhoudsniveau van een voertuig vertonen mensen risicomijdend gedrag. Waar een voertuig zich in 3 verschillende toestanden (uitstekend, gemiddeld en ondergemiddeld) kan bevinden, ieder met een bepaalde kans, zorgt een hogere kans op een ondergemiddeld voertuig voor een hevigere daling in de nutswaarde dan dat een hogere kans op een uitstekend voertuig voor een stijging zorgt. Een 10% grotere kans op een uitstekend voertuig door de kans op een ondergemiddeld voertuig hiermee te verlagen zorgt bijvoorbeeld voor een potentiële prijsstijging van €0,37, terwijl de omgekeerde situatie een prijsverlaging van €0,89 zou moeten geven; de prijs die men wil betalen voor een uitstekend voertuig is dus lager dan de prijsverlaging die nodig is om het negatieve effect van een ondergemiddeld voertuig tegen te werken. Het is dus erg belangrijk om het onderhoudsniveau van een voertuig boven ondergemiddeld te houden. Het is daarnaast belangrijk het resterend bereik van een voertuig boven 50% te houden. Mensen zijn bereid €0,83 extra te betalen voor een deelscouter met een resterend bereik van 50% vergeleken met een bereik van 20%, terwijl dit maar €0,36 is voor een bereik van 80% tegenover 50%.

Het belang van de factoren kan verschillen per sociaal-demografische groep. Zo werd het bijvoorbeeld duidelijk dat personen die reeds een deelscooter hadden gebruikt minder gevoelig zijn voor de prijs van een rit. Dit komt waarschijnlijk door het veranderd beeld van de waarde van deelscooters dat deze personen hebben. Daarnaast zijn mensen die redelijk vaak, zo'n 3 tot 4 keer per week, reizen met woon-werkverkeer als doel ook minder gevoelig voor de prijs van een rit. Dit heeft mogelijk als reden dat de prijs van woon-werkverkeer reeds in hun budget is meegenomen, waar dit voor mensen die minder vaak met deze reden reizen niet zo is. Mensen die 3 tot 4 keer per week voor vrijetijdsbesteding reizen vinden het minder belangrijk een volgeladen voertuig te hebben vergeleken met mensen die minder vaak met dit doel reizen. Zij reageren ook minder heftig op een scooter met een laag resterend bereik. Een reden hiervoor kan de flexibiliteit in het reispatroon van deze mensen zijn. Mensen die dagelijks voor vrijetijdsbesteding reizen hebben een groter belang bij een volgeladen voertuig. Dit kan verklaard worden doordat zij een vaster reispatroon hebben, wat ervoor zorgt dat deze mensen meer afhankelijkheid van hun vaste manier van reizen tonen.

Concluderend heeft dit onderzoek het belang van de kosten, de toegangstijd, het onderhoudsniveau en het resterend bereik van een voertuig in de keuze voor deelscooters onderzocht. Hierbij werd rekening gehouden met onzekerheid en risico door middel van het gebruik van CPT. Hierbij werden verliesaversie, de afhankelijkheid van een referentiepunt, en kansvervorming meegenomen in het keuzeproces. Dit onderzoek heeft de kennis over de factoren die een rol spelen in de keuze voor deelmicromobiliteit verbreed. Hierbij zijn inzichten gegenereerd die beleidsmakers en dienstverleners kunnen helpen bij het creëeren van een omgeving waarin het gebruik van deelscooters wordt gestimuleerd.

Vervolgonderzoek kan in verschillende richtingen worden gedaan. Zo kunnen nieuwe factoren worden toegevoegd, kan een gelabeld onderzoek worden toegepast om het gedrag omtrent het wisselen van vervoerswijze te analyseren, of kan een simulatiemodel worden ontwikkeld waarbij de impact van verschillende situaties of beleidsveranderingen gesimuleerd kan worden. Er zijn enkele limitaties aan dit onderzoek waar rekening mee gehouden moet worden, zoals de beperkte generaliseerbaarheid door de verdeling van de respondenten en de aannames die horen bij het gebruik van het multinomiaal logit model.

Abstract

Urban mobility is facing challenges in the effective and efficient transportation of people within cities, especially regarding the first- and last-mile of transportation. A potential solution for this is shared micro-mobility, however, limited usage in urban environments limits the potential economical and sustainable benefits. In order to increase uptake, broadened understanding of the importance of different attributes in the decision-making process for shared micro-mobility is necessary. A particular element of interest is the number of uncertainties and risks involved. While uncertainties and risks such as safety and availability have been brought to light, the impact of these uncertainties on mode choice has been scarcely researched. Therefore, this research investigates the impact of different attributes on decision-making for shared micro-mobility, while considering the risks and uncertainties associated with the mode using Cumulative Prospect Theory (CPT). A stated-choice experiment has been distributed in the region of Enschede to collect data on choices for shared e-mopeds in scenarios that involve uncertainty. The results of this experiment are analyzed using a multinomial logit model that includes a utility function involving Cumulative Prospect Value functions. Coefficients describing the importance of attributes as well as parameters that capture human behavior are estimated. Results show that costs, access time, maintenance level, and the remaining range of the vehicle play a role in decision-making. Users prefer walking an extra distance to save money, highlighting the importance of costs, while access time is increasingly important as the certainty of availability decreases. People are willing to pay for more certainty, showing risk averse behavior. The same behavior is shown in the fact that poor maintenance and a low remaining range decrease the likelihood of usage. Results have furthermore shown that respondents show little signs of loss aversion, but clear signs of probability distortion for gains. No probability distortion is present for losses. This research has broadened the understanding of factors that play a role in the decision-making for shared e-mopeds and results present insights to policy makers and service providers regarding the development of strategies to promote usage.

Keywords: Shared micro-mobility, transportation mode choice, decision-making behavior, cumulative prospect theory

List of Acronyms

ASC Alternative-Specific Constant. 41

CPT Cumulative Prospect Theory. 11–13, 15, 16, 18, 19, 25–32, 34, 38, 39, 41, 49, 51, 52, 62–64, 80, 82, 84, 86, 88

DCE Discrete Choice Experiment. 23–25, 30, 82

IIA Independence of Irrelevant Alternatives. 36, 50, 87

MLE Maximum Likelihood Estimation. 49

MNL Multinomial Logit. 50–52, 62, 82, 84, 87

RR Remaining Range. 12–14, 18, 34, 35, 37–39, 41, 42, 46, 70, 73, 74, 80–85

SCE Stated Choice Experiment. 11, 16, 18, 24, 31, 33, 36, 44, 46, 51, 82, 84, 86

SMM Shared Micro-mobility. 11, 13, 14, 16, 18–24, 26, 31–37, 39, 40, 59, 60, 68, 80, 82–87

VTS Value of Time Saved. 37

WTP Willingness to Pay. 36, 53

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1 Introduction

1.1 Problem definition and objective

Urban mobility has transformed over the years, but is currently facing major challenges, especially regarding the fulfillment of the first- and last-mile of transportation. As populations grow, congestion and inefficiencies in the transportation systems limit accessibility in cities. Public transport systems effectively serve corridors and strategic hubs but leave gaps in accessibility for individuals whose destination is not in these areas.

Shared Micro-mobility (SMM) has emerged as a potential solution to fulfill this first- or last-mile of transportation. SMM offers small-scale, short-term, on-demand access to transport such as bicycles, mopeds, or scooters (Behrendt et al., 2022; Shaheen et al., 2022). Even though SMM shows potential for more sustainable urban transport and advantages for travelers such as flexible usage and the absence of needing a private vehicle, usage patterns of SMM remain relatively low and many cities struggle to effectively integrate SMM into their mobility network. On different aspects, studies have shown that SMM shows negative or underwhelming results, such as unwanted modal shifts (Diallo et al., 2023), environmental benefits that are lower than expected (Sun et al., 2023), and safety issues leading to increased incidents (Mehranfar & Jones, 2024). An increase in uptake by users is required to make use of the potential benefits of SMM. In order to influence this uptake, it is important to understand how certain factors influence people to use SMM. Therefore, research into the decision-making of individuals regarding SMM is essential.

Various factors can influence the choice for SMM, ranging from cost and time ((Jie et al., 2021), (Roig-Costa et al., 2024)) to the weather conditions (Hosseinzadeh et al., 2021) and attitudinal factors ((Jie et al., 2021), (van Kuijk et al., 2022)). Besides the variety of factors, SMM involves many uncertainties, such as availability and reliability of vehicles, that potentially make the choice for the mode more complex. These uncertainties cause individuals to have to consider risk in their decisions, such as the risk of not arriving at their destination in time, or the risk of a long waiting time.

Research into transportation mode choice has for a long time focused on rational decision-making models. However, people do not always make rational decisions. Various theories acknowledge this and try to explain decision making without full rationality. One theory that offers a framework that carefully handles uncertainty and risk in decision-making is the Cumulative Prospect Theory (CPT) (Tversky & Kahneman, 1992). This theory states that individuals look at options in terms of gains or losses compared to a reference point. People often react to these losses more heavily than they would to equivalent gains and judge chances or risks differently than they are in real-life. CPT explicitly deals with uncertainty and risk by modeling how individuals interpret and weigh potential outcomes, often underweighting large probabilities while over-weighting smaller ones. Besides, CPT deals with probabilities cumulatively, meaning that it looks at the probabilities of all gains or losses together. People do not treat outcomes independently, but rather look at all outcomes that are at least as good (or bad) and add the probabilities up. While CPT has been applied in transportation mode choice for different modes, it is yet to be applied to SMM in particular, presenting a gap in understanding how individuals deal with the uncertainties of SMM when considering the mode. Applying CPT to this sector of mobility shows high potential because of the uncertainties involved with SMM, including uncertain access times, maintenance levels and the Remaining Range (RR) of a vehicle. The level of trust in SMM is lower than other modes of transport, creating a tendency to overweight small probabilities of negative events and underweighting favorable probabilities.

The objective of this research is to gain a better understanding how variables such as cost, maintenance levels and RR influence the decision-making process in transportation mode choices including SMM. Furthermore, this research wants to gain an understanding in the decision-making behavior of individuals in situations that include uncertainty. The presence or absence of psychological biases such as loss aversion, probability weighting, and reference dependence is examined. By gaining deeper understanding of the above concepts, policy makers and service providers can design a better, more effective and more attractive environment for SMM in which usage is stimulated.

Data collection for this research is carried out in the city of Enschede, in the East of the Netherlands. Enschede is a city with high potential for the use of SMM because of the travel distances around the city, and its focus on sustainable innovations. For design considerations, the context of this city has been used to shape decisions, such as the mode of SMM (shared e-mopeds), costs, and trip distance.

1.2 Research questions

As mentioned, the main goal of this research is to better understand how risk and uncertainty influence transportation mode choice using CPT, with a particular focus on psychological mechanisms such as probability weighting and reference dependence. The main research question is therefore formulated as:

What is the importance of various trip- and vehicle-related factors and characteristics of individuals in the decision-making process for shared micro-mobility, particularly considering uncertainty and risk, and how do loss aversion, reference dependence and probability weighing play a role in these considerations?

Sub-questions are formulated to help answer the main research question in detail:

1. What is the current knowledge on shared micro-mobility systems, research into shared micro-mobility and transportation mode choice, and influential factors in the decision-making process for shared micro-mobility, and how can this knowledge be applied?
2. How can the Cumulative Prospect Theory be applied to model decision-making under uncertainty and risk in mode choice involving shared micro-mobility?
3. How do trip- and vehicle-related factors influence the decision-making process for shared e-mopeds?
4. How do potential users trade-off different trip- and vehicle-related variables?
5. How do different socio-demographics influence the relative importance of different variables?

1.3 Research design

The design of this research is schematically drawn in Figure 1. In order to answer the research questions formulated before, first, a literature review focusing mainly on three elements has been performed. This review looked into current state-of-the-art research practices in SMM and transportation mode choice research in general. SMM was also explored as a whole. The results of these reviews have been combined to find factors that potentially influence the choice for SMM. The theoretical framework that has been applied in this research, CPT, was also reviewed to understand general implications and current applications of the theory. From the literature review, information has been combined to inform the development of the Stated Choice Experiment (SCE). This phase included several steps, starting with the overall design of the experiment. After this, the selection of attributes and the levels of these attributes was performed. From this, the experimental design was generated, which is combined with further questions into a survey that has been sent out. Data was gathered, processed, and cleaned to prepare for data analysis. This included the development of a multinomial logit model for analysis and the generation of fake data for model validation. The gathered and cleaned data was then analyzed to test for the level and type of influence of the design attributes on mode choice. The utility function that was used in the model included Cumulative Prospect Value functions to account for the effects of uncertainty and risk. Data was analyzed and parameters were estimated by maximizing log-likelihood function (or minimizing the negative log-likelihood function), as will be elaborated on further in this report. This was done using Python including packages such as SciPy, Pandas and Numpy. Results have been estimated and interpreted, after which a discussion of the implications of the results is provided, including recommendations for the application of the results for both scientific and societal purposes. Limitations and directions for future research are also provided.

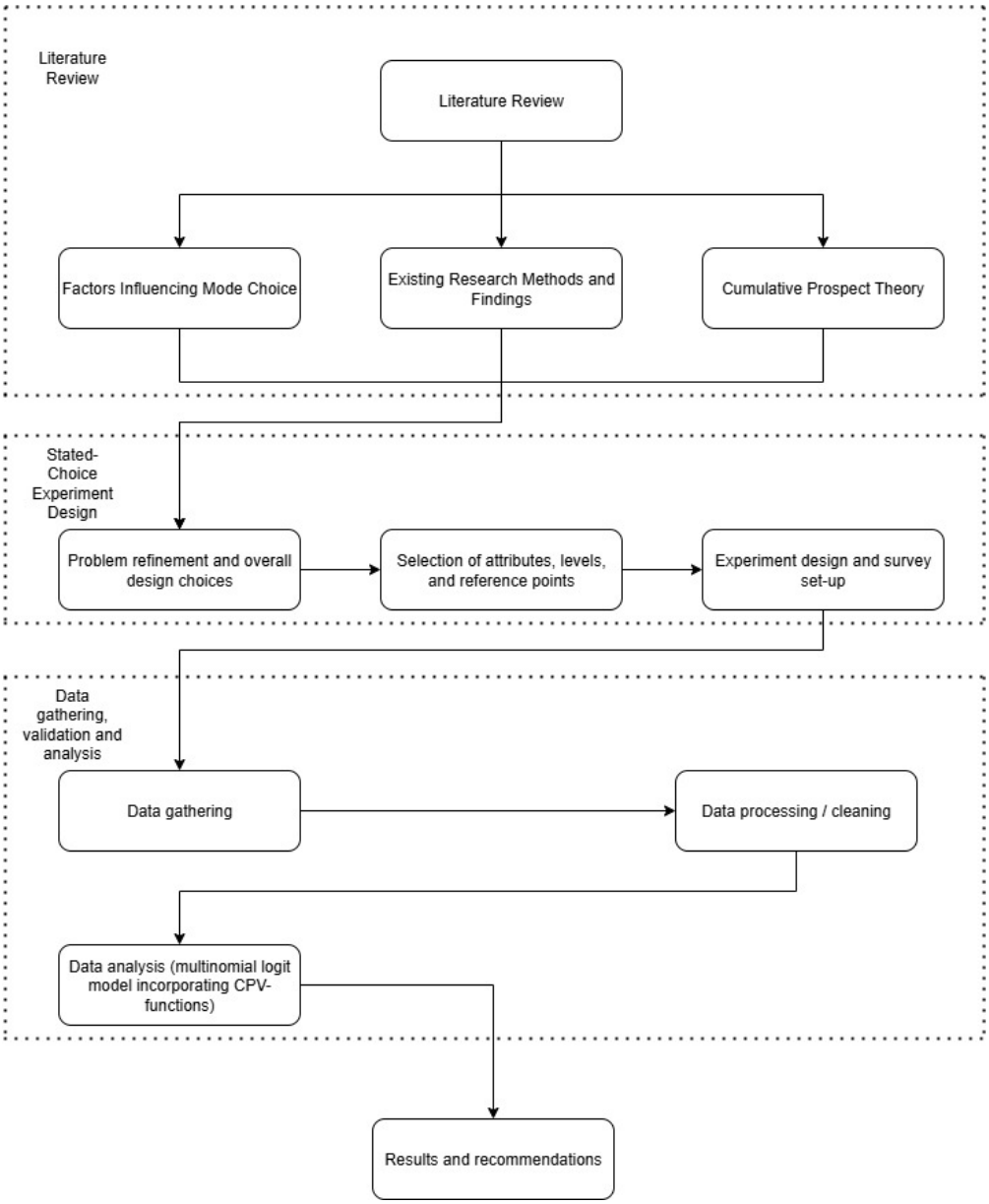

Figure 1: Research Design

1.4 Practical and scientific importance

Conducting this research has both practical and scientific relevance. Scientifically, this research fills a gap in literature where SMM-mode choice is analyzed under uncertain and risky circumstances using CPT. This helps identify the importance of various factors as well as uncertainty and risk in the choice for SMM. While this research focuses on a particular set of attributes, namely the cost of the trip, the time to walk to the shared e-moped, the maintenance condition of the vehicle, and the RR, different sets of attributes could be analyzed using the same framework. Results from this type of research can help in building more accurate predictive models for the use of SMM, contributing to current research. It adds to a broader understanding of how certain attributes influence the tendency to use shared e-mopeds, in combination with the effects of uncertainty, which can be used to increase adoption of shared e-mopeds in practice.

Practically, the parameters and coefficients that will be estimated quantitatively describe how different attributes influence decision-making for shared e-mopeds. These results can be used by practitioners such as policy makers and service providers to understand the trade-offs users make. This will broaden their understanding of how and why potential users choose for SMM and allow them to design SMM-environments that better fit the potential user. This research thus contributes to more informed decision-making and potential societal benefits.

A more elaborate description of the scientific and societal value of this research will be presented in section 6, including the results from this study.

1.5 Reading guide

This research starts with a literature review of current practices in SMM in section 2. Research and knowledge regarding transportation mode choice including applied theories and models as well as results from prior research will also be investigated. Furthermore, CPT and its applications are reviewed. Next, the methodology to be used in this research will be elaborated on in section 3. This section will describe the development of the SCE that will be designed for data collection, as well as the questions on current transport behavior and socio-demographics, which complete the survey. section 3 also describes the multinomial logit model that will be used for analysis, as well as the method for estimation and model validation. Data collection and data cleaning is discussed in section 4. section 5 presents the results from analyses, as well as implications of these results. This report is concluded in section 6, where scientific and societal relevance is discussed. Here, limitations and recommendations for future research are provided as well.

2 Literature Review

This section presents an overview of the researched literature regarding several topics. Firstly, current knowledge on Shared Micro-mobility (SMM) and its research is presented, including factors of influence, analysis methods and the impact of behavioral theories. Then, CPT is elaborated on, including its applications.

This review has been conducted in several steps. Firstly, the relevant topics were defined. Then, appropriate queries were used to find the right studies for the topics. Several queries were narrowed down to find studies closely related to the topic. These queries and results are shown in Appendix A. The articles found using these queries are screened by title to check for relevance. The most relevant researches moved to abstract screening. Those studies considered to be sufficiently relevant are used in this review, after which the results are presented below. Studies were considered sufficiently relevant if elements such as the research design, data collection methods, context, or methods for analysis aligned with those intended to be used in this study. Moreover, sources recommended by third parties such as academic advisors and experts on this topic, and individually found sources (without specific queries) have been used. A PRISMA-diagram of this review is shown in Figure 26 in Appendix A.

2.1 Shared micro-mobility

Urban mobility presents significant challenges, particularly when addressing the first- and last-mile of transportation within cities. Cities must accommodate the mobility needs of inhabitants and workers while having only limited space, leading to congestion and other urban transportation issues. Over the decades, various trends have contributed to these problems, including rapid motorization, the desire for private car ownership, urban sprawl, increased reliance on Central Business Districts (CBDs) for employment, and policies that prioritize road expansion over maintenance (Gakenheimer, 1999). In response, numerous innovations, policies, and strategies have been introduced to alleviate these challenges, with an extensive overview of these emerging innovations presented by Brebbia & Wadhwa (2006). In more recent years, interest has shifted towards sustainability in many fields of interest, including (urban) mobility. Smart Urban Mobility, including trends such as electric vehicles, alternative fuels, and IoT-based traffic management (Paiva et al., 2021) are examples of innovations and concepts emerging from the shift to more sustainable and efficient urban transport. Led by efforts during the COVID-19 pandemic, urban mobility is becoming more and more driven by human mobility data (Hu et al., 2021). More futuristic trends focus on autonomous, electric vehicles (Kovačić et al., 2022), showing the (dis)-advantages of this concept. However, there is still lack of a path to integration of these concepts in our mobility system. Despite all these innovations over the years, and current ongoing developments, many cities still struggle to effectively manage urban transportation due to the dynamic nature of cities.

While public transport, such as a metro system, is effective for transportation within cities, such systems often primarily serve corridors and strategic hubs. Individuals whose destinations are not directly served by these routes often require an additional mode of transport to bridge the gap between the transit network and their final destination. A complement to public transport could therefore be micro-mobility. Micro-mobility encompasses various small-scale, personal mobility options such as bicycles, scooters, and mopeds (Behrendt et al., 2022). These modes of transport take up significantly less space than cars and provide flexibility for urban travel.

Although micro-mobility itself is not new, the concept of Shared Micro-mobility (SMM) has gained

prominence in recent years. SMM provides users with short-term, on-demand access to micro-mobility options (Shaheen et al., 2021), allowing for efficient usage of vehicles without the need for and disadvantages of ownership. Different types of SMM can be distinguished. Firstly, there are different types of vehicles used for SMM, such as bicycles, electric bicycles, electric (standing) scooters, and mopeds. Examples of these types of vehicles are presented in Figure 2a (E-Moped) and Figure 2b (E-bike). These vehicles are offered both in a station-based (pick-up and return at a station) as well as dockless (pick-up and return on any location in the service area) manner (Shaheen et al., 2022). Hybrid options are available too. Different policies have been introduced to guarantee the safe and controlled usage of SMM in cities. Examples are presented by Shaheen et al. (2022) and include, among others, a limitation on the number of vehicles available, service area limitations, extra fees for incorrect usage, and equipment and operational requirements such as helmets and speed limits. Service providers offer SMM-services on different payment plans. Most providers work with a fixed and variable fee, where a starting fee is charged as an addition to payment per distance or time. Payment is often done on a pay-per-trip basis, but subscription models are popular too. Efforts to integrate SMM payment with, for example, public transport payment are explored as well, which could enhance transportation equity in cities and increase the likelihood of SMM-usage (Beale et al., 2023). More innovative business models are explored too, including peer-to-peer micro-mobility services, where owners of micro-mobility vehicles offer their vehicle to others through the brokering of service providers (Shaheen et al., 2022).

(a) Shared E-Moped Example (ID.nl, 2025)

(b) Shared E-bike Example (Yorkshire Times, 2025)

Figure 2: Examples of SMM vehicles

SMM is meant to be a sustainable addition to the mobility landscape. However, its integration in current mobility systems has several consequences and is not always successful. As previously mentioned, SMM could pose as a complement to public transport. Research by Ziedan et al. (2021) has shown that an increase in SMM-usage does not necessarily result in an overall decrease in public transport use (bus ridership), although this does differ based on trip purpose. Furthermore, Balac & Hörl (2021) present decreases in overall travel times in San Francisco through inter-modality in an empirical study, showing the potential advantages and effectiveness of SMM in cities. Fears are, however, that SMM could also pose as a replacement of public transport, resulting in a reduction of sustainable transport usage. Research by for example Diallo et al. (2023) has shown that in the city of Lyon, France, demand shifts from public transport and walking to SMM, acting as a competitor. Wang et al. (2023) have pointed out that SMM could replace walking and public transit trips as well, although these are mostly short trips which could be more efficient using SMM. They also

point out the potential of SMM to decrease car dependency, aligning with J. Zhu et al. (2023), who furthermore indicate the potential of SMM to mitigate traffic congestion, as well as decrease exhaust emissions.

While most forms of SMM have no emissions and are therefore seen as a sustainable solution for the future, there are doubts about the environmental impact of this type of mobility. In a study by Sun et al. (2023), it was found that because of the low utilization of free-floating e-bikes, the mode is not as environmentally friendly as first expected. Environmental indicators such as fine particulate matter formation, fossil resource scarcity, global warming, and water use were investigated using the total passenger kilometers over the life-cycle of an e-bike. Evidence showed that on many of the investigated indicators, the e-bike performs worse than, for instance, cars or buses. Similar evidence is shown from big data in a study by Sun & Ertz (2022). When investigating different SMM-programs, they found that because of over-commercialization, meaning that companies rapidly deploy vehicles without careful consideration of demand, resulting in low usage, and the general low utilization of these vehicles, e-bikes and e-scooters contribute significantly to the emission of greenhouse gases. The emissions from production, maintenance, and eventual disposal are not countered by efficient usage (except for docked bikes). Similar studies have examined the environmental impact of shared bikes and e-bikes in three Chinese cities, showing evidence of benefits by substituting driving trips (Zhang et al., 2024). However, extra carbon emissions are generated by substituting public transit and walking.

Another topic of concern is the safety of SMM. General concerns include frequent single-vehicle incidents leading to injuries, violations of traffic rules such as speeding and alcohol consumption, and a lack of knowledge of (traffic) rules and poor riding skills (Mehranfar & Jones, 2024). Because of these concerns, many cities banned or temporarily suspended e-scooters due to severe accidents, while in the Netherlands, e-scooters are even illegal. Looking at these e-scooters, results from research by Ma et al. (2021) show increased safety challenges due to increased vibrations, frequent speed variations, and constrained riding environments. These challenges are not only a concern to policy makers, but also to the users themselves. Research in five European cities has pointed out that safety concerns about riding in traffic and poor road conditions are barriers to usage for potential users (Filipe Teixeira et al., 2023), highlighting the importance of taking this element into account.

This points out that both the safety of the vehicle itself, as well as the surrounding traffic conditions and the state of the infrastructure for micro-mobility is a precondition for the successful integration of (shared) micro-mobility. Although it has been shown that SMM has the potential to bring (sustainable) benefits to urban mobility, contradictory research has shown that it could possibly replace readily present and more sustainable modes of transport such as public transport and walking. Concerns such as environmental impact and safety give reason for careful consideration and strategic implementation if cities choose to adopt the use of SMM.

Beyond general concerns such as safety and environmental impact, uncertainty and risk are very important when considering SMM. While modes of transport such as one's own car or bike show a security of availability, and public transport provide certainty as they drive according to timetables, SMM provides a lot less security looking at the availability of vehicles because of their shared nature (Zheyan Chen & Ettema, 2020). Along with that comes the maintenance of these vehicles, which is not checked on and maintained as frequently as other modes (Bretones et al., 2023), and elements such as the range of the vehicle or varying cost schemes. These forms of uncertainty will have an impact on users choosing for SMM, and thus on the effectiveness of such modes in general.

This section has pointed out that despite the fact that SMM is a valuable addition to the current (urban) mobility landscape, there are still many concerns that influence both policy makers to integrate SMM into mobility systems and people to potentially use SMM. Safety and environmental concerns are only two of the possible many reasons SMM has not fulfilled its potential yet. The uncertainty that SMM carries with it also influences people's choice and is therefore an important consideration. In order to effectively integrate SMM, it is important to understand under which circumstances people are willing to use the mode.

2.2 Current research and knowledge

This section elaborates on current knowledge in transportation mode choice concerning SMM and state-of-the-art research practices.

2.2.1 Influential factors in mode choice

As elaborated on previously, many cities face challenges in making people choose for SMM and effectively integrating it into their mobility system, as users base their mode choices on various factors. It is fundamental to understand on what basis people make decisions regarding their transportation mode to be able to increase usage patterns.

Mode choice and travel behavior are fundamental areas in transportation research. Numerous studies have explored the factors influencing individual transportation decisions. Functional and attitudinal factors play a role in transportation decisions. Jie et al. (2021) identified cost, distance, availability, and user attitude towards SMM as influential factors. Trip distance has also been found to impact the decision to use a (shared) bicycle, as noted by Gutiérrez et al. (2025), who additionally identified income as an influential factor. However, the role of income remains debated; while Campisi et al. (2024) also found income to influence mode choice, along with age, gender, and employment type, W. Yang et al. (2024) denied its statistical relevance, confirming only age and gender as significant factors. This difference could be explained by the way both studies treated income as a variable. van Kuijk et al. (2022) have found age as a significant factor as well, while also identifying the context of the trip and current cycling behavior (user attitude) as influential. Next to trip- and service characteristics and socio-demographics, multiple built environment characteristics influence transportation choices. Weather conditions and street hindrances represent environmental constraints that affect mobility (Hosseinzadeh et al., 2021), while city regulations on vehicle allowance can help positively shape mode choice for micro-mobility (Roig-Costa et al., 2024). Additionally, infrastructural support plays a crucial role in determining transport decisions (Frolich et al., 2024; Hermawan & Le, 2022).

Non-functional factors, such as the willingness to be a green traveler and satisfaction with the cycling environment (Li & Kamargianni, 2020), riding experience, and social perception, have been investigated as well. Furthermore, the Ease of Travel (EoT), consisting of people's motivations, travel skills, and travel options, significantly impacts travel mode choice (De Vos et al., 2025). Hosseinzadeh et al. (2021) have found differences in usage on different days of the week, while finding that major holidays or special events only marginally increased usage. Table 1 below provides a comprehensive overview of the relevant papers and factors mentioned.

These aforementioned factors, however, do not influence decision-making in the same way for everyone. Personal preferences and socio-demographic factors can influence the importance of particular factors in transportation mode decision-making. Research has shown that gender shapes how individuals weigh certain attributes. Davidich & Galkin (2025) have found that women

Table 1: Factors influencing transportation mode choice by source

Source	Cost	Distance	Availability	User Attitude	Income	Age	Gender	Employment Type	Appropriate Infrastructure and Rules	Social Perception	Ease of Travel	Weather Conditions
Jie et al. (2021)	X	X	X	X	X							
Gutiérrez et al. (2025)		X			X				X			
Campisi et al. (2024)					X	X	X	X				
W. Yang et al. (2024)	X					X	X					
Hosseinzadeh et al. (2021)												X
Roig-Costa et al. (2024)	X								X			
Frolich et al. (2024)					X	X			X	X		
Li & Kamargianni (2020)									X	X		
De Vos et al. (2025)											X	
Jaber & Hamadneh (2024)	X					X	X	X				X
Liu et al. (2022)		X							X			
van Kuijk et al. (2022)				X		X						
Hermawan & Le (2022)				X					X			
Jaber et al. (2023)	X	X			X	X	X	X				
Krauss et al. (2022)	X	X	X									

prioritize safety and comfort while men focus mostly on travel time and cost considerations in (sub)urban passenger travel, though women do identify affordability as an important factor. This distinction is also found by Jaber & Hamadneh (2024). Lifestyle orientation, including values and attitudes, furthermore impacts which factors influence individuals to use micro-mobility (Chatziathanasiou et al., 2024). Salazar-Serna et al. (2024) identify differences across socio-economic groups when analyzing the mode choice of urban commuters. Research thus shows that a range of factors influence the decisions of people and choices are not merely based on a single aspect, while influencing factors also differ across different groups. From Table 1, it is clear that socio-economic factors (such as age, gender, and income), cost, distance and the presence of appropriate infrastructure and rules are confirmed by several researchers to impact the choice for SMM. The impact of the availability of vehicles is however limitedly researched.

2.2.2 Data collection methods for mode choice analysis

In order to understand to what extent factors have an influence on mode choice, or any dependent variable, a common method is the Discrete Choice Experiment (DCE). In a DCE, one wants to quantify how certain attributes influence, for example, the choice behavior of respondents. In a DCE, respondents are presented with either real-life or hypothetical choice situations, otherwise known as treatment combinations (Hensher et al., 2015). These treatment combinations contain

multiple factors or attributes, which are systematically varied across the hypothetical scenarios. From analysis of the responses, a quantification of the influence of the different attributes can be generated. To achieve this quantification, models such as the multinomial or mixed-logit model are two among the most commonly used methods to estimate a DCE. DCEs are used in many sectors to understand reasons behind certain choices. Examples are location-choice analyses (dell'Olio et al., 2023; Mouate & Travers, 2024), healthcare choice research ((Hole, 2008; Xie et al., 2025; Campbell et al., 2025), or, in general, research aiming to find influential attributes for any dependent variable, such as factors influencing the choice of businesses to move to science parks (Ng et al., 2022). This type of research is also very popular in the area of transportation research, as it allows researchers to capture how individuals make choices under different circumstances.

A particular type of DCE is the Stated Choice Experiment (SCE) (otherwise known as stated preference experiment or stated preference survey), which presents respondents with only hypothetical scenarios. Examples of studies that have investigated transportation mode choice involving SMM using an SCE are research by Jaber et al. (2023), who have investigated preference for SMM-modes in Budapest, and Krauss et al. (2022), who researched mode preference in the 83 largest cities in Germany to understand what influences choice for either conventional modes of transport or SMM-modes. While a SCE uses data purely from hypothetical scenarios, revealed data can also be acquired and used to make research more realistic. An example of this is research by Capodici et al. (2025), who incorporated both revealed and stated preference data in Napels, Italy, to investigate micro-mobility choices.

An SCE has several attributes that make it applicable for research on transportation mode choice, as mentioned by Bliemer & Rose (2024). The experiment type allows for the manipulation of attributes and levels in each scenario that is presented to the respondent. This allows for the studying of specific factors and the trade-offs that participants make present insights into which factors influence their preference. A second advantage is that, using statistical models, the results can be quantified. For applicability, the results from SCEs and subsequent analyses can be used to forecast hypothetical scenarios.

Comparing this method to other methods for data collection, SCEs provide significant advantages. Comparing to interviews, SCEs allow for better structuring and analysis of the results because of the quantitative data that is generated. Comparing to observational studies, an SCE allows for the inclusion of hypothetical scenarios and thus for manipulating each of the attributes to be studied. Observational studies rely on real-world conditions which should either exist already or be created. These studies do not allow for testing trade-offs in the same way an SCE does, making the method less suitable for this research. Lastly, the survey including the SCE can easily include questions on socio-demographics along with the scenarios. Even though other methods can also collect this type of data, it is a convenient additional benefit next to the advantages mentioned above.

From the above discussion, it is clear that the SCE is well-suited for this type of transportation mode choice research. Using this type of data collection allows to present respondents with hypothetical scenarios including the attributes that will be selected in the research design. The quantitative data that is produced from analyzing the results from the SCE will be used to evaluate the importance of each of the attributes, as well as the effects of the elements of risk and uncertainty involved in the design. The SCE will be embedded in a survey that could include questions on socio-demographics and mobility patterns, which can also be used in analysis. The SCE is better suited for this type of research than, for example, interviews or observational studies, as outlined above.

2.3 Behavioral theories

This subsection elaborates on behavioral theories commonly used in decision-making research, as well as an extensive elaboration of CPT.

2.3.1 Expected Utility Theory

To analyze the responses of DCEs, using rational decision-making frameworks such as Random Utility Theory (RUT) (Cascetta, 2009) or Expected Utility Theory (EUT) (Biglieri, 2022) is common practice. These frameworks model how individuals evaluate alternatives and eventually make a decision. Utility functions are used to represent the value of an alternative for a decision-maker. A utility U is often modeled as the sum of multiplications of all relevant attributes by the weights of these attributes. Under the EUT, a decision-maker evaluates each possible outcome based on the utility U and the weight of that outcome.

A utility function can be modeled as:

$$U_i = \sum_j \beta_j X_{ij} \tag{1}$$

where:

- X_{ij} are the attributes j of alternative i
- β_j are the weights a decision-maker associates with attribute j

Many theories often assume that decision-makers choose the alternative that maximizes their utility. However, in some situations, one does not choose an alternative from a list, but rather needs to make a decision that can involve multiple different outcomes, each with their own probability or weight. In this case, it is valuable to consider the total expected utility of the choice at hand to see whether the expected outcome is positive or not. The total expected utility EU of a set of possible alternatives is given by:

$$EU = \sum p_i U_i \tag{2}$$

where:

- p_i is the probability of alternative i occurring
- U_i is the utility of alternative or scenario $_i$.

2.3.2 Random Utility Theory

RUT follows similar logic, however, an element of randomness is involved. In RUT, the total utility of an option is expressed as:

$$U_i = V_i + \epsilon_i \tag{3}$$

where:

- U_i is the total utility of option i,
- V_i is the systematic (deterministic) component of utility,

- ϵ_i is a random error term capturing unobserved influences.

A key shortcoming of these frameworks is, however, the fact that individuals often show irrational rather than rational behavior when making choices. Researchers recognize the role of this irrational behavior in transportation decisions.

2.3.3 Regret Theory and Prospect Theory

Researchers have used regret theory (Bell, 1982) to understand decision-making among travelers. This theory is mostly used when researchers want to include the emotional effect of losing out on something and suggests that, rather than maximizing expected utility, one wants to minimize expected regret. This has been used in transportation research, for example by Chorus et al. (2008), who computed the expected regret of a decision according to a probability density function in a Random Regret-Minimization model.

Beyond regret theory, Prospect Theory (Kahneman & Tversky, 1979) is an alternative to the expected utility theory, where decision-makers evaluate outcomes relative to a reference point. This theory captures elements of diminishing sensitivity and loss aversion. In practice, Koh & Chin (2022) used prospect theory to evaluate how perceived gains and losses, and reference points influence trip decisions, showing evidence of loss aversion when travelers are faced with changing road prices caused by Electronic Road Pricing.

As previously mentioned, the use of SMM brings uncertainty and risk for the user. Uncertainties such as costs and availability as well as risks like the maintenance level of the vehicle have an impact on whether a user is willing to choose for SMM or not. In studies into the usage of SMM, it is therefore crucial that the effects of these forms of uncertainty are taken into account. This means that the effect of probabilities on a person's decision-making is crucial to consider. Looking at risk, it is important to consider the different effects a loss and a gain have on a person. Because of the numerous inconveniences that might arise using SMM, and the fact people often weight these disadvantages stronger than the advantages, it is important to take this into account in analysis. Studies using the aforementioned theories however do not take this into consideration. EUT, for example, assumes that individuals make decisions that maximize expected utility based on probabilities. People, however, do not always see these probabilities objectively, skewing the expected value as seen by the user. Also, SMM-users often lack complete information of the situation, and are influenced by perceived risks, making objective probabilities unrealistic to consider. The Regret Theory looks at the potential regret of making a decision, also ignoring probability distortion. While Prospect Theory recognizes the different effects a gain and a loss have on a person (loss aversion) and understands that people distort probabilities, it looks at each possible outcome individually instead of as a whole. In SMM, however, there can be multiple outcomes that should be considered together, for example various different travel times or maintenance conditions. If a vehicle can be in different states, of which at least some are undesirable to the user, the probability of these outcomes should not be considered individually but rather as a whole. The Cumulative Prospect Theory (CPT) accounts for all the effects desirable for analyzing SMM: loss aversion, probability distortion, and the evaluation of multiple possible outcomes collectively rather than individually.

2.3.4 Cumulative Prospect Theory

2.3.4.1 Theoretical Framework

CPT (Tversky & Kahneman, 1992) is an extension on the regular Prospect Theory (Kahneman & Tversky, 1979), which better represents risk and uncertainty in decision-making. In regular expected or random utility theory, probabilities are evaluated linearly. In CPT, however, probabilities are weighted non-linearly, suggesting that small probabilities are often overweighted by individuals, while larger probabilities are often underweighted. Prospect theory handles each probability independently, while CPT looks at these probabilities cumulatively, taking all probabilities of an outcome at least as good or bad into account. Loss aversion refers to the psychological phenomenon where losses feel more painful than equivalent gains feel pleasurable. People tend to weight losses more heavily than gains of the same magnitude. For example, consider a scenario where one finds €50 on the street, resulting in a positive emotional response. Later that day, the same individual accidentally loses €50 from their pocket. Although the net financial outcome is neutral over the day, the psychological impact is skewed: the distress caused by losing money is perceived as significantly greater than the satisfaction derived from finding the same amount. Loss aversion is closely connected to reference dependence, which is a key aspect of CPT. Instead of looking at outcomes objectively, people generally tend to view these relative to a reference point. While cycling for 60 minutes is quite a long duration, if it was expected that a trip would take 65 minutes, the situation results in a gain. By looking at situations taking reference dependence into account, choice behavior can be more accurately captured.

Figure 3 shows the value function for CPT, identifying clearly the behavior of individuals in situations of gains and losses. While the outcome of a gain increases, people tend to not value them as highly anymore, showing convex behavior. This shows the effect of diminishing sensitivity, where equal losses at a larger outcome do not show as much effect as closer to the reference point (cycling for 20 minutes instead of 10 minutes feels bad, but 40 minutes instead of 30 minutes does not have an equally bad effect). From the graph, this is apparent in the steep decline close to a reference point, but the less-heavily inclined slope further away from the reference point. Loss aversion can be seen as well, as equivalent gains and losses, so equally far from the reference point, tend to cause different magnitudes of effect (losses have a lower than an equivalent gain has a positive value.

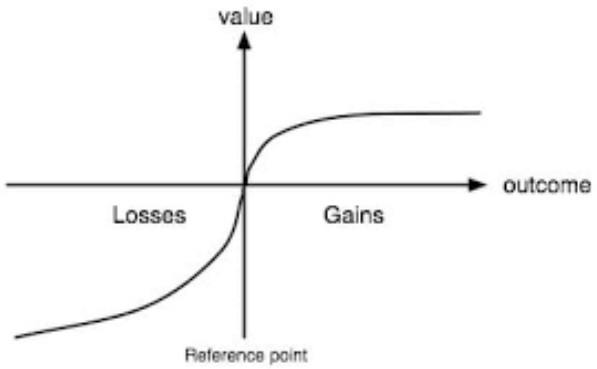

Figure 3: Value function of the CPT (Annaswamy & Nair, 2022)

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For CPT, consider a stochastic variable u, which represents an outcome that could take on different

values, such as a given amount of money or a certain travel time. CPT assumes that outcomes are not valued objectively, but rather subjectively, based on a reference point (R), a level of loss aversion, and diminishing sensitivity. The subjective value $v(u)$ of an outcome u can therefore be calculated as:

$$v(u) = \begin{cases} (u-R)^{\beta^+} & \text{if } u \geq R \\ -\lambda(R-u)^{\beta^-} & \text{if } u < R \end{cases} \tag{4}$$

Outcomes can be seen as losses or gains respective to the reference point R. A gain is therefore present if $u \geq R$, while there is a loss if $R > u$. β^+ and β^- are parameters that shape the function for losses and gains. They are typically measured between 0 and 1 and cause a concave curve for gains and a convex curve for losses. This means that both gains and losses have a diminishing marginal value. Lastly, λ is the loss aversion coefficient. If $\lambda > 1$, from Equation 4, the value function of actual value u is adjusted to be more heavily negative in the case of a loss, multiplying the impact.

It is crucial to consider what u represents when applying CPT. Outcomes must be defined relative to the reference point, such that desirable outcomes are treated as gains, and undesirable outcomes as losses. Longer travel times are often seen as losses rather than gains, giving reason to carefully formulate Equation 4 according to the attribute at hand.

Next, Equation 5 and Equation 6 can be used to determine how probabilities are weighted and determines the curve in Figure 4. This is dependent on the levels of probability distortion δ and γ. δ is the parameter for losses, while γ indicates the weighting parameter for gains. The probability weighting $w(\cdot)$ resulting from Equation 5 and Equation 6 can then be interpreted as the probability as perceived by respondents.

$$w^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \tag{5}$$

$$w^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}} \tag{6}$$

Probabilities should be translated to decision weights. In order to do this, consider a scenario where a lottery provides several outcomes. CPT assumes some of these are perceived as gains, while others are losses. These outcomes should be sorted from worst to best. Every outcome above the reference point R is a gain, outcomes below are losses. This results in two domains: a loss and a gain domain. For gains, the decision weight π_u^+ for an outcome u is then calculated as:

$$\pi_u^+ = w(p_u + ... + p_{k^+}) - w(p_{u+1} + ... + p_{k^+}), 0 < u < k^+ \tag{7}$$

Equation 7 determines the decision weight of a gain. This means that the sum of probabilities of which the associated outcome is at least as good as outcome u is taken, as well as the sum of probabilities of the outcomes strictly better than u, and the latter is deducted from the former. This is done as CPT assumes people evaluate prospects cumulatively, instead of as individual probabilities (Tversky & Kahneman, 1992). In Equation 7, k^+ thus indicates the total number of positive outcomes.

Regarding the losses, the decision weight π_u^- is determined as:

$$\pi_u^- = w(p_{-k^-} + ... + p_{-u}) - w(p_{-k^-} + ... + p_{-u-1}), -k^- < u < 0 \tag{8}$$

Here, outcomes should first be sorted from worst to least bad. Then, the probabilities associated with those outcomes at least as bad as outcome u should be summed, as well as the outcomes strictly worse than u. The latter is again deducted from the former.

k^- indicates the total number of loss outcomes. In Equation 8, the sum of the probabilities associated with outcomes strictly worse than u are thus deducted from the sum of probabilities associated with values at least as bad as u (thus including outcome u).

The total utility (value), using CPT, is then given by:

$$V(f^+) = \sum_{u=1}^{k^+} \pi_u^+ \cdot v(u); \quad V(f^-) = \sum_{u=-k^-}^{-1} \pi_u^- \cdot v(u) \tag{9}$$

$$V(f) = V(f^+) + V(f^-) \tag{10}$$

This means that the decision weight, as calculated for each possible outcome u, is multiplied by the subjective value of that outcome $v(u)$ (Equation 4). The Cumulative Prospect Value of each outcome, and thus of all gains and losses, are summed to arrive at a total Cumulative Prospect Value. It is important to note that for gains, so for example for reduced travel times, Equation 5 should be used, and vice versa, since losses are distorted differently compared to gains.

Four different types of risk attitudes can be derived from CPT, depending on whether the outcome is perceived as gain or a loss, and the probability an individual is confronted with. As mentioned, people overweight small probabilities while underweighting high probabilities. This results in the behavior seen in Table 2. The following examples explain these risk attitudes in practice.

If an individual is presented with the opportunity to have a sure travel time of 20 minutes, but can also choose a scenario where there is a 80% chance for 15 minutes, people underweight the chance of getting a short trip and choose the sure bet, thus showing risk-averse behavior. If there is however a low chance at getting a shorter trip time, for example 5% at 10 minutes, and a 95% chance at 30 minutes instead of the 20 minutes for sure, people tend to be risk-seeking and gamble, since they overweight the probability that they have a faster trip. For losses, this works the other way around. If one is presented with a sure delay of 15 minutes, or an option where there is a 20% chance at having no delay but an 80% chance at having 25 minutes of delay, people tend to be risk-seeking, again over-weighting the probability that there will be no delay. If the situation would be the other way around, with a sure short delay and a situation where there is a high chance of shorter delay and a small chance of very high delay, people tend to be risk-averse, over-weighting the probability of a high delay. This phenomenon is also visible in Figure 4, where the decision weight function shows areas of over- and under-estimation. From these examples, it is clear that people make different choices depending on the outcome and probability of an event.

It is important to note that, in these instances, expected values do not always have to be equal for the two different options. However, to purely focus on attitudes of risk, expected values should be kept close to each other and on occasions where values are not similar, this should be taken into account in conclusions (Tversky & Kahneman, 1992).

Table 2: Usual Patterns of Risk Attitudes in CPT

Probability Level	Gains	Losses
Moderate and High	Risk-averse (prefers sure gain)	Risk-seeking (prefers gamble to avoid sure loss)
Small	Risk-seeking (lottery effect)	Risk-averse (insurance effect)

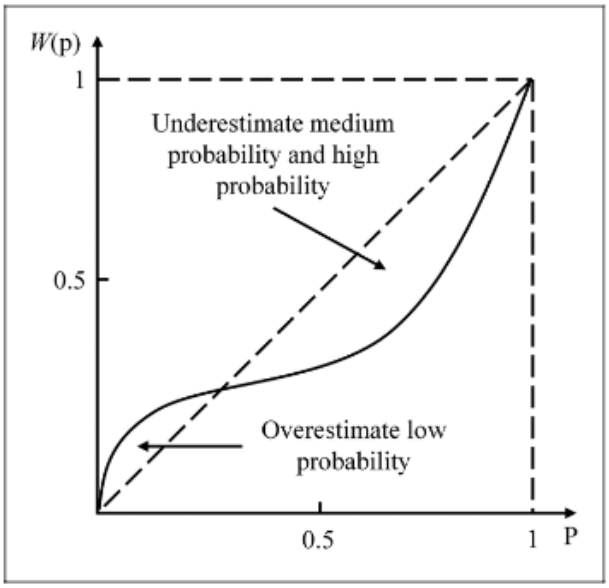


Figure 4: Decision weight function under CPT (Q. Geng et al., 2024)

2.3.4.2 Applications of Cumulative Prospect Theory in Transportation Studies

Behavioral models have been used in transportation mode choice before, as previously mentioned. Individuals all look at situations differently, determining for themselves what the best choice under given circumstances would be. These circumstances often involve uncertainties, showing the relevance of CPT in this field. de Palma et al. (2008) describe, theoretically, how risk and uncertainty, using CPT, can be incorporated in DCEs. An interesting study by Annaswamy & Nair (2022) uses CPT on mobility choices involving shared ride-hailing and taxis. In their research, passengers got to choose between three options (public transport, shared ride pooling service or exclusive ride hailing services), of which both public transport and exclusive ride hailing services are considered certain prospects looking at travel time, while for this is uncertain for shared ride pooling. CPT was used to model risk preferences to predict decision making under such uncertainty. Findings showed that loss aversion influences respondent's decisions as well as the presence of risk-averse and risk-seeking behavior, as previously discussed. Guan et al. (2019) also apply CPT in the context of shared mobility, particularly in uncertain travel times of on-demand shared mobility services, showing in their results the impact of loss aversion and probability weighing. Ghader et al. (2019) used CPT to understand how travel mode choice is affected by travel time reliability, considering cost and time as determinants of utility, with the time of driving being uncertain compared to a certain rail trip time of a train alternative. C. Chen et al. (2017) consider only expected travel time and travel time variability as determinants of utility in their research analyzing train station choice regarding park-and-ride commuting patterns. Similar research by Xin & Ma (2024) considered only travel time, determining the cost of arriving early and late at work, and determined the Cumulative

Prospect Value of each alternative mode of transport to determine the optimal choice for respondents under uncertainty. This was studied by Y. Chen et al. (2021) as well, who considered uncertain delay rates to determine optimal congestion prices on the Melbourne highway network. Ceder et al. (2013) analyzed choice preference in situations of transfer routes under uncertainty, finding risk-averse preferences for transfer routes with lower uncertainty. In another field of mobility, namely aviation, Wen et al. (2019) investigated the impact of uncertain delay times for flights on the choice for alternative travel arrangements using CPT.

The results of such experiments mentioned above are often highly sensitive to the reference point that is chosen. In economics, when monetary values are involved, often losses and gains are determined from the €0 reference point (Avineri & Bovy, 2008). However, in mode choice studies, such an obvious reference point is not available. When for example considering uncertain travel times, multiple options for selecting a reference point are available. Avineri & Bovy (2008) mention several options, including considering the average or median travel time of a trip or using respondent knowledge, for example through asking respondents for their estimate or expected trip time or taking the travel time of a car/bus, which is a rather certain number on smaller distances. C. Yang et al. (2017) evaluates the multiple ways of setting reference points, involving average travel times of two modes, anticipated travel times, and effective reserved time. Through using the imperfect memory effect, that defines a memory length of periods that can be remembered by an individual, the model using anticipated travel time as mentioned by respondents presented the best results. Zheng et al. (2025) used average desired costs and K. Geng et al. (2023) used three different reference points (Earliest Acceptable Arrival Time, Work Starting Time, and Latest Acceptable Arrival Time) for the arrival time of commuter to find the best fitting method. For this research, advantages and disadvantages considering the context of this research will be evaluated to choose the best fitting method for selecting reference points.

2.4 Conclusion and research gap

A literature review of the most important elements of this research has been conducted above. SMM has been identified as a mode with high potential for urban transport, especially for the first- and last-mile, as well as a potentially sustainable addition to the mobility landscape. However, several factors are limiting the potential benefits of SMM. Low usage leads to a reduction in the environmental benefits of electric mobility, which could even make shared electric vehicles less environmentally friendly than petrol vehicles. Over-commercialization can have the same effect, while the safety of single vehicles modes of SMM discourages people to use them. Furthermore, several elements of risk and uncertainty are accompanied with SMM, which are carefully considered by potential users. In order to make use of the benefits of SMM, it is important to understand how an increase in uptake can be achieved, meaning it must be known under which circumstances people are willing to adopt SMM. Research has been performed in this area. Several factors have been identified as important for potential users, such as cost, travel distance, and availability. Socio-demographic factors also have an impact on whether one is willing to use SMM, while these factors also influence the importance of other factors, such as cost or travel distance. It is important to consider both these trip- and vehicle-attributes, as well as socio-demographic variables in this research, which will be elaborated on in section 3. In order to investigate these influential factors, different methods can be used. One commonly used data collection method is the SCE, where individuals are confronted with hypothetical scenarios, asking them to choose the scenario or alternative they would prefer. This method is especially applicable for this research because of its ability to manipulate attributes and levels, and quantifiable results. In the analysis of the responses to such an SCE, behavioral

theories are used to assume and predict human behavior. Various theories have been applied in practice, but one that is especially useful in situations that involve uncertainty and risk is CPT. Cumulative Prospect Values are used to better represent the value of outcomes, taking loss aversion, probability distortion, diminishing sensitivity, and cumulative probability weighing into account. In this way, the influence of risk and uncertainty on decision-making can be estimated, which is yet to be performed on transportation mode choice involving SMM.

3 Methodology

This section describes the methodological approach used in this research. It will first expand on the creation of the experimental design, after which the utility function to be used will be explained. The method used for parameter estimation will be expanded on, as well as an elaboration of model checks and the way in which results will be interpreted.

In order to quantify to what extent factors have an influence on the choice to use SMM, an SCE will be designed. This first section will outline the experimental design of this SCE. Following the typology of Hensher et al. (2015), such an experiment analyzes the effect on a dependent variable through changing the levels of one or more other variables. These variables can be referred to as the factors that might influence the dependent variable. In this case, the dependent variable will refer to the choice for a SMM-vehicle. The attributes used in the model together describe an alternative in the set of possible combinations. Each possible combination can be referred to as a treatment combination.

The design of an SCE follows several steps as defined in Figure 5, which will also be followed in this section.

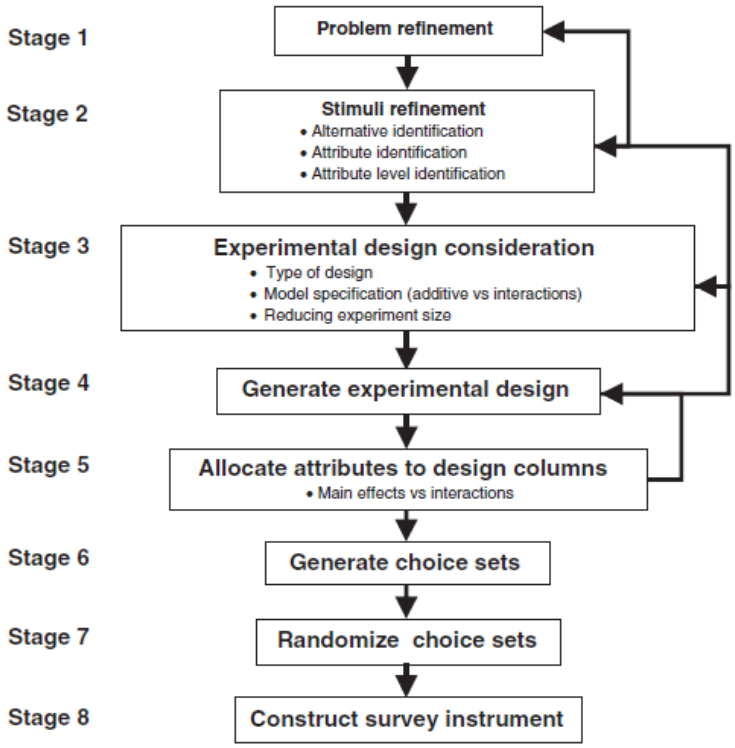


Figure 5: Experimental Design Process (Hensher et al., 2015)

3.1 Experimental Design Process

3.1.1 Stage 1: Problem Refinement

In stage 1, the problem needs to be clearly defined to understand what exactly is being researched. A clear definition of the problem is required to formulate realistic alternatives, choose the most

valuable attributes and correct attribute levels, and lay the groundwork for other considerations in terms of experiment design, including the type of design and model specifications.

This research is centered around identifying the importance of uncertainty and risk in decision-making concerning transportation modes, SMM in particular. It is therefore highly important to identify the type(s) of uncertainty and risk that will be investigated. Besides, the impact of gains and losses relative to a reference point will be researched as part of the framework of CPT, as well as the extent to which certain factors have an influence on decision-making.

The use of SMM can involve various uncertainties. One of the main uncertainties is the availability of vehicles. As a result of the shared nature of the vehicles, availability will present an uncertainty when there is demand by users, especially in a dock-less sharing system (Zheyan Chen & Ettema, 2020). However, the same situation arises in docked systems, where availability at a nearby dock might be scarce, while other docks have plenty of vehicles available. The uncertainty of available vehicles has a direct influence on the total trip time of a user, but more directly on the access time. The access time can be defined as the time it takes a user to get to the vehicle, most often by foot. This concept is for example applied by Kim et al. (2017a) and Kim et al. (2017b), who use the access time to a mode as an attribute in their research. This uncertain access time plays a big role in the attractiveness of SMM as a mode of transport, since it has a large impact on the total duration of the trip and can be a large barrier to usage.

Trip times can also be impacted by other circumstances such as busy traffic, incorrect navigation, and mandatory detours during the trip itself, which in turn leads to uncertain costs. Because of the cost schemes of SMM-systems, which often involve variable fees calculated using the minutes of use, uncertain travel times result in uncertain costs. These circumstances are often exogenous, meaning there is little influence by service providers or other parties.

The fact that the vehicle is shared, not owned, presents an uncertainty in the maintenance level of the vehicle. Although operators periodically check vehicles for maintenance, and users have the possibility to report any defects to the operator, vehicles remain in use without a 100% maintenance level. Next to this, shared vehicles have high maintenance costs, both for recharging as well as replacing broken vehicles (R. Zhu et al., 2020), showing that it is not unusual that (partially) defect vehicles are in use. The use of broken vehicles could influence trip satisfaction, depending on the extent of the defects and the perception of the user, and even present risk of injury if the vehicle malfunctions severely. It is never certain in what state the vehicle is when booking or reserving a vehicle, and a vehicle could have hidden malfunctions as well. It could impact one's decision-making, especially if a user has encountered a broken vehicle before. The maintenance level of a shared vehicle has been identified as a barrier to usage for users in literature as well by Bretones et al. (2023).

Since some SMM-modes are electric, batteries need to be recharged. As previously mentioned, relatively high costs are associated with this for service providers. For any trip, this could present the situation of not having enough charge to complete the trip, presenting another uncertainty for users. Although many operators show the current RR and distance that can be driven, users tend to be hesitant to usage when the RR of a vehicle is low, considering the fear of not being able to finish the full trip or not knowing how long their trip will take. This results in an area of risk for the user.

Because of all these uncertainties, users of SMM have to accept a level of risk when traveling. This risk stems from various uncertainties that differ from the risk and uncertainties present in other modes of transport such as public transport and private vehicles, where for example delays

and congestion are of more significance. In the end, the user will make a decision to choose for the mode of transport best fitting with their level of risk aversion, considering the uncertainties of all transport modes. For SMM-users, this means taking into account all relevant uncertainties, including uncertain maintenance levels, the RR, and uncertain access times, and then determining whether they are willing to face the risk caused by these uncertainties, thus accepting the possibility of a more inconvenient or disrupted trip.

Following the research questions formulated at the start of this research, the influence of trip- and vehicle-related characteristics, as well as risk and uncertainty, on mode-choice decisions will be investigated. In order to investigate this, situations involving risk and uncertainty should be presented to the user. Based on two options with a particular combination of attribute levels (treatment combinations), involving the elements of risk and uncertainty previously identified, the respondent should decide which of the alternatives would be chosen. The elements of uncertainty and associated risk that will be used are uncertain access times, uncertain maintenance levels, and varying remaining ranges, which introduces uncertainty about whether the remaining battery charge is sufficient for the trip to be completed. Further elaboration on attribute selection will be provided in paragraph 3.1.2.2. Especially in docked SMM-systems, access time can be significant and impact mode choice, while uncertainty in these times commonly occurs. The maintenance level of a vehicle can be a significant barrier to choosing for SMM, while the RR will also impact the attractiveness of the mode of transport.

3.1.1.1 Case: the city of Enschede

Data collection for this research,as mentioned before, will be carried out in the city of Enschede. To create a realistic experiment design, it is import to understand the context in which this research takes place. Enschede is a medium-sized city in the East of the Netherlands. Enschede is known for being the greenest city in the Netherlands, with high levels of bike-usage usage in and around the city. The city hosts the 'University of Twente', which attracts a lot of students to the city, from both the Netherlands and abroad. This is reflected in the population of Enschede, which is relatively young, with a higher percentage of people between 15 and 25, and 25 and 45 than in the Netherlands on average. Enschede is a rather compact city, with inner-city distances of a maximum of 25 minutes by bike and 20 minutes by car. Busy areas outside the city center are the business park and university campus next to each other at, on average, a 15 minute trip from the center of the city. Travel distances in the city of Enschede are around 4 kilometers. Enschede is a city that is eager to increase SMM-usage, as has been stated by the municipality (Gemeente Enschede, 2025).

For this research, a mode of SMM to be researched must be selected. Enschede offers both shared e-mopeds as well as e-bikes. Bolt offers 136 shared e-bikes, while Felyx offers 270 shared e-mopeds. Looking at the dominance in presence of shared e-mopeds over e-bikes, as well as interest from both the municipality of Enschede as well as personal interest in the uptake of shared e-mopeds, it is chosen that the shared e-moped will be researched. This also aligns well with the fact that many people in Enschede already own a bike themselves, lowering the tendency to use a shared e-bike for trips.

The next stage introduces the context of the trip, attributes that have been selected and the levels of these attributes that will be used. These will be aligned with the context of the city of Enschede as outlined above.

3.1.2 Stage 2: Stimuli refinement

Stage 2 of the experimental design process involves stimuli refinement. In this stage, the alternative(s) is (are) identified and attributes to be included are chosen. For those attributes chosen, the levels to be used are defined too.

3.1.2.1 Alternative selection

The goal of this research is to investigate the impact of various attributes on mode choice, as well as understanding how uncertainty and risk play a role in decision-making. In an SCE, the design of the experiment can be either labeled or unlabeled, each with their purpose, advantages and disadvantages, as elaborated on by Hensher et al. (2015). Looking at the goal of this research, an unlabeled design is best fitting. In an SCE with an unlabeled design, the respondent is, in the context of transportation mode choice, confronted with two or more alternatives of the same mode of transport, each with varying attribute levels, and chooses the alternative they would prefer to use. Even though an unlabeled design shows less realism than a labeled design, where alternatives of different modes of transport are shown that can be tailored to the context of the research, it allows for analyzing the importance or trade-offs of different attributes in the choice for shared e-mopeds specifically. In a labeled design, mode-specific preferences could be analyzed. In such experiments, the label, i.e. mode of transport, has an influence on choice, which is not fitting to this study. An unlabeled design limits the bias towards a particular mode of transport. Labeled designs also do not meet the Independence of Irrelevant Alternatives (IIA) assumption, stating that choices for alternative A or B are independent of a possible third alternative C. In a labeled design, this is violated, while in an unlabeled design, differences are purely attribute-driven. Besides, the unlabeled design allows for focusing on the elements of risk and uncertainty of shared e-mopeds, which is key to this research.

Each respondent will be shown two hypothetical trips with a shared e-moped. Each shared e-moped will have the same attributes at different levels. To choose a fitting hypothetical case, the context of Enschede, and of the Netherlands in general, is taken. From a report by Movares (2023), it was found that the average distance traveled using a shared e-moped in the Netherlands is 3,5 kilometers. As mentioned before, the average trip in Enschede is around 4 kilometers. Therefore, a trip of 4 kilometers is chosen. This trip length will have an impact on the cost of the trip, which is one of the attributes to be used in the design. An elaboration on the selection of the other attributes will follow in paragraph 3.1.2.2, as well as a discussion on the levels of each attribute and reference points.

3.1.2.2 Attribute selection

Next, the attributes to be used in the experiment must selected. From section 2, different factors that have proven to be influential in decision-making for SMM have been summarized (Table 1). In light of this research, a limited number of these factors can be selected as attributes in the experiment. The study must remain feasible in terms of complexity, while also ensuring focus on the elements of risk and uncertainty mentioned earlier.

Cost has been identified as influential when being examined in decision-making. Currently, the costs of SMM are often considered relatively high. It is therefore highly interesting to analyze the impact of costs on the choice for SMM, as this could help towards better structuring the pricing strategy of SMM-modes. Using an attribute measured in monetary terms will also allow for the measure of Willingness to Pay (WTP). This measure can provide information on the amount of money someone is willing to pay for benefits on some other attribute. It can for example be valuable to determine

the Value of Time Saved (VTS) (Hensher et al., 2015), or the amount of money one is willing to pay for an increase in comfort.

While it is assumed that the total travel time is of importance to the user, the context of this research limits the applicability of this attribute. As two trips using an e-moped will be presented, which are expected to travel at approximately the same speed and therefore have equal travel times over the same distance, varying this attribute would present unrealistic alternatives, especially since the city of Enschede currently runs only e-mopeds with a maximum speed of 45 km/h. Access time, however, can differ per e-moped to be used. Especially when considering uncertain availability rates, access time is expected to have a significant influence on mode choice. It will therefore be considered as an attribute, along with an element of uncertainty.

As previously mentioned, availability can have major impact on the access time to a vehicle, and therefore on total trip duration. However, by including an element of uncertainty in access times, availability is inherently considered as well and will therefore not be used explicitly as an attribute.

The maintenance level of a vehicle, as well as the RR have previously been mentioned as causes for risk and uncertainty in the use of SMM. These will therefore both serve as attributes of the alternatives. The levels of these attributes will be elaborated on further in this section. For the maintenance levels, it is never certain in what state a vehicle is when a user starts the rent. This level of uncertainty in the state of the vehicle should be taken into account as well.

3.1.2.3 Attribute levels

Lastly, the attribute levels need to be defined. Hensher et al. (2015) provide various guidelines when selecting attribute levels. Regarding the number of levels, while complexity increases with a larger number of levels, this does provide a more detailed understanding of the utility function people inherently use. This behavior can be seen in Figure 6. One must find a balance between enough variation and keeping the experiment manageable. It is also advised to choose the same number of levels for each attribute. Therefore, it is chosen to use three levels per attribute. Next, choosing the end-points must be done carefully. The extreme values should be based on observed, real-world data, but extending just slightly beyond these observed values might be beneficial for the model. The values must however remain realistic for the respondent to take the experiment seriously. Lastly, when selecting attribute levels for a certain attribute, the attribute level labels (names) must be clear and understandable.

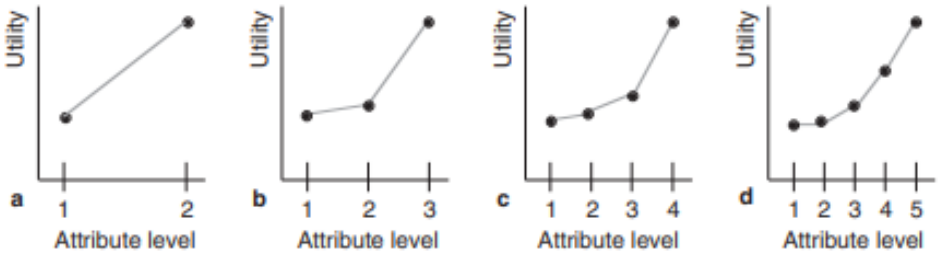


Figure 6: Part-worth utility (Hensher et al., 2015)

Starting with the attribute levels for costs, it is important to understand the true costs of SMM in Enschede. In the city, currently, service operator Felyx operates e-mopeds. For the e-mopeds, Felyx uses a €1 fixed fee for starting a trip, while charging €0,37 per minute. These costs will be used to

determine the cost of the alternative, centering the different attribute levels around this cost. From van Kuijk et al. (2022), the average speed of an e-moped in urban environments is 18 km/h, and 20 km/h in suburban environments. Based on this, a trip of 4 kilometers at 18 km/h costs €4,51. Centering values around this, the other levels are chosen to be both 37,5% higher and lower than €4,51, at respectively €6,20 and €2,82. This will make sure both gains and losses are evaluated, which is essential for the application of CPT.

As previously mentioned, in Enschede, hubs where e-mopeds can be parked have been carefully placed around the city, ensuring each hub is placed at a logical location, and within 300 meters of another hub (Gemeente Enschede, 2025). In the context of this research, the access time will range from 0 to 5 minutes by foot, considering this 300 meter range. In the case that the presented base access time is not true (which means no e-moped is available at the pick-up location), it can be assumed that the additional access time for a respondent would be walking to the next hub, where it is assumed an e-moped is available. Therefore, the additional access time, given that the first vehicle was not available, is therefore set at four minutes.

Regarding the probabilities associated with uncertain access times, three different levels are defined at 80%, 60%, and 40%. These levels are chosen to analyze risk aversion at a wide range of levels, while making sure respondents are given a realistic probabilities. In the situation where there is no vehicle available i.e. the base access time is not true, the total access time will be prolonged by four minutes at a $1 - p$ probability.

In the survey, as will also be elaborated on in the next paragraph, the respondent will be asked to provide an acceptable access time as a reference point. When presented with scenarios, respondents will receive an access time (x) that is three minutes more, less, or equal to the acceptable time indicated. This access time will be presented at a p% chance, while $(x + 4)$ will be presented at a $1 - p$% chance. The four minutes, as explained earlier, come from the fact that the maximum walking distance to a vehicle, if one is not available at the current hub, is 300 meters i.e. 4 minutes walking.

For the maintenance level, defined as X_{ML}, of the e-moped, different categorical values will have to be determined. To generalize, a vehicle can be in three different conditions: excellent, average and poor. Excellent conditions mean there is no delay or discomfort caused by maintenance issues, and the vehicle is in the same state as when it left a production facility. If the vehicle is in an average state, there are some minor inconveniences but the vehicle is still drivable. In poor conditions, there are major disruptions that impact the ride significantly. It will be explained to the respondent what is represented by which category to make sure the respondent has a realistic view of the vehicle in the scenario. For analysis using CPT, each outcome should be accompanied by a value. The value of, for example, an excellent maintenance level is different for each respondent. To reduce complexity, it is chosen to value excellent maintenance as $X_{ML,e} = 1$, average maintenance (baseline) as $X_{ML,a} = 0$, and poor maintenance as $X_{ML,p} = -1$. In this way, each respondent is treated equally.

Next to this, the probabilities of a vehicle being in a certain state should be defined. The maintenance level and probability distribution are then combined as one attribute. Lastly, the vehicle has a particular RR. An overview of the attributes, variable names, and accompanying levels can be seen in Table 3.

Table 3: Attribute levels for each of the attributes

Attribute	Variable	Level 1	Level 2	Level 3
Cost of use (compared to trip costs of SMM)	X_C	-37.5% (€2.82)	+0% (€4.51)	+37.5% (€6.20)
Access time (compared to reference level)	X_{AT}	-3	0	+3
Uncertainty Levels Access Time	p_{AT}	80%	60%	40%
Maintenance level (condition)	X_ML	Excellent	Average	Poor
Maintenance level (probabilities)	p_ML	20/60/20%	30/40/30%	40/20/40%
Remaining Range	X_{RR}	80%	50%	20%

3.1.2.4 Reference point

As mentioned in section 2, in order to use CPT and understand the impact of gains and losses, reference points must be selected in order to determine the subjective value of an alternative, and see the effects of gains and losses. There is an ongoing debate on how to select reference points. As mentioned before, both C. Yang et al. (2017) and Avineri & Bovy (2008) have provided options for selecting these reference points, showing advantages and disadvantages for several options. However, several other researches have applied different methods to set reference points, often dependent on the context of the research.

For this research, reference points for cost as well as access time must be determined. Since the RR of the vehicle will mainly serve as an explanatory variable in the utility function, it will not be analyzed using CPT-based value functions, and therefore no reference point needs to be selected. Wen et al. (2019) have used a similar approach in investigating behavior under uncertain air travel delays, using a CPT-based value function for delay times in combination with other explanatory variables. Since the trip used in this study is arbitrary (around four kilometers), it is difficult to ask respondents for the maximum acceptable or expected cost of the trip. The transport mode mentally used as a baseline will differ for each respondent, and expected costs will therefore be highly dependent on the context of the respondent. To address this, and ensure consistency across respondents, the reference cost is calculated based on the average travel time of an e-moped. As mentioned in paragraph 3.1.2.3, this is set at €4,51.

Regarding access time, there are different ways to set reference points, as has been argued earlier. From section 2, multiple different papers have used different methods, each with their advantages and disadvantages. From Table 4, it is visible that each method has several pros and cons. In the context of this research, it is important to capture a value that respondents will be able to relate to, since gains and losses will be measured. Therefore, it is chosen to ask respondents for an acceptable access time to a vehicle. This will make sure that a value is used that will capture both gains and losses for the respondent, while still ensuring simplicity and making sure the value that is chosen is representative for the context.

In terms of costs, simplicity and the clear rationale underlying the choice are highly valued advantages of choosing an average value (average costs), especially since the 'desired' value is very difficult to determine for respondents and might lead to low reliability. The dependency on the context is not as important in this situation, since the context is not very detailed and even purposely kept rather broad.

For the maintenance level, since it is difficult to determine exactly how much people value an excellent or poor bike, it is chosen to choose an average level of maintenance as the reference point ($R_{ML} = 0$).

Table 4: Advantages and disadvantages of methods to set a reference point

Method	Pros	Cons
Average, mode, median value	Simplicity (Avineri & Bovy, 2008) Clear rationale underlying choice (Avineri & Bovy, 2008)	Too dependent on context (Avineri & Bovy, 2008) Values reflect only the actual conditions, not perceptions (C. Yang et al., 2017)
Direct setting of value by respondent	Ability to capture 'desired' time (Avineri & Bovy, 2008)	Doubt in trustworthiness of respondents' responses (Avineri & Bovy, 2008) Doubt in ability to find a representative value of the reference point (Avineri & Bovy, 2008)
Pre-determined reference point	Simplicity (Avineri & Bovy, 2008) Treat all respondents equally	Lack of personalization

3.1.3 Stage 3: Experimental Design Considerations

In stage 3 of the experimental design process, considerations regarding the design of the experiment are made. The decisions made in this stage regulate the behavior that can be analyzed with the experiment. Different designs are elaborated on by Hensher et al. (2015).

As previously mentioned, this research will be unlabeled to fit with the purpose of identifying the importance of each of the chosen attributes in the choice for SMM. By using an unlabeled design, this research can isolate how respondents consider trade-offs of different attributes and uncertainty.

The most general design available is the full factorial design. In this design, all possible treatment combinations are presented to the respondent. The total number of treatment combinations can be determined as L^H, where L represents the number of levels, and H the number of attributes. In this situation, this means there are $3^5 = 243$ combinations. Although the level of uncertainty in access time is not explicitly an attribute, it does lead to more unique treatment combinations.

Presenting respondents with 243 different situations is unfeasible. Several strategies can be applied to decrease the number of treatment combinations (Hensher et al., 2015). The first is reducing the number of levels, which is not very well fitting for this research as the number is already relatively limited and the non-linear effects of using 3 levels is of added value.

A second option is reducing the size of the experimental design, resulting in a fractional factorial design. The stages required for creating a fractional factorial design can be seen in Figure 7. Several statistical concepts need to be conformed with. First, orthogonality must be guaranteed, which implies that there may be no correlations between different attributes. The effects of one attribute can then be estimated separately of any other attribute in the model. Second, perfect balance must be guaranteed, requiring each level of each attribute to appear an equal amount of times across all the choice tasks.

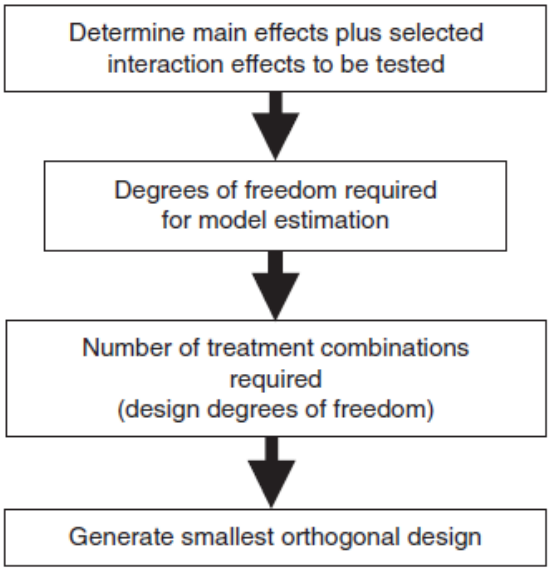


Figure 7: Stages in deriving a fractional factorial design (Hensher et al., 2015)

Since the goal of this research is to understand the impact of various attributes, as well as risk and uncertainty, on transportation mode choice, the model to be analyzed is a main effects only model. This is chosen to reduce complexity in the experiment design and model estimation, and to put focus on understanding the impact of risk and uncertainty, which is key to this research. No interactions between each of the design attributes will be analyzed and this will be accounted for in the design of the experiment.

3.1.3.1 Coding Scheme

Cost, access time, and maintenance level will be considered as continuous variables (CPT-based value functions). RR, however, has to be coded. The two options for coding are dummy coding and effects coding. In dummy coding, two new variables are created, e.g. X_1 and X_2, for an attribute of three levels. Taking RR as an example, X_1 represents an 80% charge, while X_2 represents a 50% charge. If, in the choice scenario, the RR of the vehicle is 80%, $X_1 = 1$ and $X_2 = 0$, and vice versa. In the case that the RR of the vehicle is 20%, $X_1 = X_2 = 0$. This means that the effect of a low RR is accounted for in the Alternative-Specific Constant (ASC), which accounts for all unobserved or un-researched effects. However, since the ASC is not used in this research, this method is not well-suited. In effects coding, if the RR is low, $X_1 = X_2 = -1$, providing a measure for utility contribution for low RR rather than incorporating this in the unobserved effects (Hensher et al., 2015). It is thus more appropriate to use effects coding.

The coding scheme for this research can be seen in Table 5.

Table 5: Coding Scheme for Attributes in Stated Choice Experiment

Attribute	**Variable(s)**	**Level**	**Coding**
Cost	X_C	-37.5% 0% +37.5%	
Access Time	X_{AT}	-3 min 0 min +3 min	
Maintenance	X_M	Excellent Average Poor	
Remaining Range	(X_{RR1}, X_{RR2})	80% (High) 50% (Medium) 20% (Low)	(1, 0) (0, 1) (-1, -1)

For RR, new variables need to be created. In practice, and from Table 5, this means that for RR (80% and 50% or high and medium battery charge levels) two variables are created.

3.1.4 Stage 4: Generate Experimental Design

In stage 4, the experimental design, based on the defined attributes and design considerations, is generated. This can be done using SAS Studio. SAS Studio is an online tool to generate experimental designs using various macros.

Generating an experimental design requires several steps. The first step is selecting the number of runs in an experimental design, suggesting a reasonable size. It tries to find a size where perfect balance and orthogonality is guaranteed. If these cannot be found, sizes in which violations of orthogonality and balance are minimized are suggested. The required input is the number of levels of each attribute. In this research, five attributes with three levels are present. In SAS Studio, this is determined by the following macro:

$$\%MktRuns(3^{**}5) \tag{11}$$

This results in the table shown in Figure 8. For this research, to have a perfectly balanced and orthogonal experiment, a design size of either 18 or 36 could be selected.

```
Saturated      = 11
Full Factorial = 243
Some Reasonable                        Cannot Be
   Design Sizes       Violations       Divided By
             18 *                0
             27 *                0
             36 *                0
             12                 10     9
             15                 10     9
             21                 10     9
             24                 10     9
             30                 10     9
             33                 10     9
             11 S               15     3 9
* - 100% Efficient design can be made with the MktEx macro.
S - Saturated Design - The smallest design that can be made.
    Note that the saturated design is not one of the
    recommended designs for this problem.  It is shown
    to provide some context for the recommended sizes.
```

Figure 8: Valid experimental designs considering the attributes of this research

A design must be selected that maintains data quality, focuses on the types of effects that this research considers, and does not introduce respondent fatigue. For these reasons, an orthogonal array of 18 is chosen. This type of design handles main effects well while also limiting respondent fatigue.

The orthogonal design can then be created using the following macro:

$$\%MktEx(3^{**}5, N = 18) \tag{12}$$

Formatting is applied to the design, after which it is evaluated for correlations using $\%Mkteval$. The results are visible in Figure 9, showing no correlation among the variables. The full code for generating the design is visible in Appendix B

	Cost	AccessTime	CertaintyLevelAvailability	MaintenanceLevelDistr	RemainingRange
Cost	1	0	0	0	0
AccessTime	0	1	0	0	0
CertaintyLevelAvailability	0	0	1	0	0
MaintenanceLevelDistr	0	0	0	1	0
RemainingRange	0	0	0	0	1

Figure 9: Correlations in the orthogonal design

3.1.5 Stage 6 - 7: Generating and Randomizing Choice Sets

Since the model to be estimated is a main effects only model, stage four and five of the experimental design process by Hensher et al. (2015) happen simultaneously. In stage six and seven, the choice sets are generated and randomized. Using the macros previously mentioned, a randomized choice set can be generated based on the chosen experimental design decisions.

The treatment combinations belonging to the generated orthogonal array is visible in Figure 10.

Obs	Cost	AccessTime	CertaintyLevelAvailability	MaintenanceLevelDistr	RemainingRange
1	282	-3	80	20% Excellent, 60% Average, 20% Poor	80
2	282	-3	60	30% Excellent, 40% Average, 30% Poor	20
3	282	0	80	40% Excellent, 20% Average, 40% Poor	20
4	282	0	40	20% Excellent, 60% Average, 20% Poor	50
5	282	+3	60	40% Excellent, 20% Average, 40% Poor	50
6	282	+3	40	30% Excellent, 40% Average, 30% Poor	80
7	451	-3	80	40% Excellent, 20% Average, 40% Poor	50
8	451	-3	40	20% Excellent, 60% Average, 20% Poor	20
9	451	0	60	30% Excellent, 40% Average, 30% Poor	50
10	451	0	40	40% Excellent, 20% Average, 40% Poor	80
11	451	+3	80	30% Excellent, 40% Average, 30% Poor	20
12	451	+3	60	20% Excellent, 60% Average, 20% Poor	80
13	620	-3	60	40% Excellent, 20% Average, 40% Poor	80
14	620	-3	40	30% Excellent, 40% Average, 30% Poor	50
15	620	0	80	30% Excellent, 40% Average, 30% Poor	80
16	620	0	60	20% Excellent, 60% Average, 20% Poor	20
17	620	+3	80	20% Excellent, 60% Average, 20% Poor	50
18	620	+3	40	40% Excellent, 20% Average, 40% Poor	20

Figure 10: Orthogonal Design for the SCE

The treatment combinations should be paired to determine the choice sets a respondents receives. The combinations can be randomly paired. The result is visible in Table 18 in Appendix C. Pairing has been performed by a small Python algorithm that randomly connects the alternatives into pairs. A list of 18 numbers is generated and looped over, randomly selecting two numbers at a time and connecting them in a tuple.

3.1.6 Stage 8: Constructing the survey

The last stage of the experimental design process involves constructing the survey which includes the experiment. In addition to the experiment, this survey includes questions regarding socio-demographics and general transportation patterns, as well as extra information regarding the survey and the experiment that is necessary for the respondent to be able to adequately fill out the survey.

First of all, the respondent is required to agree to a consent form, which has been approved by the Ethical Review Board of Eindhoven University of Technology. The survey starts with some warm-up questions that serve both as a gentle introduction of the topic to the respondent, as well as an opportunity to collect information about the respondent's typical travel behavior, main modes of transport used, familiarity with and frequency of shared e-moped usage, and reasons for choosing shared e-mopeds. These are asked to get a general idea of the travel pattern of respondents and for possible interactions with each of the attributes. Also, the maximum acceptable access time to a shared e-moped is asked here.

Before moving to the SCE, the respondent is introduced to the several maintenance states the vehicle can be in. The levels are described as follows:

- Excellent: the vehicle is fully functional and in perfect shape, like it just came from the manufacturer.
- Average: the vehicle is operational but has some non-critical issues and noticeable visual damage. The vehicle has been in use for some time and therefore shows some wear.

- Poor: the vehicle has one or more critical issues, such as malfunctioning brakes or a crooked steering wheel, and significant visual damage. It can still be used but with difficulties.

These descriptions are accompanied by AI generated images of shared e-mopeds in various states, available in Figure 11.

(a) Shared E-Moped in Excellent state (ChatGPT, 2025b)

(b) Shared E-Moped in Average state (ChatGPT, 2025a)

(c) Shared E-Moped in Poor state (ChatGPT, 2025c)

Figure 11: Examples of shared e-mopeds in various states

Figure 12 below shows an example of one of the stated-choice scenarios presented to the respondents.

Stated-Choice Scenario

	Shared E-moped A	Shared E-moped B
Cost of the trip	€2.82	€2.82
Access time	3 minutes (40% chance) 7 minutes (60% chance)	3 minutes (80% chance) 7 minutes (20% chance)
Maintenance level	30% chance of Excellent state 40% chance of Average state 30% chance of Poor state	40% chance of Excellent state 20% chance of Average state 40% chance of Poor state
Remaining range	80%	50%

Figure 12: Example of a Stated-Choice Scenario

Then, after all the choice scenarios, the respondent is asked for several socio-demographics. An overview of the chosen socio-demographics and answer categories is summarized in Table 19 in Appendix D. These have been chosen based on the literature review conducted. This review suggested several socio-demographic variables that potentially influenced transportation mode choice behavior. Some of the variables have been chosen based on logical reasoning, predicting that it could influence the importance of one or more attributes. Based on this, age, gender, income, occupation, level of education, and living environment have been selected. The answer categories have been selected based on previous studies (e.g. An et al. (2023) and Hoobroeckx et al. (2023)), commonly chosen categories in national statistics (CBS), and logical reasoning. For example, age categories have been chosen based on what is usually used in national statistics, while adding some more categories to be able to potentially show the contrast between more age groups.

The survey has been constructed using LimeSurvey.

3.2 Utility Function

The SCE is outlined in the above sections. In order to make decisions, respondents combine the attributes into a utility function. The section below presents an elaboration on this utility function and its elements, both with and without the interaction of socio-demographic variables.

3.2.0.1 Main effects model

The utility function of an alternative i in the choice for an e-moped is:

$$U_i = \beta_C V(X_c)_i + \beta_{AT} V(X_{AT})_i + \beta_{ML} V(X_{ML})_i + \beta_{RR1} X_{RR1,i} + \beta_{RR2} X_{RR2,i} + \epsilon_i \tag{13}$$

where β_C, β_{AT}, β_{ML}, and $\beta_{RR1,2}$ describe the coefficients of costs, access time, maintenance level and remaining range respectively. $V(X_c)_i$, $V(X_{AT})_i$, and $V(X_{ML})_i$ describe the Cumulative Prospect Value functions of cost, access time, and maintenance level respectively for alternative i. $X_{RR1,i}$ and $X_{RR2,i}$ are vectors of attribute RR for alternative i. ϵ_i indicates the unobserved utility of alternative i. This unobserved element of utility is independent and identically Gumbel distributed in compliance with the assumptions of the multinomial logit model (Hensher et al., 2015).

For each alternative, the utility level of that alternative is made up of an observed and an unobserved component. The observed components covers each of the independent variables, while the unobserved component includes elements in the decision-making process over which the researcher has no control. They are tendencies in the decision-making behavior of the respondent unrelated to one of the design attributes. Given the distribution of this error term, for each alternative, ϵ_i is independent from any other alternatives.

For the attributes cost, access time, and maintenance level, the value functions $V(\cdot)_i$ for each alternative i will be determined. For costs, this gives:

$$V(X_c)_i = \begin{cases} -\lambda(X_{c,i} - R_c)^{\beta^-} & \text{if } X_{c,i} > R_c \\ 0 & \text{if } X_{c,i} = R_c \\ (R_c - X_{c,i})^{\beta^+} & \text{if } X_{c,i} \leq R_c \end{cases} \tag{14}$$

In this equation, λ is the parameter for loss aversion, β^+ and β^- are the parameters for diminishing sensitivity for gains and losses respectively, and R_c is the reference point for costs.

For access time, it is slightly more complicated, since probabilities and multiple outcomes are involved. First, the value function $v(\cdot)$ of each possible access time $X_{AT,ij}$ of alternative i should be determined. This can be done according to:

$$v(X_{AT,ij}) = \begin{cases} (R_{AT} - X_{AT,ij})^{\beta^+} & \text{if } X_{AT,ij} < R_{AT} \\ 0 & \text{if } X_{AT,ij} = R_{AT} \\ -\lambda(X_{AT,ij} - R_{AT})^{\beta^-} & \text{if } X_{AT,ij} > R_{AT} \end{cases} \tag{15}$$

R_{AT} is the reference point for access time while the rest of the parameters remain the same as in Equation 14. Decision weights for both gains and losses should also be determined. For this, the outcomes should be ranked from low to high. This creates a loss and a gain domain. In both these domains, each outcome $X_{AT,ij}$ should be indexed from low to high for gains, and from least bad to

worst for losses. This means, for example, that if a loss of 2 (i.e. -2) and a loss of 4 (i.e. -4) are presented, the loss of 2 is indexed as 1, while the loss of 4 is indexed as 2. The probability of seeing access time $X_{AT,ij}$ of alternative i is then defined as $p_{AT,j}$. Decision weights can now be determined by:

$$\pi_j^+ = w^+(p_{AT,j} + \cdots + p_{AT,k^+}) - w^+(p_{AT,j+1} + \cdots + p_{AT,k^+}), \quad 0 < j < k^+ \tag{16}$$

where k^+ indicates the total number of gains and j is the rank of outcome $X_{AT,ij}$ in the ordered list of gains. In the case where both outcomes $X_{AT,ij}$ are smaller than the reference value, both outcomes are gains, and k^+ equals 2. For losses, this works in the same way, according to:

$$\pi_j^- = w^-(p_{AT,-k^-} + ... + p_{AT,-j}) - w^-(p_{AT,-k^-} + ... + p_{AT,-j-1}), -k^- < -j < 0 \tag{17}$$

where k^- indicates the total number of losses and j is the rank of outcome $X_{AT,ij}$ in the ordered list of losses. Here, if both outcomes $X_{AT,ij}$ are larger than the reference value, both outcomes are losses, and k^- equals 2.

In order to determine the decision weights using Equation 16 and Equation 17, probability weighting should be applied. These can be determined using Equation 18 and Equation 19 below. In these formulas, γ and δ are parameters for probability weighting, gains and losses respectively.

$$w^+(p_{AT}) = \frac{p_{AT}^\gamma}{\left(p_{AT}^\gamma + (1 - p_{AT})^\gamma\right)^{1/\gamma}} \tag{18}$$

$$w^-(p_{AT}) = \frac{p_{AT}^\delta}{\left(p_{AT}^\delta + (1 - p_{AT})^\delta\right)^{1/\delta}} \tag{19}$$

Ultimately, the total utility, or cumulative prospect value, of access time of alternative i can be determined according to Equation 20 and Equation 21.

$$V(X_{AT}^+)_i = \sum_{j=1}^{k^+} \pi_j^+ \cdot v(X_{AT,ij}); \quad V(X_{AT}^-)_i = \sum_{j=-k^-}^{-1} \pi_j^- \cdot v(X_{AT,ij}) \tag{20}$$

$$V(X_{AT})_i = V(X_{AT}^+)_i + V(X_{AT}^-)_i \tag{21}$$

Within the sum of Equation 20, each weighted subjective value is determined by multiplying the value function $v(X_{AT,ij})$ of an outcome $X_{AT,ij}$ with the decision weight $\pi_j^\pm$ of each outcome. For both the gains and losses, these are summed to obtain $V(X_{AT}^+)_i$ and $V(X_{AT}^-)_i$, which are then accumulated to obtain the Cumulative Prospect Value $V(X_{AT})_i$ of alternative i.

The Cumulative Prospect Value of each possible maintenance level ($X_{ML,ij}$) of alternative i is determined in the same way. First, the value function $v(\cdot)$ can be determined according to:

$$v(X_{ML,ij}) = \begin{cases} (X_{ML,ij} - R_{ML})^{\beta^+} & \text{if } X_{ML,ij} > R_{ML} \\ 0 & \text{if } X_{ML,ij} = R_{ML} \\ -\lambda(R_{ML} - X_{ML,ij})^{\beta^-} & \text{if } X_{ML,ij} < R_{ML} \end{cases} \tag{22}$$

Since $R_{ML} = 0$, the formulas can be simplified to:

$$v(X_{ML,ij}) = \begin{cases} (X_{ML,ij})^{\beta^+} & \text{if } X_{ML,ij} > R_{ML} \\ 0 & \text{if } X_{M,ij} = R_M \\ -\lambda(-X_{ML,ij})^{\beta^-} & \text{if } X_{ML,ij} < R_{ML} \end{cases} \tag{23}$$

Since, for each scenario, there will be exactly one loss and one gain with a certain probability, decision weights π_j^+ and π_j^- can be respectively determined through:

$$\pi_j^+(p_{ML}) = \frac{p_{ML}^\gamma}{\left(p_{ML}^\gamma + (1 - p_{ML})^\gamma\right)^{1/\gamma}} \tag{24}$$

$$\pi_j^-(p_{ML}) = \frac{p_{ML}^\delta}{\left(p_{ML}^\delta + (1 - p_{ML})^\delta\right)^{1/\delta}} \tag{25}$$

The Cumulative Prospect Value of maintenance level $V(X_{ML})_i$ of alternative i can then be determined through:

$$V(X_{ML}^+)_i = \sum_{j=1}^{k^+} \pi_j^+ \cdot v(X_{ML,ij}); \quad V(X_{ML}^-)_i = \sum_{j=-k^-}^{-1} \pi_j^- \cdot v(X_{ML,ij}) \tag{26}$$

$$V(X_{ML})_i = V(X_{ML}^+)_i + V(X_{ML}^-)_i \tag{27}$$

3.2.0.2 Interaction effects model

An interaction effects model includes each significant interaction of the independent variables with socio-demographic variables. These socio-demographic variables can be used to test for differences in importance of attributes between different social groups, such as gender, ages, income groups and educational levels.

The basic elements of the utility function (Equation 13) remain the same. However, when testing the interaction of a socio-demographic variable with one of the independent variables, a separate coefficient β is generated for each group of interest. For example, when testing the interaction effect of age on cost, it can be examined whether younger age groups are more or less sensitive to costs. In the case of this research, an example of this could be:

$$
\begin{aligned}
U = \beta_C V(X_c) \\
&+ \beta_{C(18-24)} \times D_{(18-24)} \times V(X_c) \\
&+ \beta_{C(25-34)} \times D_{(25-34)} \times V(X_c) \\
&+ \beta_{C(35-44)} \times D_{(35-44)} \times V(X_c) \\
&+ \beta_{C(45-54)} \times D_{(45-54)} \times V(X_c) \\
&+ \beta_{C(55-64)} \times D_{(55-64)} \times V(X_c) \\
&+ \beta_{C(65+)} \times D_{C(65+))} \times V(X_c) \\
&+ \beta_{AT} \times V(X_{AT}) \\
&+ \beta_M \times V(X_{ML}) \\
&+ \beta_{RR1} \times X_{RR1} \\
&+ \beta_{RR2} \times X_{RR2} + \epsilon
\end{aligned}
\tag{28}
$$

where D_{25-34} indicates a variable that equals 1 if the respondent is between 25 and 34 years old, and 0 otherwise. This analysis can be performed for each combination of independent and socio-demographic variable deemed relevant to test for a potential significant interaction.

Before testing for each interaction, correlations between each of the variables will be tested. From this analysis, pairs of variables that are correlated are found. When entering these correlated variables in the model together, misleading results might arise. Therefore, combining these variables in the model together should be avoided. After testing each of the socio-demographic variables that are deemed relevant, those that are (close to) significant and not correlated will be combined in an interaction effects model. Based on the results of the interaction effects model, insignificant interactions or interactions that do not add to model quality will be removed in a step-wise manner until an interaction model with significant interactions is reached.

For each of the socio-demographic variables, groups that are not represented sufficiently enough will be omitted from analysis or, preferably, combined with other groups to form a sufficiently large set. For example, two age groups could be combined to form one larger age group if the sizes of one or both of these groups are limited. Only if there is no viable way to combine different groups will datapoints be removed from the dataset in order to maximize the available data and estimate results as accurately as possible. The results of testing each interaction, as well as the performance and results of the final interactions model will be reported in section 5. For the interaction model, the CPT-parameters as estimated in the main model will be used to not make the model too complex to accurately estimate.

3.3 Parameter Estimation

From the results of the survey, parameters and coefficients as defined in the utility function (Equation 13) will be estimated. This will be done using Maximum Likelihood Estimation (MLE). MLE is a common approach for estimating parameters from discrete choice data, and is thoroughly elaborated on by Hensher et al. (2015). In this approach, a likelihood function is defined that is used to maximize the predictions obtained by a model. For a given situation where alternatives are shown to respondents, asking them to choose one, the likelihood function is formulated as:

$$L_{NS} = \prod_{n=1}^{N} \prod_{s \in S_n} \prod_{j \in J_{ns}} (P_{nsj})^{y_{nsj}} \tag{29}$$

where y_{nsj} equals 1 if alternative j is chosen by a decision-maker n in choice situation s, and 0 otherwise. N is the total number of respondents or decision makers and S_n is the set of choice situations. P_{nsj} is a function of the data and all unknown parameters. In discrete choice modeling, the Multinomial Logit (MNL) model is commonly used to determine the probability that an alternative is chosen among a choice set, as for example elaborated on by Franses & Paap (2001). Based on the observable part of utility U_{nsj} of alternative j in choice situation s, the probability that alternative j is chosen, P_{nsj}, is determined as:

$$P_{nsj} = \frac{e^{V_{nsj}}}{\sum_{k \in C_{ns}} e^{V_{nsk}}} \tag{30}$$

Here, C shows the set of alternatives belonging to choice set s shown to decision-maker n. V_{nsk} is the observed element of utility. Commonly, not the likelihood function but rather the log of the likelihood function is maximized. This is done since the product of a lot of probabilities results in a small number, which might cause errors in rounding. The function that is then maximized is:

$$LL_{NS} = ln(\prod_{n=1}^{N} \prod_{s \in S_n} \prod_{j \in J_{ns}} (P_{nsj})^{y_{nsj}}) \tag{31}$$

or

$$LL_{NS} = \sum_{n=1}^{N} \sum_{s \in S_n} \sum_{j \in J_{ns}} y_{nsj} ln\,(P_{nsj}) \tag{32}$$

The MNL model includes various assumptions about the choice scenario. First of all, an MNL model assumes choices are made based on an observable element and an unobservable element. This is translated in the utility function (Equation 13) as the deterministic part with independent variables and the error term. The MNL model further assumes that the unobserved part, or the error term, is i.i.d. and Gumbel distributed. This means that, within each choice task, the error terms of each alternative are independent of each other, but both follow the Gumbel distribution. This error term is dealt with through Equation 30. Even though the error term is not directly included in this equation, by assuming this error term is Gumbel distributed, it can be integrated out, leaving Equation 30 to inherently include the randomness of the error term. MNL models furthermore hold well for models with no correlation between independent variable, which is the case in the research design that has been generated. Next, the MNL model assumes Independence of Irrelevant Alternatives (IIA), meaning that the choice for an alternative does not depend on, in the case of this research, a third, unavailable alternative. Respondents decide purely based on the alternatives shown to them. The relative odds of choosing either one of the two alternatives would remain the same even if another alternative is added. Lastly, MNL assumes choice tasks are dealt with independently. This means that the choice made in choice task A will not influence the choice of any further tasks.

Furthermore, it must be assumed that the unobserved elements of utility of each alternative in a choice set are independent of each other. This means that within choice tasks, different elements might be of unobserved influence for each alternative. Even though this is a heavy assumption to make, it is worthwhile considering the computational advantages of the MNL model over other models that do not follow this assumption. Lastly, each choice task is dealt with independently. Given the fact that each respondent gets nine choice task, this is also a strong assumption, but must be considered in order to use the computational advantages of the MNL model over other, more complex models.

The utility function (Equation 13) includes the unknown parameters λ, γ, δ, β^-, and β^+ belonging to CPT. Using the data that will be collected through surveys, next to the reference points mentioned earlier, utility functions including only these unknown parameters and the unknown coefficients of each attribute can be formulated. According to Equation 30, choice probabilities can be formulated, which are then used in Equation 31 or Equation 32. Maximizing either one of these equations will present values for parameters and coefficients that best fit the distribution of the data. In order to start maximization, initial guesses will be used as values for all parameters. Using these initial guesses, a current value for the log likelihood formula can be found, which will then be maximized. This maximization can be done in Python, for example using SciPy. By maximizing the log likelihood function, or minimizing the negative log likelihood function, values for unknowns are estimated that replicate the presented data set as closely as possible.

The parameters for diminishing sensitivity (β^+, β^-) can usually be determined in similar fashion to the other parameters. However, in this research, only a limited number of levels is used in the SCE due to complexity constraints. Since diminishing sensitivity estimates the extent to which losses or gains further away from the reference point impact the value of an attribute, using only one gain and one loss at similar distance to the reference point will most probably not result in accurate estimates of β^+ and β^-. It is therefore chosen to use the estimates as identified by Tversky & Kahneman (1992) at $\beta^+ = \beta^- = 0.88$.

3.4 Model Checks

Before the survey is distributed, fake data is generated according to the orthogonal design to test whether the parameters could be predicted. A Python script is written for an MNL model, along with a Python script to generate fake data. This script generates choice alternatives based on the orthogonal design. Then, using pre-defined values for the parameters and coefficients, choices are made based on the utility function as described in Equation 13. The values are described in Table 6.

Table 6: Values used for model checking

Coefficient / Parameter	Value
λ	2.25
δ	0.61
γ	0.69
β_C	1.4
β_{AT}	1.0
β_{ML}	0.7
β_{RR1}	0.2
β_{RR2}	0.5

When choosing the alternative, choices are made according to a choice probability. This is determined for each alternative according to:

$$P_1 = \frac{e^{U_1}}{e^{U_1} + e^{U_2}} \tag{33}$$

just as described in subsection 3.3, where U_1 and U_2 are the observed elements of utility of both alternatives of a choice set calculated using the pre-defined values of coefficients and parameters mentioned above. Based on this probability, one of the alternatives is chosen. This process makes sure the unobserved elements of utility are taken into account when choosing one of the alternatives, instead of determining purely based on highest utility.

The MNL is then used to estimate the coefficients and CPT-parameters. The input for this is an Excel or CSV-file including each of the choice tasks and the chosen alternative in each choice task. Numerical optimization using the BFGS-algorithm is then applied. This is a local search optimization algorithm that optimizes an objective function by minimizing the gradient of each of the parameters, that is how much a change in a parameter value changes the objective function, and adjusting the parameter values accordingly. This optimization method allows to set boundaries to the values of the coefficients in order to help with realistic estimation. The algorithm tries to find the maximum value of the negative log-likelihood by minimizing the gradient of the function. One disadvantage of numerical optimization is that overfitting could occur, causing the parameters to diverge and become unrealistic, for example when some parameters are weakly defined, meaning that the data input does not provide a lot of insight on the true values of the coefficients or parameters. In this case, the log-likelihood function is nearly flat in some directions, meaning that even a large change in a parameter value only leads to very small improvements in the log-likelihood function. The model continues to adjust the parameters to further maximize the log-likelihood even though the improvements are close to negligible, leading to poor convergence of the estimates. It is therefore common to set a stopping criterion to the iterative process, as also expanded on by Train (2009). Common MNL estimation packages in python such as Biogeme use these stopping criterion as well, basing them for example on relative improvement of the log-likelihood function, number of iterations, or the gradient value (Bierlaire, 2020). To incorporate this in the model and avoid overfitting, a minimum relative improvement of 0.01% and a minimum number of iterations of 25 has been chosen based on the graph of the log-likelihood over time. If an optimal value is reached, optimization stops before either one of these thresholds has been reached. The test parameters as mentioned in Table 6 were estimated with reasonable accuracy and statistical significance, granting the assumption that the model can estimate results, considering the stopping criteria.

3.5 Interpretation of results

As has been explained before, the MNL will be analyzed using the BFGS-algorithm that will minimize the negative log-likelihood from the utility function, as explained in subsection 3.3. This will result in estimates for all coefficients and CPT-parameters that explain decision-making behavior of respondents.

Because of the way the utility function is designed, the coefficients for each of the attributes resulting from the estimation cannot be directly interpreted. It is for example expected that cost has a negative impact on utility. However, since the Cumulative Prospect Value used in the utility function can be either positive or negative, the coefficient is expected to be positive. This does however not reflect that cost has a positive impact on utility, but rather depends on the Cumulative Prospect

Value resulting from a certain cost level. It is thus more useful to consider the impact of a certain value for each of the attributes on utility. Therefore, in the results and discussions, graphs will be generated for each of the attributes that show how attribute values impact utility. These graphs can show the impact of a negative or positive change in an attribute value. Here, the presence and implications of psychological phenomena such as risk and loss aversion, and reference dependence will be presented as well

As part of the research questions formulated, the trade-offs between attributes potential users make will be analyzed. This can generate insights on, for example, the amount of money one would pay to walk one minute less to their vehicle, and vice versa. In order to do this, utility contributions of different values of attributes will be compared. For cost and access time, for example, the positive impact on utility from a change in access time can be countered by the negative impact from a change in cost to keep the utility value the same. This results in implications on the trade-offs one would make. When looking at the cost variable, this can result in WTP-measures, but these measures can also be generated for the other variables, such as the willingness to walk further for a vehicle that has a higher charge. Measures of, for example, the Value of Time can also be generated and compared to averages of the Netherlands to see how the sample compares to national averages.

4 Data Collection, Cleaning and Sample Distribution

This section elaborates on data collection and cleaning. First of all, the methods of data collection will be explained, followed by descriptives of the data sample. The approach used for data cleaning will be elaborated on, including a representation of the final data sample to be used.

4.1 Data collection

The data of this study is collected among respondents in the region of Enschede. The data has been collected from the 26th of May to the 12th of June using Limesurvey. The target population of respondents is, as identified before, people living in or around the city of Enschede. There are no restrictions on who can fill out the survey, aside from a minimum age requirement. Participants must be over 18. Since e-mopeds are available to the general public, the data sample includes individuals with diverse characteristics to accurately reflect the potential group of users. In order to distribute the survey, multiple channels have been used.

Data is, first of all, collected through fieldwork conducted in Enschede. In total, 4 days have been spent addressing people in public. Potential respondents are approached and invited to complete the survey. This is mainly done in areas where people are taking a break, so that they are not disturbed during work or study and can give their full attention to the survey. Also, flyers with QR-codes, both in English and Dutch, have been distributed around the university campus and business park. These flyers have also been pinned to notice boards and placed on tables in common areas. These locations have been chosen since the number of potential users of shared e-mopeds in these areas is relatively high and the distribution of flyers in these locations is quite common. Secondly, personal relationships, including colleagues of Keypoint living in the region of Enschede, are used to distribute the survey. These people are asked to share the survey with acquaintances in the target area, resulting in responses from second-degree contacts. Thirdly, several parties are reached out to to distribute the survey. These include the municipality of Enschede, the Enschede merchants' association, and several study and student associations. Finally, social media is used to distribute the questionnaire. LinkedIn, Instagram, X, and TikTok have all been used to reach out to potential respondents in Enschede. Instagram, LinkedIn, and X mainly help to reach personal contacts and give these contacts the chance to distribute among others, while TikTok offers the possibility to reach a larger audience of unknown people in the region of Enschede. Considering the distribution of the survey online, in all messages on social media, it was clearly stated that only people in the target population, those living in the region of Enschede, should fill out the survey, showing significant effort to address the target audience and therefore to support data quality. Since the place of residence was not asked, it was however not possible to confirm this.

All respondents that were reached out to have been provided with an informed consent form, stating what the research is for, the purpose of the data, and how the data will be dealt with. Each potential respondent had the opportunity to read this form and reach out for questions. Participation is not possible without agreeing to this form. In this form, anonymity is clearly stated.

It is clear that each channel has both advantages and disadvantages. Personal contacts and addressing people in public yield a higher response rate, meaning a larger proportion of the people contacted actually participate. However, these methods typically reach fewer people overall. Distributing through social media results in a much larger range, while the response rate is lower. Channels that require less effort, such as putting up flyers, result in less respondents attracted, while addressing people directly increases the number of respondents, but also increases the effort required. Next

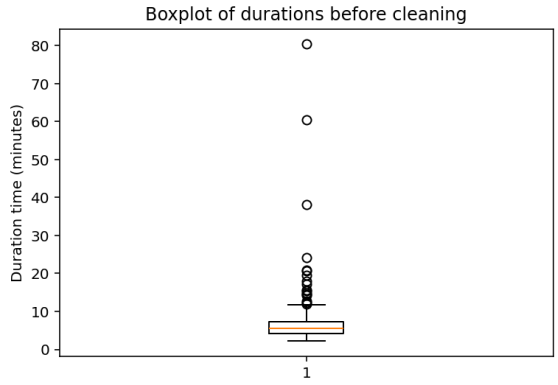
to this, directly approaching people could have resulted in unintentional selection bias. For these reasons, a combination of all these methods has been used to attract as many respondents as possible. While the use of personal and social networks is suitable for reaching respondents, this might result in the under-representation of certain groups. In the case of this research, young adults who frequently use social media and students could be overrepresented because of the channels used. Adults with full-time jobs, who are less active on channels such as Instagram and TikTok, and out of reach of the personal network, could therefore be under-represented. This could limit the ability to generalize the results over a larger population.

4.2 Data cleaning

In total, 450 people started the survey. 280 people have fully completed the survey, with 170 people only partially completing the survey. This results in a completion rate of 62.2%.

Data cleaning is an essential part of the analysis. Every study includes data entries that cannot be used for various reasons, such as missing data or incomplete surveys, clear outliers, or non-serious participation from the respondent. Outliers can be detected through generating descriptive statistics. From these statistics, plots could be generated, and these combined can be used to detect extreme values. Non-serious participation can be identified in various ways. For example, answers to questions with text input from the respondent can be analyzed. If answers do not make sense, there is a large chance that the survey was not filled out seriously. It could also be identified by looking at the time it took the respondent to fill out the survey and comparing this to the average of the sample, or, in the case of this research, identifying a pattern in the way the choice tasks have been answered. If all choice tasks are answered with 'Shared E-moped A', there is a high chance the tasks were not taken seriously. It was indicated that the survey should take, on average, 5 to 10 minutes.

First of all, data points have been removed that show durations of filling out the survey that are unrealistic. The indicated expected time of the survey was 5 to 10 minutes. In order to find these datapoints, boxplots of the durations have been created. The inter-quartile range (IQR), which is the range between the 25th and the 75th percentile of the data, has been determined. Then, values 1 times the inter-quartile range below the 25th percentile are removed. While the common threshold is 1.5 times the inter-quartile range, it is chosen to set the boundary closer to make sure unrealistically short durations are removed. This method is chosen as no clear distribution in the data could be found. This meant methods using, for example, z-scores could not be used. In this case, the IQR-method is reliable and robust. Usually, using this method, upper outliers, i.e. those values 1.5 times above the inter-quartile range, are removed as well. However, it could still be realistic that individuals who took this long needed more breaks or more carefully considered choices, resulting in realistic surveys. Therefore, it is chosen to only remove extreme values, as these interruptions might have resulted in a loss of knowledge on the survey. The boxplots can be seen in Figure 13. It has been chosen to remove the three largest outliers, resulting in the exclusion of in total three responses. The average time taken for the survey after data removal was 6.2 minutes (6 minutes and 12 seconds).



(a) Boxplot of survey durations before cleaning

(b) Boxplot of survey durations after cleaning

Figure 13: Comparison of survey durations before and after cleaning

Secondly, data points that contain unrealistic values for the acceptable access time for the respondent have been removed. The access time is, as mentioned in the design, the time it takes someone to move towards the e-moped. The IQR has been determined and those values 1.5 times the IQR above the 75th percentile, and 1.5 times below the 25th percentile have been removed from the data. This method has been chosen with the same reasoning as with survey durations, with the distribution shown in Figure 14. This resulted in the exclusion of 14 responses. The boxplots before and after removing these datapoints can be seen in Figure 15. After cleaning, the average acceptable access time is 5.923 minutes (5 minutes and 55 seconds)

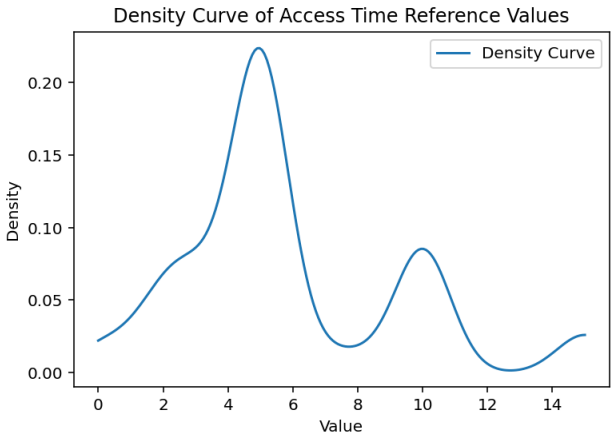
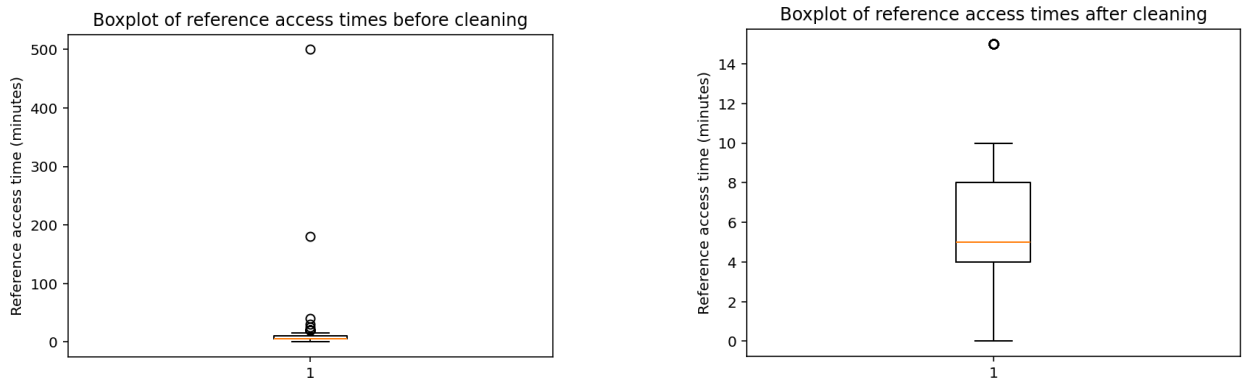


Figure 14: Density curve of reference values for access time



(a) Boxplot of access times before cleaning

(b) Boxplot of access times after cleaning

Figure 15: Comparison of access times before and after cleaning

Thirdly, the data points have been checked for certain patterns in responses. Each response has been checked on either having only answered with 'Shared E-Moped A' or 'Shared E-Moped B', or alternated between A and B. This resulted in the exclusion of one response.

Lastly, the dataset has been manually checked for any answers that might direct towards non-serious participation. This resulted in the exclusion of three responses, leaving a total of 259 responses to be considered. An overview of the number of respondents removed after each step is available in Table 7.

Table 7: Steps in data cleaning

Removal step	Number of removals	Number of respondents left
0	N.A.	280
1 (Duration of survey)	3	277
2 (Acceptable access time)	14	263
3 (Pattern in responses)	1	262
4 (Non-serious participation)	3	259

4.3 Sample distribution

An overview of the socio-demographics of the considered responses is visible in Table 8. An overview of the transport behavior of the considered responses is reported in Table 9.

Table 8: Overview of socio-demographics of the data sample

Category	Group	Percentage	Regional Average (Category)	Regional Average (Percentage)
Age Group	18 - 24	49.42%	15 - 25	16.23%
	25 - 34	32.05%	25 - 45	26.22%
	35 - 44	10.04%		
	45 - 54	6.56%	45 - 65	25%
	55 - 64	1.93%		
	65+	0.0%	65+	18.42%
Gender	Male	26.64%	Male	51.13%
	Female	72.59%	Female	48.1%
	Non-binary / third-gender	0.77%		
Occupation	Student	43.24%		
	Employed (full-time)	30.89%		
	Employed (part-time)	17.37%		
	Unemployed	2.7%		
	Self-employed	1.93%		
	Retired	0.0%		
	Other	1.93%		
	I prefer not to say	1.93%		
Income	Less than €750	25.48%		
	€750 - €1500	19.69%		
	€1500 - €4000	37.45%		
	€4000 - €10.000	11.2%		
	More than €10.000	1.16%		
	I prefer not to say	5.02%		
Education	Primary education	0.77%	Basic Education	27.1%
	Secondary education	25.87%	Middle level Education	43.3%
	Vocational education	19.69%	Higher Education	29.6%
	Associate degree	28.96%		
	Bachelor's degree	14.67%		
	Master's degree	8.49%		
	Doctorate degree	0.0%		
	I prefer not to say	1.54%		
Living environment	Urban	40.15%	Urban	48.15%
	Suburban	47.1%	Suburban	45.49%
	Rural	12.74%	Rural	6.36%
Experience	Yes, I have used one before	42.86%		
	Yes, I have seen or heard of them before, but not used them yet	54.83%		
	No, I do not know what shared e-mopeds are	2.32%		
Usage Frequency	Rarely (1 - 3 times a year)	83.93%		
	Occassionally (1 - 3 times a month)	13.39%		
	Frequently (1 - 3 times a week)	2.68%		

Table 9: Overview of transport behavior of data sample

Transport type	Frequency	Percentage
Commuting	Never	3.86%
	1 or 2 times per week	6.18%
	3 or 4 times per week	30.89%
	(Almost) Daily	56.76%
	No answer	2.32%
Errands	Never	3.86%
	1 to 2 times per week	47.10%
	3 to 4 times per week	23.17%
	(Almost) Daily	16.99%
	No answer	8.88%
Leisure	Never	1.16%
	1 to 2 times per week	33.20%
	3 to 4 times per week	35.91%
	(Almost) Daily	16.99%
	No answer	12.74%

Data on the regional averages has been gathered from AlleCijfers.nl (2025). Data on incomes and occupation could not be gathered. Looking at age groups, the categories as defined in statistics are divided in larger ranges. However, the percentages of age groups in this data sample can be combined and compared to the regional averages. Education is divided in three levels; basic, middle level, and higher education. In this context, primary and secondary education can be combined to form basic education, vocational education and associate degrees can be compared with middle level education, while bachelor's, master's, and doctorate degrees are forms of higher level education. Information on experience with the use of shared e-mopeds is currently not available.

The age distribution in the sample is heavily skewed towards younger people (18 to 34) and is predominantly female (72.59%) compared to the actual population of the region of Enschede. This could be a result of the distribution channels that have been used. As the survey has been mainly spread through social media and on-campus approaching and flyering, the survey might have reached a younger audience. The dominant number of female respondents could have been caused by spreading through social media. This distribution might result in some biases. As has been mentioned in the literature review, women and men find different things important when considering SMM. Also, younger people might find different attributes more important than oler people. However, young age groups do fit the target audience for SMM. This means the distribution of ages might fit the purpose of the study.

Looking at occupation, a large majority of the sample is either a student (43.24%) or employed either part-time or full-time (48.26%). Again the large number of students might result from the use of social media and distribution on university campus. Although this might result in a bias based on the different lifestyles of these groups, these people generally are more flexible and digitally active, making the distribution still suitable for this research. The distribution of income matches the distribution of occupations, with a large portion earning less than €1500 (45.17%), which matches roughly a student income and a large part earning between €1500 and €10000 (48.65%), matching an average part-time or full-time job. This might result in correlation among

these socio-demographics, which will be investigated later.

Looking at highest education level obtained, the population is skewed towards higher education, again following logically from the main distribution channels used. This might result in some bias. Compared to the population of Enschede, the sample is more highly educated, especially considering the survey has been distributed on university campus, where people might be in the first years of their bachelor studies and therefore only have a secondary education as current highest. In terms of the living environment of people, the urban and suburban areas are heavily represented, with only around 10% living in rural areas. Looking at the typical areas in which SMM is available, this suits the research well. Lastly, the majority of respondents is at least familiar with shared e-mopeds, where 42.86% have actually used shared e-mopeds before. It is useful for this study that people know about shared e-mopeds, as they will be aware of the advantages and risks that shared e-mopeds can bring. Of the 110 (42.86%) people that indicated to have used shared e-mopeds, the majority use them only rarely, as can be seen in Figure 16 and Table 8.

The survey asked people to indicate reasons for not using shared e-mopeds for trips. This creates an understanding of barriers to usage. An overview of the reasons and number of times this was mentioned can be seen in Figure 17. Availability and costs are important considerations for people, as well as the tendency to prefer different modes of transport. Safety and weather conditions do not seem to be clear barriers.

In the above section, multiple potential biases have been mentioned. It is important to consider these when interpreting the results. These may not be fully generalizable for the broader population, as the results might reflect tendencies of a younger, more highly educated, women population. These might differ from other population groups in the area of Enschede. This will be reflected on at the end of this research.

Lastly, the average number of minutes people would be willing to walk towards a shared e-moped is, in this sample, just under six minutes, which is very close to the distance the municipality of Enschede specified as a maximum. This is beneficial for this research, as the distances will be realistic for the case study area.

In general, the sample represents a section of the population that is highly interesting for providers of SMM, which are young, educated individuals that are open to new modes of mobility. However, biases must be considered when interpreting these results. As mentioned in section 2, different people find different elements important when considering their transport. Gender is one example of this, where males and females differ in what they find the most important. Considering the fact that the sample is predominantly female, this might shape the coefficient values. The fact that the population is both young and quite highly educated may shape these coefficients as well. Young people are generally more flexible in their transportation options while costs are potentially a bigger driver for them. The concern for safety might also be lower. Next, the number of people that occasionally or frequently use shared e-mopeds is limited. Usage frequency potentially influences the perceived added value of e-mopeds and thus adjusts coefficients negatively. This leads to results that might not be fully representative of the population of Enschede and thus limit the generalizability of this research.

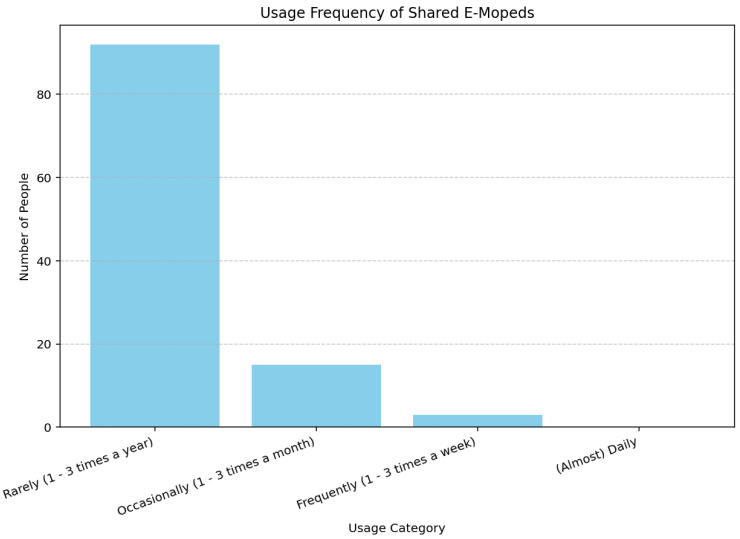


Figure 16: Usage frequency of people that have used shared e-mopeds

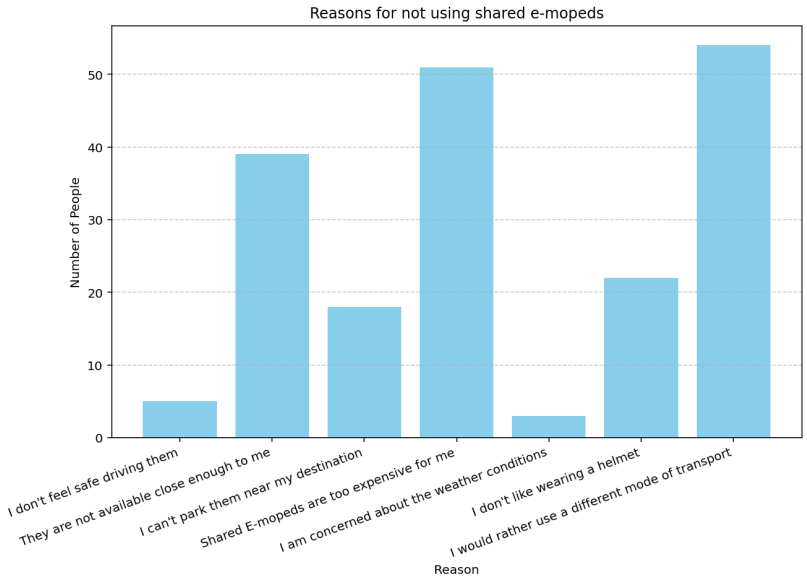


Figure 17: Reasons for not using shared e-mopeds

5 Results

This section will elaborate on the results obtained from data analysis and discuss insights. First, the results from the main effects model will be presented, including information on statistical significance. These results will be placed in context by looking at how changes in each of the attribute values contribute to utility, and comparing different attributes to each other. This presents insights into the trade-offs potential users make when looking at the different attributes. Then, a more detailed analysis will be conducted by examining interactions of the attributes with socio-demographic variables as mentioned in paragraph 3.2.0.2. This allows for a better understanding of the differences among different groups in the data sample.

5.1 Main effects model

5.1.1 Model Performance

Estimating the MNL using the BFGS-algorithm generates values for both the CPT-parameters as well as the β-coefficients for each of the independent variables. As previously mentioned, the model runs until optimization, or until the improvement in the negative log-likelihood is smaller than 0.01% and there have been at least 25 iterations. This is done to avoid overfitting. Figure 18 shows the level of the log-likelihood over the iterations, describing clear flattening in the improvements as the number of iterations increases. The log-likelihood at the final iteration is 1175.03. The performance of the model can be determined using McFadden's Pseudo R^2. This KPI compares the performance of the final model against the performance of the model without the use of explanatory variables. The formula used to determine this KPI is:

$$R^2 = 1 - \frac{-LL_{\text{Final}}}{-LL_{\text{Null}}}$$

For this, the negative log likelihood of the model without any predictors (the null log likelihood) must be determined. This can be determined by counting all the times alternative A and B were chosen respectively, determining the probability either one of these is chosen, and then summing the log of all these probabilities. For this model, 'Shared E-moped A' has been chosen 1417 times (0.6079) while 'Shared E-moped B' has been chosen 914 times (0.3921). This results in a negative null log likelihood of -1561.0264 and thus an R^2 of 0.247. Typically, values between 0.2 and 0.4 show an excellent fit for the model (Louviere et al., 2000). A score of 0.247 shows the estimated model performs 24.7% better than the null-model.

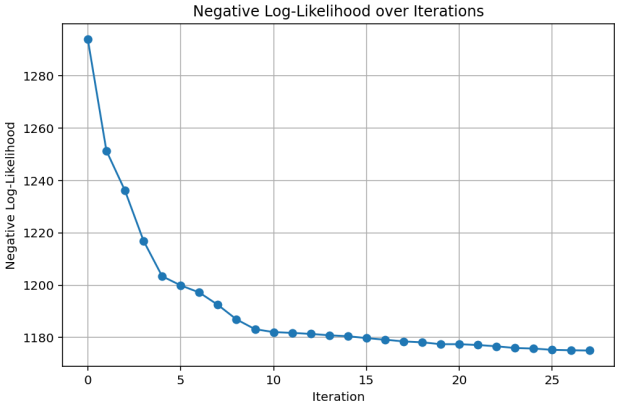


Figure 18: Level of negative log-likelihood over iterations

5.1.2 CPT-Parameter Estimation

Table 10 shows the estimated values for the CPT-parameters, the standard errors, t-values, and p-values. All parameters are statistically significant. The meaning of each of these parameters is discussed below.

Table 10: CPT-parameter estimates

Parameter	Value	St. Error	t-value	P-value
λ (loss aversion)	1.0115	0.1556	6.4987	< 0.0001
γ (prob. distortion gains)	0.3397	0.0686	4.9503	< 0.0001
δ (prob. distortion losses)	1.0000	0.1714	5.8355	< 0.0001

Starting with loss aversion (λ), the value is estimated at 1.0115. This indicates very limited loss aversion: losses are interpreted approximately the same as gains. From Tversky & Kahneman (1992), λ was estimated at 2.25 in the context of monetary gambling, indicating that people are averse towards losing money. Even though the context of this research differs from that of Tversky & Kahneman (1992), where the focus was only on identifying these parameters and aimed at monetary values only, the sample in Enschede shows very different levels of loss aversion. This could be related to the fact that loss aversion is measured not only for 'Cost', but also for 'Access time' and the 'Maintenance level'. λ is in this context thus measured for losses related to shared e-mopeds in general, not for only one aspect such as cost or time. Nevertheless, this affects the way value functions and utility contributions behave for different values of each of the attributes. With a higher loss aversion parameter, losses, for example more expensive trips, should result in a steeper negative utility contribution than equivalent gains result in positive contributions. In this research, this difference will not be as present, where losses are not treated more heavily than gains.

Looking at probability distortions, probabilities related to gains are heavily distorted ($\gamma = 0.3397$), while probabilities related to losses are not distorted at all ($\delta = 1.000$) and thus interpreted objectively. Probabilities for gains are perceived differently than they actually are, indicating that people underestimate large and medium-level probabilities at a gain, while overestimating small probabilities. This will have an impact on the value functions for the access time and maintenance level-attribute and thus on their contributions to utility. Large and medium-level probabilities of gains will be interpreted much lower, reducing the impact a gain will have on utility contribution,

causing losses to overshadow gains and thus generally lower and more negative utility contributions. From Tversky & Kahneman (1992), γ was estimated at 0.61, while δ was estimated at 0.67, indicating that the sample distorts probabilities very differently. Again, the context of this research is different. Rather than money, this research focuses probability distortion on time and maintenance levels, which could explain the difference in values compared to Tversky & Kahneman (1992).

5.1.3 Attribute Coefficients and Utility Contribution

Table 11 shows the estimated values for the coefficients for each of the design attributes, including the standard errors, t-values, and p-values. Each of the estimates is statistically significant.

Table 11: Attribute Coefficient Estimates

Independent variable	β	Std. Error	t-value	P-value
Cost	1.3203	0.1257	10.5046	< 0.0001
Access Time	0.7418	0.1124	6.5976	< 0.0001
Maintenance Level	4.9317	1.7093	2.8852	0.0039
Remaining Range: 50%	0.2037	0.0439	4.6395	< 0.0001
Remaining Range: 80%	0.7240	0.0859	8.4254	< 0.0001

As previously mentioned, the importance of each of the attributes should not be concluded purely based on the value of the coefficient. This has been elaborated on by Lancsar et al. (2007), who indicate that the value of a coefficient should not be directly interpreted as the importance of that attribute, but should rather be placed in the context and scale of the attribute. The interpretation of each of the coefficients should consider this scale or context and, for comparison, should be measured using a common measure. This common measure is, in the case of this research, utility contribution. As an example, attributes 'Cost' and 'Maintenance level' are measured at different scales. The Cumulative Prospect Value of maintenance level is measured on a significantly smaller scale than that of cost. Even though the coefficient value of the maintenance level-attribute is much larger, the utility contribution for cost might be greater. In order to analyze and compare each of the attributes, the utility contribution at various attribute values should be determined by using the coefficients in Table 11 and the Cumulative Prospect Values. Below, for each of the attributes, graphs are generated and can be found from Figure 19 to Figure 21 that show how utility is affected by attribute values.

Starting with costs, Figure 19 shows the Cumulative Prospect Value of the cost-attribute at different trip prices, as well as the utility contribution of cost at that price level. These values have been calculated using the estimates for the CPT-parameters, and the coefficient value of cost ($\beta_C = 1.3203$). This graph shows how much the price of the trip contributes to the utility function for different cost values, and thus how the willingness to use changes for different trip prices. Since the reference value for cost was set at €4.51, this value results in zero contribution to utility. All prices below €4.51 are treated as gains, while any value higher than €4.51 indicates a loss. The graph is almost symmetric, showing that losses and gains are not judged very differently, resulting from the value of λ close to 1, as previously explained. Near the reference point, the utility contribution is a little steeper than further away from the reference point, showing small signs of diminishing sensitivity. This results from the contribution of β^+ and β^- in the value function. It can logically be concluded that a trip-price cheaper than the reference value has a positive impact on utility contribution, while a more expensive trip results in negative contribution to the utility contribution.

People will be less eager to use shared e-mopeds as they get more expensive, while making the e-mopeds cheaper can increase the willingness to use.

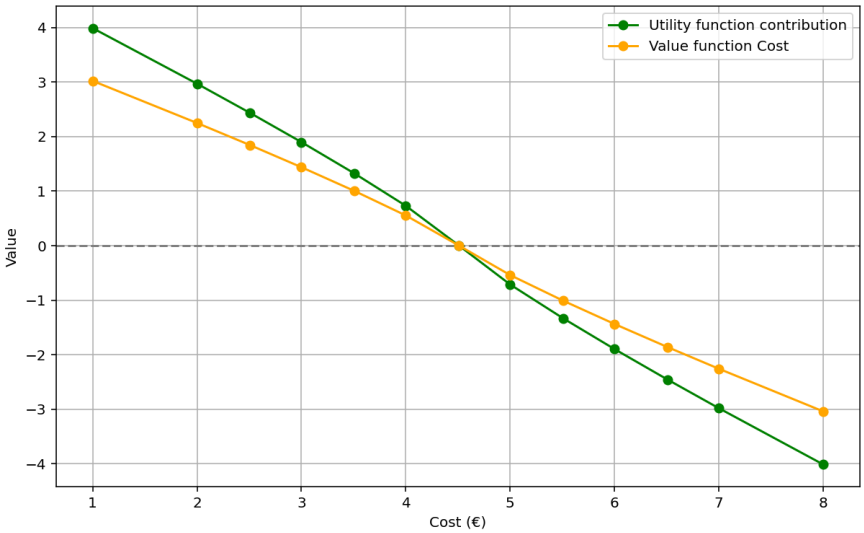


Figure 19: Utility Function Contribution and Value Function for Cost at Different Cost Levels

The estimate for the coefficient of the access time-attribute is $\beta_{AT} = 0.7418$. Similar graphs as presented for the cost-attribute can be generated to show how values for access time contribute to utility. Access time, however, includes an element of uncertainty regarding the base access time. The base access time is the access time as seen by the respondent when wanting to use a shared e-moped. It is the number of minutes first guaranteed to a user: this might increase by four minutes if the e-moped is not available. Different levels of uncertainty present different results. In Figure 20 below, the utility function contribution and Cumulative Prospect Value at different access times under different levels of uncertainty are shown. These have been generated by multiplying the Cumulative Prospect Value at different base access times by $\beta_{AT} = 0.7418$. As a reference point, the average acceptable access time of respondents of six minutes has been taken. In the graphs, this point is visible from the bend in the graph.

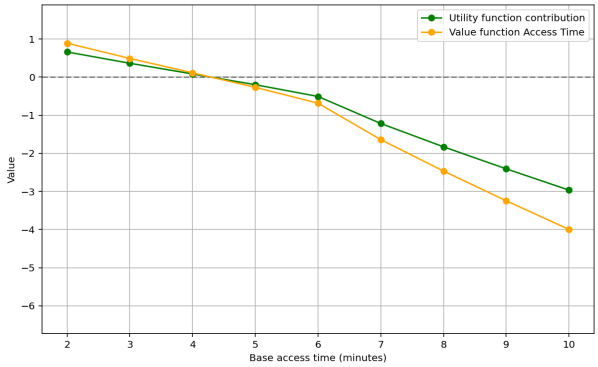
Generally, access time has a negative impact on utility contribution. As uncertainty increases, utility contribution values become more negative for the same base access times, especially near the reference point and for losses. For example, at 80% certainty, the negative contribution to utility at 6 minutes is around -0.5, while this is at -2 for 20% certainty. This indicates clear risk aversion: the more risk of not finding an e-moped at the base access time, the more negatively the access time is perceived. It is also clear that as uncertainty increases, access time gets more important to the respondent. In scenarios of large gains, for example at a base access time of one or two minutes, utility contribution is positive, but this does not hold for scenarios with high uncertainty.

Negative utility contributions occur mainly in cases of small gains, for example 4 of 5 minutes base access time, and for losses. Even though a base access time of 4 or 5 minutes is objectively a gain, there is a chance that a loss is experienced. As there is high probability distortion for gains ($\gamma = 0.3397$), while there is none for losses ($\delta = 1.000$), even at high levels of certainty, this situation negatively contributes to utility, showing the impact of probability distortion on decision-making. As certainty decreases, the gains are more and more overshadowed by the losses, as the likelihood of losses increases very much compared to gains. This explains the steep decline in utility contribution,

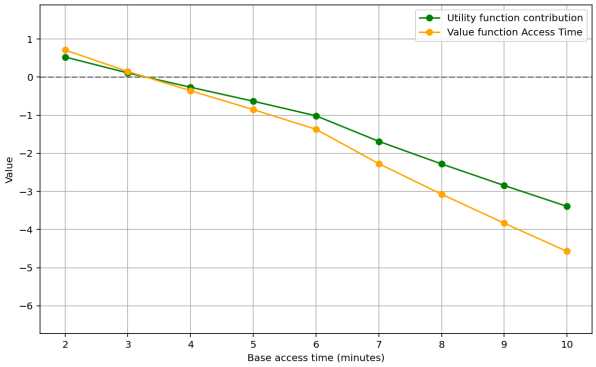
even at a base access time that is objectively a gain. Large gains are not affected as much, since either there is no chance at a perceived loss, or the loss is relatively small compared to the potential gain. However, as there is more uncertainty, even a gain of 3 minutes can result in a negative contribution to utility. For losses, the slope for different certainty levels stays around the same, as there is no probability distortion. The increased negative impact of losses in these situations can be explained by the increased chance of a large loss.

If there would have been less probability distortion for gains, or more for losses, the graph would have looked differently. Decreasing probability distortion for gains makes sure the gains are not as overshadowed, resulting in a more positive utility contribution. If there would have been probability distortion for losses, at higher uncertainty, the probability of a loss would have been overweighted, again showing less impact on overall utility contribution.

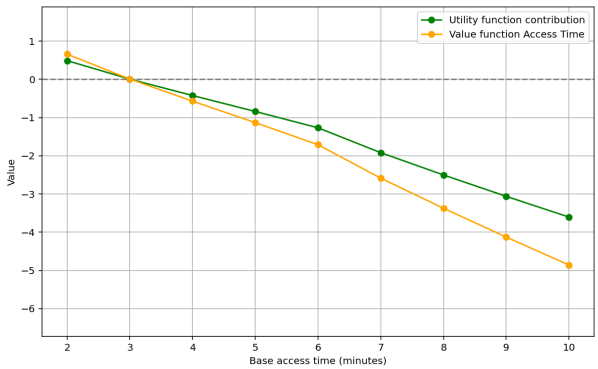
These graphs thus show how perceived losses and gains, as well as probability distortion and uncertainty, influence the impact of a certain base access time on utility. It shows that people value certainty and as certainty reduces, the willingness to use shared e-mopeds decreases. This willingness also decreases as the access time gets longer. The point at which access time positively contributes to utility is below the reference point because of the uncertainty involved. As the situation gets more uncertain, this point shifts further from the reference point, meaning a shorter access time is required to make sure the access time-attribute positively contributes to utility and thus help in increasing the willingness to use. As uncertainty increases, the access time-attribute gains importance.



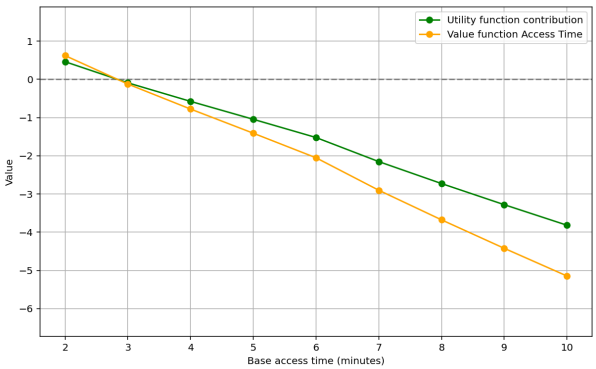
(a) Utility Function Contribution and Value Function Different Access Time Values at 80% certainty of base access time



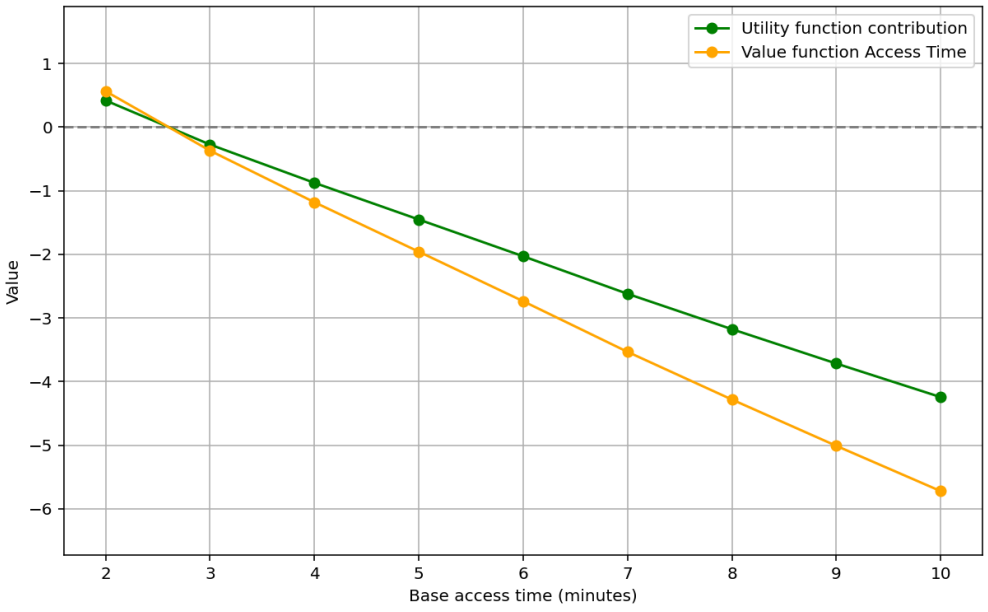
(b) Utility Function Contribution and Value Function Different Access Time Values at 60% certainty of base access time



(c) Utility Function Contribution and Value Function at Different Access Time Values at 50% certainty of base access time



(d) Utility Function Contribution and Value Function at Different Access Time Values at 40% certainty of base access time



(e) Utility Function Contribution and Value Function at Different Access Time Values at 20% certainty of base access time

Figure 20: Utility Function Contribution and Value Function at Different Access Time Values

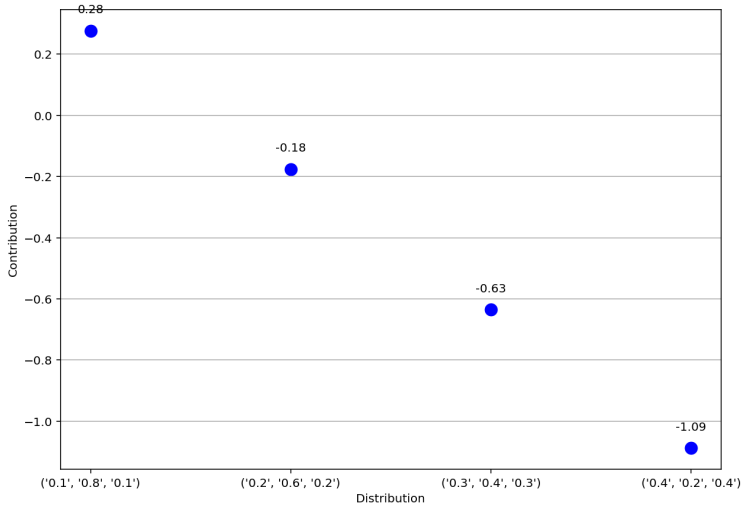
The coefficient for the maintenance level-attribute is estimated at $\beta_{ML} = 4.9317$. While this value is much higher than the estimates of both the access time and cost-attribute, the utility contribution does not necessarily have to be higher. For the maintenance level-attribute, the value of each of the states of the vehicle is known (1 for excellent, 0 for average, -1 for poor). It is however the distribution of probabilities that affects the Cumulative Prospect Value, and therefore the contribution of the maintenance level-attribute to utility. Several scenarios can be investigated that show how the maintenance level of a vehicle contributes to utility. Some example scenarios are shown in Figure 21. In these graphs, each of the distribution is shown as ('Excellent' state probability, 'Average' state probability, 'Poor' state probability).

Starting with Figure 21a, this figure shows different scenarios where the expected value of the maintenance level of the vehicle is 0, meaning the vehicle is expected to be in the 'Average' state. However, since this depends on probabilities, and the probabilities associated with gains are heavily distorted ($\gamma = 0.3397$), this results in different Cumulative Prospect Values and thus different utility contributions for each distribution. Although the probabilities for both 'Excellent' and 'Poor' states increase equivalently, the utility contribution decreases from positive for the first scenario to quite heavily negative in the last scenario. This indicates that people are more hesitant towards using shared e-mopeds that have a higher chance of being in a poor state, even though the probability of finding one in an 'Excellent' state is equally high and the vehicle is expected to be in an 'Average' state. This is caused by the fact that people distort the probability of an 'Excellent' state, causing the 'Poor' state to overshadow. This also indicates risk aversive behavior, as respondents are not willing to take a higher chance of a 'Poor' vehicle, even if they can find an 'Excellent' vehicle at the same probability (objectively). They do not distort the probability of a 'Poor' vehicle, while they do for the 'Excellent' vehicle.

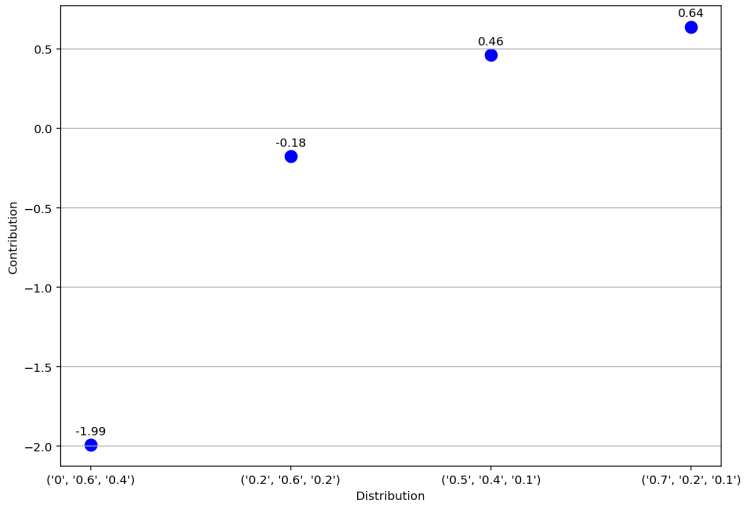
Figure 21b shows scenarios where the expected state of the e-moped gets closer to 'Excellent'. By reducing the probability that the vehicle is in a 'Poor' state, using a shared e-moped gets increasingly more attractive. Reducing the probability of an 'Average' state also has a positive effect on utility contribution, but the increase is not as significant as reducing the likelihood of a 'Poor' e-moped, as can be seen in the difference in the rise from the first to the second distribution, and from the third to the fourth. It shows the impact a 'Poor' e-moped has on utility and thus on the willingness to use.

Lastly, Figure 21c shows scenarios where the probabilities shift between the states. Comparing the first three distributions shows that an increase in the chance at an 'Excellent' vehicle does not result in the same positive influence as an increase in the chance at a 'Poor' state results in a negative influence on utility contribution. This emphasizes the negative impact a larger chance at a 'Poor' vehicle has on utility, which can be attributed both to loss aversion (although only to a limited extent) and probability distortion. It shows the risk aversive behavior of respondents due to the distortion of positive probabilities. Looking at further scenarios, the same effects can be seen in the fourth and fifth scenario, where the negative impact of the 'Poor' state is heavier than the positive impact of the 'Excellent' state (-1.28 compared to +0.54), and the same holds for the last scenarios (-1 compared to +0.08).

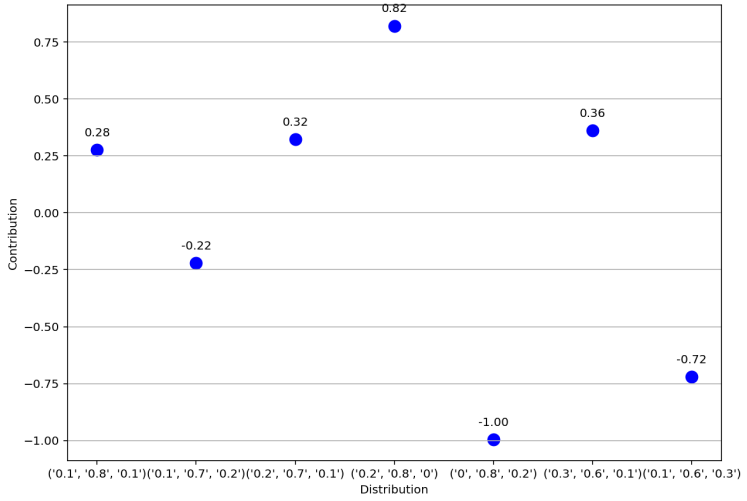
The utility contribution values can mainly be attributed to the distortion of probabilities, as respondents do not objectively look at probabilities of an 'Excellent' state, even distorting low probabilities. This results in respondents avoiding shared e-mopeds that have an increasing chance of being in a 'Poor' state, even if the chance at an 'Excellent' state increases accordingly. Finding the maintenance level as a statistically significant attribute shows the added value of understanding the impact of risky scenarios in mode choice for SMM.



(a) Utility Function Contribution for Different Maintenance Level Distributions where Expected Maintenance Level is Average



(b) Utility Function Contribution for Different Maintenance Level Distributions where the Chance of 'Excellent' State Increases



(c) Utility Function Contribution for Different Maintenance Level Distributions where Probabilities Shift

Figure 21: Utility Function Contribution for Different Scenarios of Maintenance Level Distributions

For the RR of the vehicle, no Cumulative Prospect Values are calculated. As β_{RR1} and β_{RR2} only take on either 1, 0, or -1, utility contribution can be determined directly from the estimated coefficients. This means that having an e-moped at 80% charge contributes $\beta_{RR1} = 0.7240$ to the total utility and a 50% charge contributes $\beta_{RR2} = 0.2037$ to the total utility. Having a 20% charge contributes $-\beta_{RR1} - \beta_{RR2} = -0.9277$ to utility. Having an 80% or 50% charged e-moped thus contributes positively to utility, with the higher charge contributing significantly higher. A shared e-moped with 20% charge reduces utility significantly, dropping the willingness to use this e-moped. This shows, again, risk aversive behavior: Even though the range in meters of a shared e-moped that is charged to a certain percentage is unknown, people are negative towards the risk of using a shared e-moped with a low charge battery.

5.2 User Trade-offs

By comparing the utility contributions of each of the attributes, the trade-offs users make can be analyzed.. Each of the variables can be compared with each other to see how a decrease in utility can be compensated by a change in another variable. This will, as explained in subsection 3.5, present metrics such as the Value of Time and Willingness to Pay.

5.2.1 Cost and Access Time

Figure 19 showed the utility contribution of the cost-attribute at different trip prices. Based on the slopes of the graph, the change in utility for a given price change can be determined. The equivalent of changes in the cost and access time-attributes can be analyzed by looking at the utility contribution at a certain trip price, and comparing this to the change in the access time-attribute that causes the same effect in the opposite direction, and vice versa.

Table 12 shows the Value of Time under different scenarios, both when saving time and saving money. Figure 22 shows these values on a graph, showing the relations between availability levels and the Value of Time when saving and spending money. It shows the price reduction and increase one is willing to accept for a 1 minute increase and decrease of access time respectively. Looking at the first scenario (80% certainty of availability), people would be willing to pay €0,21 to save 1 minute of time. The other way around, if people could save money by spending additional time, one would be willing to walk 2.15 minutes (2 minutes and 9 seconds) further. Translating this to the value of 1 minute of time, people would be willing to walk 1 minute further for a €0,47 price reduction. This shows that people in the region of Enschede would rather walk some additional time to save money than spend money to save time, showing that money has higher importance. The value of 1 minute of time is thus higher for saving money than for saving time. As the scenarios get more uncertain, people are more willing to spend more money to save time (the Value of Time for saving time increases). People are willing to spend nearly twice as much to save time in situations of lower certainty, showing that time becomes more valuable when it is not guaranteed that it is well spent. Still, the Value of Time when saving money remains higher, even though the difference decreases (Figure 22). When money can be saved, people are willing to walk further as uncertainty increases, resulting in a decrease in the Value of Time. This shows that people are willing to accept an increased risk of not finding an available shared e-moped to save the same amount of money, and walk an extra distance. However, the willingness to walk further to save money as uncertainty increases is not as high as the willingness to pay more money to find a vehicle closer by, showing that access time increases in importance with increasing uncertainty levels. This can be seen in Figure 22 as well, where the slope of the line showing time savings is steeper than the slope of the line showing monetary savings.

Comparing this to the value of walking for transport in the Netherlands, according to KiM Netherlands Institute for Transport Policy Analysis (2024), time is valued higher by respondents in this research. In the Netherlands, the average value of time for walking is €0,17 per minute while in the sample, this ranges from €0,47/minute to €0,42/minute when money can be saved, and ranges between €0,21/minute and €0,40/minute when time can be saved. This indicates that people in Enschede see their time as more valuable when walking to a shared e-moped compared to walking for transport in general.

Table 12: Trade-offs between Access Time and Cost

Change in variable	Probability Distribution (Available / Not Available)	Change for compensation	Value of Time
- 1 minute base access time - €1	80% / 20%	+€0,21 +2.15 (2 min 9 sec)	€0,21/minute €0,47/minute
- 1 minute base access time - €1	60% / 40%	+€0,26 +2.22 (2 min 13 sec)	€0,26/minute €0,45/minute
- 1 minute base access time - €1	50% / 50%	+€0,29 +2.26 (2 min 16 sec)	€0,29/minute €0,44/minute
- 1 minute base access time - €1	40% / 60%	+€0,33 +2.3 (2 min 18 sec)	€0,33/minute €0,43/minute
- 1 minute base access time - €1	20% / 80%	+€0,40 +2.39 (2 min 23 sec)	€0,40/minute €0,42/minute

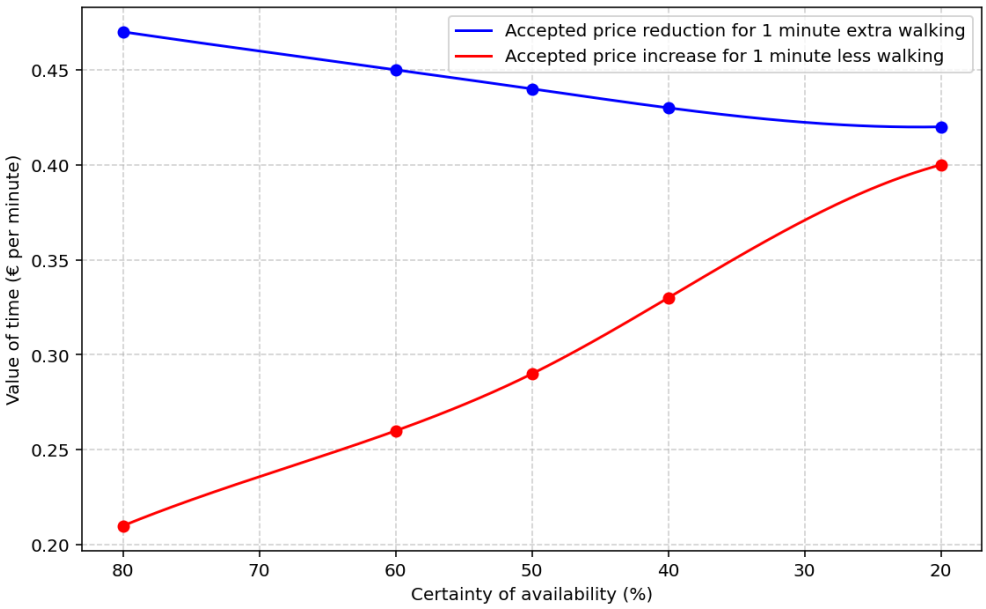


Figure 22: The Value of Time under different levels of availability certainty

5.2.2 Cost and Maintenance Level

For cost and maintenance level-attributes, it is interesting to see how much respondents are willing to pay for a certain increase in maintenance level, and the impact of a negative change. In each of the distributions mentioned in Table 13, the percentages show 'Excellent', 'Average', and 'Poor' respectively. For each of the scenarios, the utility contribution values as shown in Figure 21 have been used to calculate the in- or decrease in utility contribution, and the associated cost in- or decrease to compensate this change has been taken from Figure 19.

Table 13: Cost Changes for Shifts in Probability Distributions Maintenance Level

Old Maintenance Level Distribution (Excellent, Average, Poor)	New Maintenance Level Distribution (Excellent, Average, Poor)	Utility Contribution Change	Compensation Cost
(10%, 80%, 10%)	(10%, 70%, 20%)	- 0.5	- €0,35
(10%, 80%, 10%)	(10%, 60%, 30%)	- 1	- €0,70
(10%, 80%, 10%)	(10%, 50%, 40%)	- 1.5	-€1,15
(10%, 80%, 10%)	(0%, 80%, 20%)	- 1.28	- €0,89
(20%, 60%, 20%)	(0%, 60%, 40%)	- 1.81	- €1,42
(10%, 80%, 10%)	(20%, 70%, 10%)	0.04	+ €0,03
(10%, 80%, 10%)	(30%, 60%, 10%)	0.06	+ €0,04
(10%, 80%, 10%)	(40%, 50%, 10%)	0.14	+ €0,10
(10%, 80%, 10%)	(20%, 80%, 0%)	0.54	+ €0,37
(20%, 60%, 20%)	(40%, 60%, 0%)	1.08	+ €0,72

From Table 13 it is clear that avoiding poor maintenance is more important than getting a vehicle in the 'Excellent' state. People are willing to pay €0,89 to reduce the probability of having a poorly maintained vehicle by 10%, while they are only willing to pay €0,37 for a increase of 10% in the probability of finding a vehicle in 'Excellent' state (when keeping the chance of an 'Average' state equal). If a 10% chance could be shifted from and to the 'Average' state, people would be willing to pay €0,35 to have a slimmer chance of getting a poorly maintained vehicle, while only paying €0,03 to increase the chance of finding a vehicle in an 'Excellent' state. Similar conclusions can be drawn from larger probability switches.

The asymmetry between positive and negative shifts indicates risk aversion among respondents, as e-mopeds with a riskier maintenance level decrease utility more heavily, showing that people might avoid the use of these e-mopeds. Again, probability distortion for gains play a role: while people see probabilities of a poorly maintained vehicle objectively, probabilities for vehicles in an 'Excellent' state are distorted. Due to the level of distortion, even a 40% probability is seen as smaller if it is a gain, therefore decreasing the positive utility contribution of an 'Excellent' state and the smaller willingness to pay compared to decreasing the chance at a 'Poor' vehicle. In conclusion, people are more willing to pay for lower chances at a 'Poor' vehicle than for higher chances at an 'Average' or 'Excellent' vehicle, showing the importance of keeping the probability of finding a vehicle in a 'Poor' state low.

5.2.3 Cost and Remaining Range

For cost and RR, it can be determined how much one would be willing to spend for a vehicle that has a higher charge level, compared to the reference point of €4,51. Increasing the RR from 20% to 50% is an increase of 1.1314 in utility. Looking at the cost of the trip, an equivalent reduction of the utility function means a cost increase of €0,83. Increasing the range from 50% to 80% results in a cost increase of €0,36.

When looking at this the other way around, similar values are found, showing that people are equally willing to save or spend money on a vehicle that is respectively less or higher charged. The big difference in what people are willing to pay between a 30% increase in RR from 20% or from 50% shows the importance of maintaining the RR at at least 50%.

5.2.4 Access Time and Remaining Range

Aside from the willingness to pay, it is interesting to compare how far one would walk for a shared e-moped with a different (higher) RR, also considering the probability that it is available. This results in a willingness to walk. Distances are compared to the reference point of 6 minutes meaning that the access time as shown to the user is 6 minutes, and thus the access time if the shared e-moped is not available is 10 minutes. By comparing the utility increase of a vehicle with higher RR to the equivalent decrease of utility by having a larger access time, one can compare the importance of the charge of a vehicle to the time it takes to get to it. It is clear from Table 14 that people would be willing to walk much further for an increase from 20% to 50% compared to an increase from 50% to 80%, showing the importance of having an e-moped with at least 50% RR.

It is interesting to see that people are willing to walk further for an e-moped with higher RR as the probability of finding an available e-moped decreases. This shows the importance of RR for users over access time. However, when comparing the additional time someone is willing to walk to the expected access time, which increases with higher uncertainty, people are willing to walk relatively less long, as can be seen in the last column. For example, under 80% certainty of finding an available e-moped at 6 minutes, the expected walking time is 6.8 minutes, while this is 9.2 minutes at 20% certainty. The relative time people are willing to walk further is lower at 20% certainty than at 80% certainty, showing that access time gains importance as the situation gets more uncertain. This also shows signs of risk aversion, as people are willing to walk relatively less far for a shared e-moped with higher charge as uncertainty increases.

Table 14: Impact of RR on Access Time

Change in RR	Probability Distribution (Available / Not Available)	Access Time	% Increase Compared to Expected Access Time
20% to 50%	80% / 20%	1 min 41 sec	24.7%
50% to 80%		44 sec	10.8%
20% to 50%	60% / 40%	1 min 46 sec	23.2%
50% to 80%		47 sec	10.3%
20% to 50%	50% / 50%	1 min 50 sec	22.9%
50% to 80%		48 sec	10%
20% to 50%	40% / 60%	1 min 52 sec	22.1%
50% to 80%		50 sec	9.9%
20% to 50%	20% / 80%	1 min 58 sec	21.3%
50% to 80%		53 sec	9.6%

5.2.5 Uncertainty and costs

It has been mentioned how much money people are willing to pay for a decrease in access time under scenarios with differing uncertainty. It is also interesting to understand the impact uncertainty has on the cost-attribute if the base access time is fixed at the reference value. By analyzing the utility contribution of access time at the reference point (t = 6 minutes) from Figure 20 and comparing this to the equivalent increase in utility by the price of the trip (Figure 19), the required decrease in cost from the reference point of €4.51 to keep the shared e-moped equally attractive can be determined. Table 15 shows the decrease in cost required to make the shared e-moped equally attractive under different levels of uncertainty compared to full certainty of availability. This is also shown in Figure 23. Generally, the cost to utility ratio (cost decrease / utility increase) increases as there is more uncertainty, showing that the price of a trip is increasingly important to people as there is higher uncertainty. As there is more uncertainty, the cost reduction required also goes up, showing that with increasing uncertainty, an increasingly higher cost compensation is necessary.

Table 15: Cost Considerations under Different Uncertainty Levels

Probability Distribution (Available / Not Available)	Utility contribution at Reference Level	Required Cost Change	Cost Reduction Ratio (Cost Decrease / Utility Increase)
80% / 20%	-0.508	- €0,35	0.69
60% / 40%	-1.015	- €0,75	0.74
40% / 60%	-1.523	- €1,18	0.77
20% / 80%	-2.030	- €1,64	0.81

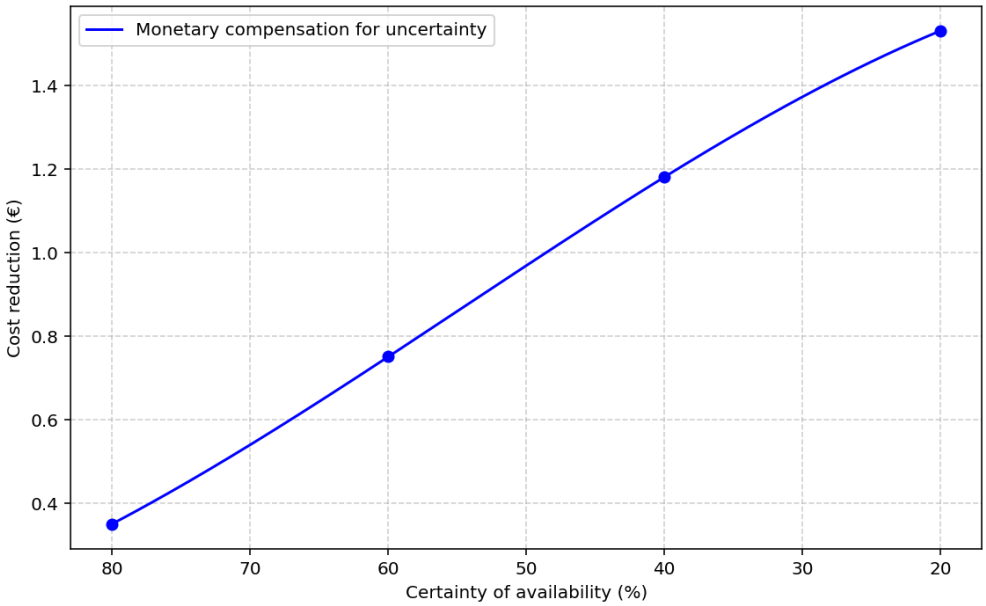


Figure 23: Monetary compensation for increasing levels of uncertainty in availability

5.3 Interaction effects model

Following the estimation of the main effects model, socio-demographics and other variables can be used to test for interaction effects. Interactions might show differences in how different socio-demographics respond to the attributes. Before these effects can be tested, correlations between the socio-demographics must be tested for, as explained before in paragraph 3.2.0.2.

5.3.1 Correlations and group merging

There are different types of socio-demographic variables. Age, income, education, and each of the travel behavior variables (commuting, errands, and leisure) are ordinal variables, whereas gender, occupation, living environment, and experience with shared e-mopeds are nominal variables. To test the correlation between two ordinal variables, Spearman's Rho can be applied (Okoye & Hosseini, 2024). This test assumes no distribution in the data and can be applied to categorical datasets, as it acknowledges the relation between the different levels of an ordinal variable. To test for the independence of two nominal variables, the two-way chi-square (χ^2) can be used (Wuensch, 2025). For testing for correlation between nominal and ordinal variables, the chi-square test will be used as well. When using Spearman's Rho test, it is assumed variables are correlated if the test statistic is larger than 0.5 or below -0.5 and show significance < 0.05. For the variables for which the χ^2-test is used, correlation depends on the test-statistic, the significance level that is chosen, and the degrees of freedom. Based on these three outcomes, if the test-statistic is above a pre-determined threshold (University of Arizona, Department of Mathematics, n.d.), there is a significant correlation between the variables. The results of these correlation tests can be seen in Appendix E. Testing for correlation at the 0.05 significance level, the following combinations of variables are correlated:

- Age and Income
- Age and Occupation
- Income and Gender
- Income and Occupation
- Gender and Occupation
- Education and Gender
- Education and Occupation
- Commuting behavior and Occupation
- Errands behavior and Living Environment

Several conclusions can be drawn from this analysis. The correlation between age and income is often found in literature, while relationships between age and occupation, income and occupation, and education and occupation are also commonplace. These correlations can intuitively be interpreted. Income is correlated with gender, suggesting that the level of income depends on gender. Gender is also correlated with occupation and education, suggesting different societal roles among different genders, stemming from a different level of education and thus different types of occupation. This also explains the correlation between income and gender.

The relationship between commuting behavior and occupation shows that different types of occupation require more or less commuting. Someone with a part-time job might not have to commute every

day, while this is different for students or full-time employed people. Lastly, living environment and errands behavior are correlated. This suggests that people who live in urban environments run errands more often than people in rural areas, possibly because of travel distances to shops.

Based on the correlation between each of the variables, a combination of variables that are correlated should not be together in the full interactions model. This means that in case both variables show significant interactions, either one of the two variables should be selected. Usage frequency will not be used as an interaction variable, as both the number of entries for this demographic is significantly lower than for other variables, and most of these are answered with 'Rarely'.

Interaction effects have been tested for each of the socio-demographic variables with the four design attributes, as explained in section 3. For each of these variables, each social group should have a large enough size to conclude representative answers. This means that, in some occasions, groups are combined to form significantly large groups. While it could be chosen to exclude certain socio-demographic groups, given the limited number of responses, combining groups is the preferred method to deal with small sample sizes in order to use as much available data as possible. For the interactions with gender, there is an exception. The 'Non-binary / Third gender'-group has been removed due to the low number of observations for this group and no reasonable possibility to combine this group with another. For the interactions with age, age groups 45 - 54, 55 - 64, and 65+ have been combined to form an 'Above average' age group (the average age in Enschede is around 41). Regarding the experience with shared e-mopeds, the groups that do not know what shared e-mopeds are, and those who do know but have not used one yet have been combined to form a group that has never used a shared e-moped before, allowing for comparisons between groups of people that have experience and those that do not. Regarding leisure trips and commuting trips, the groups that answered 'Never' and '1 to 2 times per week' have been combined to form a group of low-frequency users. Looking at education, three new groups have been formed as 'basic', 'medium' and 'high' level of education. Those who have finished only either primary or secondary education belong to the group of 'basic' education, as this type of education is broad and general, not yet focusing on a particular field of work or study. People who have completed either vocational education or an associate degree belong to the group showing 'medium' level education. A bachelor's degree, master's degree, or doctorate degree constitute the 'high' level of education. In both these types of education, there is focus on a particular type of education and field of work. However, there should be distinction between university education, and vocational education or an associate degree.

The results of the steps explained above have resulted in the full interactions model described in the next section.

5.3.2 Full interaction effects model

Testing interactions and dropping insignificant relations has resulted in the following model.

$$
\begin{aligned}
U_i = \beta_C V(X_c)_i \\
&+ \beta_{AT} V(X_{AT})_i \\
&+ \beta_{ML} V(X_{ML})_i \\
&+ \beta_{RR1} X_{RR1,i} \\
&+ \beta_{RR2} X_{RR2,i} \\
&+ \beta_{C,\text{mid. level education}} D_{\text{mid. level education}} V(X_c)_i \\
&+ \beta_{C,\text{3 to 4 commute}} D_{\text{3 to 4 commute}} V(X_c)_i \\
&+ \beta_{C,\text{HasUsed}} D_{\text{HasUsed}} V(X_c)_i \\
&+ \beta_{RR1,\text{3 to 4 leisure}} D_{\text{3 to 4 leisure}} X_{RR1,i} \\
&+ \beta_{RR2,\text{3 to 4 leisure}} D_{\text{3 to 4 leisure}} X_{RR2,i} \\
&+ \beta_{RR1,\text{daily leisure}} D_{\text{daily leisure}} X_{RR1,i} \\
&+ \beta_{RR2,\text{daily leisure}} D_{\text{daily leisure}} X_{RR2,i} \\
&+ \epsilon_i
\end{aligned}
\tag{34}
$$

The null log-likelihood of the interactions model is 1615.7261. The log likelihood of the final model is 1160.2711. The improvement of the negative log-likelihood over the iterations can be seen in Figure 24. In this graph, the flattening of improvements near the final iterations is clearly visible. Using the null log-likelihood and that of the estimated model, a McFadden's Pseudo R^2 of 0.2819 has been determined, indicating slightly better performance than the main effects model. The model performs 28.19% better than the null model. The results of the full interaction model are listed in Table 16.

Figure 24: Level of negative log-likelihood over iterations

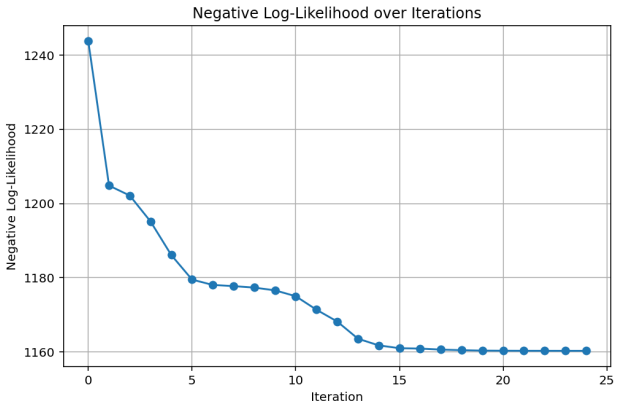
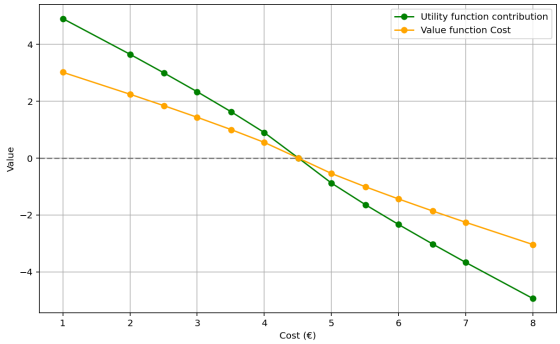


Table 16: Interaction model estimates

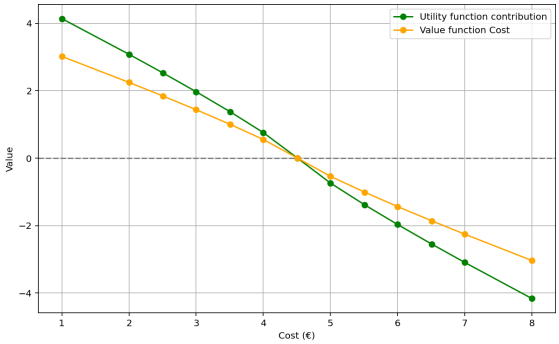
Variable / Interaction	Reference Group	β	Std. Error	t-value	p-value
Cost	N.A.	1.6250	0.1041	15.6037	$< 0.0001^{***}$
Access Time	N.A.	0.7540	0.0514	14.6789	$< 0.0001^{***}$
Maintenance Level	N.A.	5.2131	0.6954	7.4963	$<0.0001^{***}$
Remaining Range: 50%	N.A.	0.2045	0.0574	3.5618	0.0004^{***}
Remaining Range: 80%	N.A.	0.7820	0.0849	9.2098	$< 0.0001^{***}$
Cost x Mid. Level Education	Basic Education	-0.2536	0.0969	-2.6183	0.0088^{***}
Cost x Commuting 3 to 4 times per week	Never, once, or twice per week	-0.1895	0.1030	-1.8388	0.0659^{*}
Cost x Has used a shared e-moped	Has not used a shared e-moped	-0.2490	0.0971	-2.5639	0.0103^{**}
RR 50% x 3 to 4 leisure trips per week	Never, once, or twice per week	0.0969	0.0868	1.1169	0.2640
RR 80% x 3 to 4 leisure trips per week	Never, once, or twice per week	-0.2973	0.1232	-2.4135	0.0158^{**}
RR 50% x Daily leisure trips	Never, once, or twice per week	-0.1976	0.1102	-1.7931	0.0730^{*}
RR 80% x Daily leisure trips	Never, once, or twice per week	0.3032	0.1627	1.8633	0.0624^{*}

[1] * = 10% significance,** = 5% significance,*** = 1% significance

The results from Table 16 can be discussed by comparing coefficient values to those of the respective reference groups. Because of the way the utility function is shaped, the impact of each of the coefficients must be carefully analyzed. For example, a negative coefficient for one of the interactions with costs does not mean the price of a trip has a more negative impact, but should rather be viewed by determining the utility contribution of this attribute at different values. First of all, people that have finished either middle level education, i.e. vocational education or an associate degree, show less importance for the price of the trip compared to those who have only finished primary or secondary education. Figure 25 shows the difference between these two groups. Figure 25a shows the contribution of cost to utility for people who have finished lower level education, while Figure 25b shows the contribution for those who have finished middle level education. At the same price, the contribution to utility for middle level education is less extreme than for those who have only finished level education, indicating that they are less sensitive to the price of the trip. This is likely caused by the fact that these people have finished education and are probably working, allowing for a greater budget and thus less need to be cost-sensitive. People that have only finished primary or secondary education are either not working (full-time) yet, or potentially working in jobs that require less educational experience and are likely less well-payed, causing slimmer budgets and thus higher cost-sensitivity.



(a) Utility contribution of cost for lower level education



(b) Utility contribution of cost for middle level education

Figure 25: Contribution of cost to utility for different levels of education

Secondly, people that commute 3 to 4 times per week show lower importance to cost than those who commute less than this (0, 1, or 2 times per week). An explanation for this could be the fact that people who commute often acknowledge that transportation costs are a part of their daily/weekly expenses. The price of the service is of less importance, as long as they can perform their commute effectively. People who are less accustomed to commuting might be more sensitive to the cost of it, as it is not part of their daily or weekly budget and they are thus not used to paying these costs, making this attribute a bigger disutility. Thirdly, people that have previously used a shared e-moped show less importance for the price of the trip compared to those that have not yet used a shared e-moped. A reason for this might be that those people that have used shared e-mopeds have a different perception of the convenience or benefit of shared e-mopeds. The price might be of less importance to them, as long as they have on-demand access to urban transport. This shows that experience changes the value the shared e-moped has for the user; it increases the perceived value, making them less sensitive to the price of the service. While user attitude towards SMM was previously found in literature as an influential factor for the use of SMM, this did not explicitly focus on a positive attitude caused by experience. The influence experience has on the price of the trip is an addition to current literature. With CPT in mind, the lower importance of cost for these groups could be explained by the fact that the internal reference point for cost of these groups is different. The same reference value is assumed for the whole population, while this could internally be a higher value for groups that attribute less importance to cost, as they are more used to the cost of shared e-mopeds or transport in general. The model thus overestimates the impact a loss or gain has on these groups. For example, while the model assumes a reference cost of €4,51, for a person used to commuting, the internal reference cost of such a trip might be €5. Losses are overestimated by the model, which are then compensated by a lower coefficient estimate.

Next, the number of leisure trips a user makes per week influences the importance of the RR of the vehicle. For users that make 3 to 4 leisure trips per week, the utility contribution of both the RR of 50% as well as that of 80% is different than from those that have only few leisure trips per week (0, 1, or 2), although for a 50% RR, this is statistically not very strong. The importance of a RR of 80% is lower than for those that have 1 to 2 leisure trips per week. Translating this to the impact of having a RR of 20%, it shows that people who have 3 to 4 leisure trips per week react less extremely to a low RR. This could be caused by the fact that people who travel for leisure occasionally are more flexible in their transportation options. Their trips are regular, but occur on such a frequency that there is probably no high dependence on one mode of transportation. They

show adaptability to the transport circumstances, placing less importance on a fully charged vehicle, while also showing less disutility to a vehicle with a low charge. People who travel on a (almost) daily basis for leisure, however, are probably more accustomed to their way of traveling compared to people who only travel once or twice a week. They show greater reliance on their usual way of transport and have greater expectations of the ease of getting to their destination, therefore putting more emphasis on having a fully charged vehicle and showing greater disutility for a vehicle with a very low RR. It shows that these people form transport habits where consistent trips are more important and thus higher levels of risk aversion.

This analysis thus shows that different socio-demographic groups assign different levels of importance to the design attributes. The interactions identified in section 2 were however not confirmed by this research. No significant interactions were found looking at genders, while socio-economic variables (income and occupation for example) also showed no significant interactions with the attributes. Regarding gender, the fact that the distribution of the sample was heavily skewed towards women potentially influenced the results, which should be considered in comparing these findings to those in literature. Looking at income and occupation, students, probably with a lower income, are slightly overrepresented. This should be taken into account when comparing interaction findings regarding socio-economic status with other research.

6 Conclusion

This section presents the conclusions of this report. This will include a summary of the main findings, elaboration on both the scientific and practical relevance of this research, the limitations of this research and recommendations for future research.

6.1 Summary of findings

In section 2 of this report, the current knowledge on SMM, transportation mode choice research, DCEs and the potential influential factors in the decision-making process for SMM have been reviewed. From this, the cost of a trip, the access time to a vehicle, the maintenance level of a vehicle, and the RR of a vehicle have been chosen as attributes in this research to be used in the SCE to be formulated. Combined with CPT, a utility function has been formulated that includes psychological mechanisms such as reference dependence, loss aversion, and probability distortion that help to model the influence of uncertainty and risk in transportation mode choice. In this way, CPT has been used to model decision-making, analyzing the impact of risk and uncertainty on mode choice.

From this, an MNL model has been estimated to quantify the importance of the aforementioned attributes in the decision-making for shared e-mopeds. CPT was involved through estimating the level of loss aversion and probability distortion among the respondents. This meant taking reference values into account and seeing attribute values as gains or losses compared to this reference value instead of as objective values. From the results of the survey including the SCE, estimates for each of the CPT-parameters as well as coefficients for each attribute have been generated, which have been translated to utility contributions to show how attribute values influence impact the utility of a particular shared e-moped.

It was found that respondents do not show a substantial amount of loss aversion, as the estimate $\lambda = 1.0115$. λ has been measured for losses in the context of shared e-mopeds in general, not on one aspect, but it shows that gains and losses are not treated that much differently by respondents. Regarding probability distortion, there is a high level of distortion for gains ($\gamma = 0.3397$), while loss probabilities are treated objectively ($\delta = 1.000$). This changes the way gains are judged, with people underestimating high- and medium-level probabilities. An 80% probability of a vehicle being available is very much underestimated, showing that people are heavily risk averse and expect low reliability, even though the chances are quite high. Looking at reference dependence, it is clear that the impact of attribute values is shaped around the reference value, with changes caused by the fact that values are perceived as gains and losses, not as objective values.

The different attributes have been compared to each other by looking at the utility contribution of each of them. A decrease in utility caused by attribute A can be countered by an increase in attribute B, showing how different attributes compare to each other. In this way, the cost and access time-attributes have been compared to see the Value of Time. Under an 80% certainty that the shared e-moped is available, people are willing to pay €0,21 to reduce the base access time by 1 minute. As uncertainty rises, people are willing to pay more to reduce the access time by 1 minute, showing that time becomes more valuable as uncertainty increases. Translating this the other way around, it can be concluded that people would rather walk additional minutes for a cheaper price than pay for a shared e-moped closer by, with the Value of Time higher for the former. This shows the importance of cost over access time.

Regarding the maintenance level, shifts that decrease the expected maintenance level have a more

negative impact on utility than shifts that increase the expected level have a positive influence. This is logically caused by the level of probability distortion, as chances associated with an 'Excellent' state are heavily underestimated. Hence, people are willing to pay more to reduce the chance at a poor vehicle than increasing the chance at an excellent vehicle, even though the expected level stays the same. This shows clear signs of risk aversion among the respondents and confirms general concerns for the safety of using SMM-vehicles, as for example identified by Filipe Teixeira et al. (2023). Literature has however mainly identified the safety of the environment, such as road conditions, traffic, and poor riding skills, as concerns of safety. This research adds to this by showing that the safety of the vehicle itself is of concern to potential users as well, highlighting the importance of vehicle maintenance. The RR of a vehicle has significant impact on mode choice too. From results, it is clear that the charge of a vehicle should be kept above 50%. People are willing to pay more for a vehicle with a 50% charge over a 20% charge, while this difference is not as big when looking at 80% and 50%. The RR was only recently identified as an influential factor in mode choice for shared e-mopeds by Burghardt et al. (2025) in the form of range anxiety, confirming the findings of this research and highlighting the impact risk aversive behavior can have on mode choice for SMM.

The willingness to walk, i.e. the relative importance of access time, can also be analyzed. Looking at the willingness to walk to a shared e-moped with higher RR, as uncertainty increases, people are willing to walk relatively less far compared to the expected walking distance. As uncertainty increases, the expected access time increases along with it. Even though the absolute access time a respondent is willing to add increases, showing the importance of RR, access time gains importance as the certainty that an available shared e-moped is actually found decreases. Lastly, people again show risk aversion looking at the willingness to pay for certainty. As situations gain in uncertainty, the relative price one is willing to pay to counter the disutility increases. For example, when comparing the cost to utility ratio (cost decrease / utility increase) for different levels of uncertainty, more uncertain situations show a higher ratio.

Interaction effects have been analyzed to see how the importance of attributes differs over different socio-demographic groups in the sample. While the above results hold for the entire sample, differences in importance caused by different socio-demographics are present. After testing for interactions, it was found that people who commute 3 to 4 times a week, and people who have used a shared e-moped before, show less importance for the price of a trip using a shared e-moped. Regarding commuters, this hints at the fact that people who are more accustomed to commuting take the cost of it into account in their budget, while people who commute less often see this as an extra burden to usage. People who have experience using a shared e-moped might have different perceptions of the value of the on-demand, flexible convenience of the service, lowering the sensitivity to the price of the trip. People who have completed middle level education also show less importance for the price of the trip compared to people who have only completed either primary or secondary education, likely relating to the fact that their budget is higher than that of respondents who have completed basic education, lowering their price-sensitivity. Regarding the RR, people who make 3 to 4 leisure trips, and those who make (almost) daily leisure trips show a difference in importance for each of the levels of RR, hinting at the influence of mobility patterns and habits on this attribute. People who travel for leisure daily might want security in their trips, as these trips are routine, emphasizing the importance of a high RR and high disutility of a low battery charge, while occasional leisure-trip makers show their flexibility in the reduced importance of having a fully charged vehicle. It is evident that people with different transportation habits attribute different levels of importance to attributes. Reflecting on these results with the findings of the literature review in mind, this research has not found many insights that confirm previous

research. While literature pointed out the differences in importance of attributes between different genders, this study has not found these differences to be significant. The same holds for differences across socio-economic groups, with variables such as income and occupation not showing significant interactions.

Summarizing the above has formulated answers to each of the elements of the main research questions, which was formulated as:

What is the importance of various trip- and vehicle-related factors and characteristics of individuals in the decision-making process for shared micro-mobility, particularly considering uncertainty and risk, and how do loss aversion, reference dependence and probability weighing play a role in these considerations?

6.2 Scientific relevance

Answering the research questions has generated additional insight into factors that influence decision-making for SMM. From the literature review conducted in section 2, it was found that even though the use of SMM involves a number of uncertainties and risks, research taking these elements into account in transportation mode choice for SMM was only limited. This report has tried to fill this gap by formulating a utility function that includes Cumulative Prospect Values. In the research design, cost, access time, maintenance levels and the remaining range of a vehicle have been included as potential influential factors in the decision-making process for shared e-mopeds. Elements of uncertainty have been included that help observe how respondents react to uncertainties in access times and maintenance levels, while reference values have been used to shape outcomes as gains and losses rather than standalone values. The RR has been used to be able to observe the results of an additional element of risk.

Through generating this design and quantifying the results using a MNL, the relative importance of the different attributes could be measured and trade-offs respondents make in their decision-making process could be analyzed by generating the utility contributions of the attributes at different levels. This has generated insight into the importance of various attributes, how negative changes in one attribute can be countered by another, and how psychological mechanisms play a role in the decision-making process. In this way, this research has added to literature by modeling decision-making behavior for SMM-usage considering psychological phenomena that were previously not involved yet, and quantifying this choice behavior. This research has considered a particular set of variables. However, these could be altered to consider other elements of SMM, adjusting the design of the SCE accordingly. Similar research can be conducted with the same design principles and CPT-considerations in the context of SMM, with potentially different attributes and levels. This can broaden knowledge on the impact of uncertainty and risk in SMM further, using this research as a guideline.

6.3 Societal relevance

While contributing to scientific knowledge on decision-making for the use of SMM, this research has societal implications too. It has contributed to a better understanding of the attributes and psychological phenomena involved in the decision-making process, which can help in increasing the attractiveness of SMM for potential users. Two players that can help unlock the potential benefits of SMM are policy makers, such as municipalities, and service providers. Each of these parties can interpret and use the results of this research in their own way.

Regarding policy makers, it is important to understand the perspective of this party, as well as the possibilities policy makers have to make changes. The policy maker most concerned with the results of this research is the municipality of Enschede. Like many other municipalities in the Netherlands, Enschede has a positive view on the use of SMM. It has provided a strategy, which is based on the use of hubs where shared e-mopeds must be parked and picked up, along with guidelines regarding the placement of these hubs and thus availability of shared e-mopeds. The results of this research show how potential users make trade-offs between the different attributes. Preferences have been quantified, which can help the municipality in decision-making on various aspects. For example, the willingness to walk further for a decrease in trip cost could help the municipality determine optimal pricing at a certain level of availability, or determine the added value of focusing on better maintained vehicles, of vehicles with a higher RR. By anticipating on the trade-offs that users make, a SMM-landscape can be created that stimulates usage. An additional potential tool that could be used is a simulation model that can simulate usage levels for different attribute values. This could help the municipality in their decision-making and will be elaborated on further in this report.

Looking at service providers, the main goal is to make a profit. In order to do this, usage must be stimulated, as well as running a cost-effective strategy and policy. However, service providers are often dependent on the rules and regulations set by policy makers. It is therefore crucial that policy makers and service providers work together to create an environment where SMM-usage is stimulated. The trade-offs users make provide valuable information on how to create such a landscape. Information on the impact of maintenance levels and required price reductions to counter the negative effects, or the impact of longer walking distances, can be extremely valuable for service providers to run cost-effective strategies. For example, understanding the impact a low RR has on the tendency to use a shared e-moped can help service providers come up with new strategies to switch batteries or vehicles in order to keep charge levels at a minimum, increasing the likelihood of usage and thus of revenue. Again, a simulation model could be of high value for service providers. Being able to see the simulate different strategies on, for example, maintaining vehicles in a certain state can show the results of these strategies in terms of usage and thus income.

A general recommendation for service providers is to actively monitor the maintenance levels and RR of each of the vehicles. For the RR, this data is readily available, and battery- or vehicle-swapping strategies can be put in place or adjusted to maintain battery charges at a certain level. The effects of a vehicle in low charge are presented in this research, showing that a low RR discourages users. Maintenance levels should also be kept above a given value, carefully avoiding the availability of vehicles in a poor state. While this is more difficult to monitor, processes should be set in place to ensure vehicles are maintained above a level that is acceptable to potential users. This research has shown the negative impact a poorly maintained vehicle can have on utility, and the cost reduction required to counter this, while also indicating the level of risk aversion the respondents show. Aside from this, service providers should at all times prioritize the safety of users and thus maintain the vehicles carefully.

This research has thus provided valuable information for both policy makers and service providers in the decision-behavior of potential users. Using this information correctly can increase the likelihood of users choosing for SMM, adding to a more sustainable and efficient landscape while also helping to build a cost-effective business plan for service providers.

6.4 Limitations

This research includes several limitations that need to be addressed when interpreting the results and overall research. Starting with the design, four design attributes were chosen to include. However, from the literature review, several more attributes that potentially influence the choice for SMM could have been chosen. However, to keep model size manageable, only the four considered in this research were chosen. The inclusion of more or different attributes might have presented different results and could have added to this research.

As CPT was applied in this research, reference values were used to work with gains and losses in the experiment. However, only the reference point for the access time-attribute was truly chosen by the respondent. In the case of cost and maintenance level, the reference points were given. This may have caused theoretical losses or gains to be differently interpreted by the respondent. For example, while a reference cost of €4,51 was chosen, a respondent might be used to paying €6,- for trips they usually make with a shared e-moped. This might have changed their perception of the attribute values, potentially resulting in a bigger win or less heavy loss according to the respondent. This could directly translate to the estimation of λ and inflate or deflate λ compared to reality for the respondent. Along with this, loss aversion has been measured for the use of shared e-mopeds as a whole, not on a particular attribute. While people might feel heavy loss aversion for the price of the trip, they might not feel the same for losses related to the access time-attribute. This distinction is not made in this research. Lastly, due to the nature of the attribute levels used in the experiment, more losses than gains were included in the data. Even though the model has taken this into account and on trial runs has shown that parameters can be accurately estimated, this is a limitation that should be taken into account. This influences the determination of λ, δ, and γ. In future research, the number of gains and losses should be equal to each other.

As a result of applying CPT in three of the four attributes, the model has become quite complex. Many parameters occur often in the utility function. Even though results are significant and test estimations worked, a simpler model might have resulted in more accurate results and a lower log-likelihood. Combining this with the fact that more losses than gains were involved, δ could have been overrepresented, while γ was underrepresented.

Regarding the experiment design, especially the size, it was indicated by respondents that they were losing focus during the survey, most probably from fatigue by the number of choice sets. Even though it is known that 6 to 12 choice sets is a reasonable number for an SCE, the tasks can become repetitive and cause fatigue among respondents. This could have affected the results of the experiment. Furthermore, the population is prone to biases. As mentioned, social media has been used to spread the survey. While this allows for a larger audience to be reached, respondents could have been less focused while filling out the survey, potentially reducing the accuracy of their answers. Besides, potentially because of the methods used to spread the survey, the sample included a large number of students and female respondents. This could bias the results towards a younger, female, highly educated sample. This should be considered when interpreting and generalizing the results.

Lastly, regarding the model used to estimate the parameters and coefficients, a multinomial logit model has been used. As mentioned in the report, several assumptions have to be made about the data when using this model, which are potentially contradicting with reality. First, it is assumed that the unobserved element of utility in each alternative of a choice set is independent of each other. This is however unlikely, as respondents must choose between two shared e-mopeds and will likely include the same information for both alternatives as unobserved utility. Second, it is assumed

that choices are IIA and thus only dependent on the two available alternatives. It might however occur that respondents consider a third option internally, which might influence their choice. Third, the model deals with each choice independently. Panel data is thus not accounted for, while it is highly likely that this is present, as each respondent filled out 9 choice tasks. The model does not deal with correlation among answers of the same respondent, which could bias the estimation of parameters and coefficients. For this type of research, a mixed logit model could potentially have been a better fit. This model draws estimates from a distribution, incorporating randomness and thus heterogeneity in the sample. Coefficient values might differ between respondent A and B. Regarding panel data, instead of assuming that each choice is made by a unique individual and there is thus no correlation in the unobserved element of utility for one respondent, a mixed logit model presents each individual with a unique set of model parameters that are drawn from a chosen distribution. Since the same draw is used for each respondent, the same unobserved component of utility is used for each respondent, taking into account that the same elements influence people throughout all their choices.

The mixed logit model was however not chosen due to the complexity of the model. Each of the coefficients and parameters should have been assigned a distribution, which would also have been assumed. This would make the model too reliant on these assumptions and above all too complex. The use of the MNL model and thus complying with its underlying assumptions is however a limitation to this research

6.5 Recommendations for future research

From this research, several directions for future research can be explored. First of all, as mentioned in the limitations and scientific relevance section, a number of other attributes could have been explored. Several factors aside from those used in this research are potentially influential in mode choice for SMM and could include elements of uncertainty, such as trip time, weather conditions, or trip purpose. In future research, the inclusion of these attributes to describe transportation mode choices could be considered. To do this, similar frameworks as used and proposed in this research can be applied and adapted according to the chosen attributes. Also, the research design used in this research could be repeated in a different geographical context.

Secondly, as mentioned in the section on societal relevance, future research could look into the implementation of a simulation model. A simulation model could provide both service providers as well as policy makers with a tool to see the results of policy changes in action. An example of such a model could be an agent-based model, where both individuals as well as e-mopeds can be modeled as agents in an environment. Results from this research can serve as input for such a simulation model by describing how individuals make choices to use a shared e-moped or not, with the utility function serving as a behavioral rule of the user. In this simulation model, service providers and policy makers could test different scenarios and understand under which circumstances SMM-usage in- or decreases. Such a model would benefit in practice, but the creation of this model could also have scientific value, as it could also be used in different circumstances, given that similar input as generated by this research can be provided.

This research included an unlabeled design in order to focus on identifying the importance of different factors in mode choice for shared e-mopeds only. However, a possible research direction could be a labeled design. This would allow researches to understand under which circumstances respondents would prefer SMM over other modes of transport, and thus reveal information on mode switching. This research could still involve the relevant elements of uncertainty but focus on mode switching

behavior rather than identifying the importance of different attributes.

As mentioned in the limitations of this report, CPT-parameters have been estimated for shared e-moped usage as a whole. It could however be valuable to estimate parameters for each of the attributes to create a better understanding of how losses in for example cost and access time differ from each other, or whether probabilities for the maintenance level or access time-attribute are differently distorted. Next to this, diminishing sensitivity could also be estimated. In this research, because of the limited number of levels per design attribute, it was chosen to take pre-determined values for β^+ and β^- rather than estimate them in the model as well. Future research could look into adjusting the research design to accommodate for this estimation as well.

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A Appendix A

Table 17: (Highlighted) overview of used search queries

Search Query	**Number of Results**	**Number Screened**
transportation AND mode AND choice AND (micro-mobility OR (shared AND micro-mobility))	45	14
(shared AND micro-mobility AND payment)	3	1
(shared AND micro-mobility)	350	N.A.
(cumulative AND prospect AND theory AND transportation)	78	30
((transportation AND mode AND choice) AND (cumulative AND prospect AND theory))	23	10
(urban AND mobility AND challenges AND trends)	421	N.A.
((urban AND mobility AND challenges AND trends) AND overview)	35	15
(discrete AND choice AND experiment) AND examples	386	40
(shared AND micro-mobility) AND impact AND transportation AND system	40	14
(shared AND micro-mobility) AND impact AND environment	32	7
(shared AND micro-mobility) AND safety AND concerns	25	6
mode AND choice AND regret AND theory	18	4
transportation AND mode AND choice AND factors AND (shared AND micro-mobility)	10	7
"cumulative prospect theory" AND ("discrete choice" OR "choice experiment" OR "stated preference" OR "mode choice") AND ("transportation" OR "travel behavior" OR "mobility" OR "mode selection")	29	14

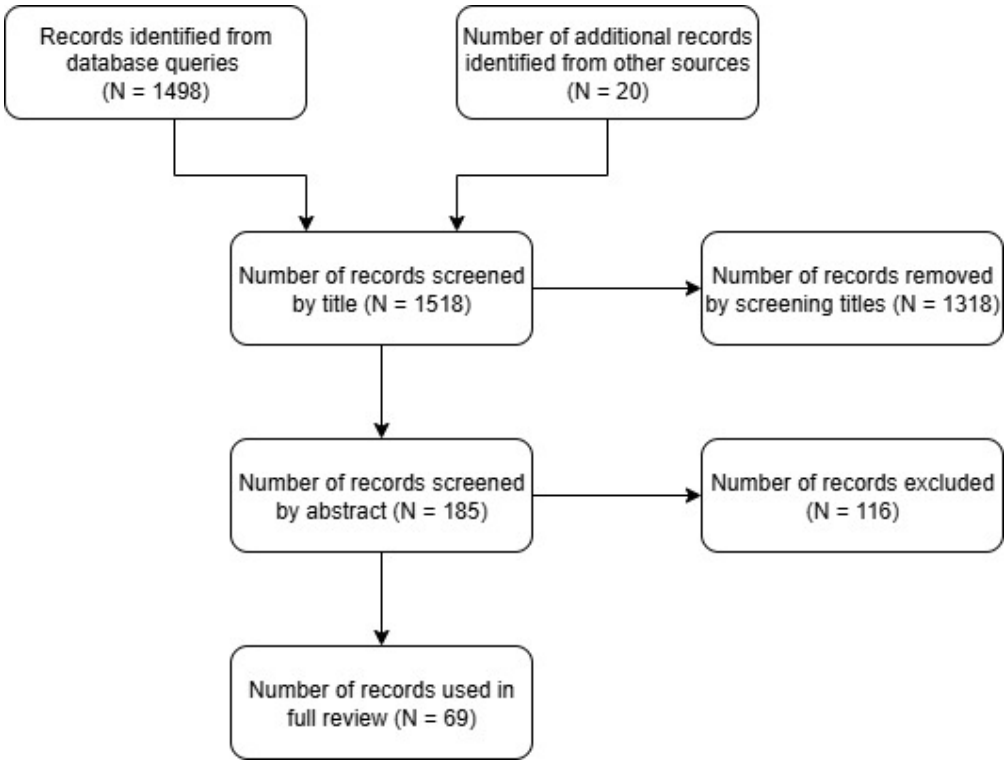

Figure 26: PRISMA diagram of systematic literature review

B Appendix B

```
title 'Design␣for␣transportation␣mode␣choice␣analysis␣involving␣SMM';
%Mktruns(3**5); /* Find out the number of runs for the design */

%mktex(3**5, n=18); /* Create a number of candidate alternatives */

proc format; /* Specify formats for the levels of the attributes */
  value Cost 1 = 282 2 = 451 3 = 620;
  value AccessTime 1 = '-3' 2 = '0' 3 = '+3';
  value CertaintyLevelAvailability 1 = 80 2 = 60 3 = 40;
  value MaintenanceLevelDistr
        1 = '20%␣Excellent,␣60%␣Average,␣20%␣Poor'
        2 = '30%␣Excellent,␣40%␣Average,␣30%␣Poor'
        3 = '40%␣Excellent,␣20%␣Average,␣40%␣Poor';
  value RemainingRange 1 = 80 2 = 50 3 = 20;
run;

%mktlab(
  data=design,
  vars=Cost AccessTime CertaintyLevelAvailability
       MaintenanceLevelDistr RemainingRange,
  out=final,
  stmts=format Cost Cost. AccessTime AccessTime.
        CertaintyLevelAvailability CertaintyLevelAvailability.
        MaintenanceLevelDistr MaintenanceLevelDistr.
        RemainingRange RemainingRange.
);

proc print; run;
%mkteval(data=final);
```

Listing 1: Design for transportation mode choice analysis involving SMM

C Appendix C

Set	Alt.	Cost	Access Time	Certainty	Maintenance Level	Remaining Range
1	6	€2.82	+3	40%	30% Excellent, 40% Average, 30% Poor	80%
	5	€2.82	+3	80%	40% Excellent, 20% Average, 40% Poor	50%
2	9	€4.51	0	60%	30% Excellent, 40% Average, 30% Poor	50%
	10	€4.51	0	40%	40% Excellent, 20% Average, 40% Poor	80%
3	13	€6.20	-3	60%	40% Excellent, 20% Average, 40% Poor	80%
	17	€6.20	+3	80%	20% Excellent, 60% Average, 20% Poor	50%
4	1	€2.82	-3	80%	20% Excellent, 60% Average, 20% Poor	80%
	2	€2.82	-3	60%	30% Excellent, 40% Average, 30% Poor	20%
5	11	€4.51	+3	80%	30% Excellent, 40% Average, 30% Poor	20%
	18	€6.20	+3	40%	40% Excellent, 20% Average, 40% Poor	20%
6	8	€4.51	-3	80%	20% Excellent, 60% Average, 20% Poor	20%
	4	€2.82	0	40%	20% Excellent, 60% Average, 20% Poor	50%
7	12	€4.51	+3	60%	20% Excellent, 60% Average, 20% Poor	80%
	15	€6.20	0	80%	40% Excellent, 20% Average, 40% Poor	80%
8	16	€6.20	0	60%	20% Excellent, 60% Average, 20% Poor	20%
	14	€6.20	-3	40%	30% Excellent, 40% Average, 30% Poor	50%
9	3	€2.82	0	80%	40% Excellent, 20% Average, 40% Poor	20%
	7	€4.51	-3	80%	40% Excellent, 20% Average, 40% Poor	50%

Table 18: Choice sets in orthogonal design with N = 18

D Appendix D

Table 19: Sociodemographic Categories Used in the Survey

Variable	Categories
Age	18–24 25–34 35–44 45–54 55-64 65+
Gender	Male Female Non-binary / third gender I prefer not to say
Occupation	Student Employed (full-time) Employed (part-time) Unemployed Self-employed Retired Other, namely: I prefer not to say
Income (€/month)	Less than €750 €750–€1500 €1500–€4000 €4000–€10,000 More than €10,000 I prefer not to say
Highest level of education	Primary education Secondary eduction (e.g. high school) Vocational education Associate degree Bachelor's degree Master's degree Doctorate degree I prefer not to say
Living area	Urban (within a city or town) Suburban (residential area near a city) Rural (countryside or small village) I prefer not to say
Experience with Shared E-mopeds	Yes, I have used a shared e-moped before Yes, I have seen or heard of shared e-mopeds, but have not used them yet No, I have not heard of shared e-mopeds before

E Appendix E

Table 20: Overview of correlation tests between ordinal variables

Variable 1	Variable 2	Test Type	Statistic	P-value
Age	Income	Spearman's Rho	0.6424	< 0.0001
Age	Education	Spearman's Rho	0.2314	0.0003
Income	Education	Spearman's Rho	0.2248	0.0004
Commuting behavior	Errands behavior	Spearman's Rho	0.0388	0.5829
Commuting behavior	Leisure behavior	Spearman's Rho	0.1157	0.1003
Errands behavior	Leisure behavior	Spearman's Rho	0.3189	< 0.0001
Age	Commuting behavior	Spearman's Rho	- 0.2084	0.0029
Age	Errands behavior	Spearman's Rho	0.1482	0.0349
Age	Leisure behavior	Spearman's Rho	- 0.0578	0.4125
Income	Commuting behavior	Spearman's Rho	- 0.2199	0.0016
Income	Errands behavior	Spearman's Rho	0.1384	0.0489
Income	Leisure behavior	Spearman's Rho	0.0557	0.4296
Education	Commuting behavior	Spearman's Rho	- 0.0597	0.3971
Education	Errands behavior	Spearman's Rho	-0.0369	0.6010
Education	Leisure behavior	Spearman's Rho	0.1092	0.1211

Table 21: Overview of χ^2 tests

Variable 1	Variable 2	Test Type	Statistic	P-value	Degrees of freedom
Gender	Occupation	χ^2	23.3603	0.0248	12
Gender	Experience with Shared E-mopeds	χ^2	6.7901	0.1474	4
Gender	Living Environment	χ^2	3.6150	0.4606	4
Living Environment	Experience with Shared E-mopeds	χ^2	5.7621	0.2176	4
Living Environment	Occupation	χ^2	6.9479	0.8610	12
Experience with Shared E-mopeds	Occupation	χ^2	9.8449	0.6296	12
Income	Gender	χ^2	26.1646	0.0002	6
Income	Occupation	χ^2	156.9326	< 0.0001	18
Income	Experience with Shared E-mopeds	χ^2	6.8124	0.3385	6
Income	Living Environment	χ^2	3.5182	0.7416	6
Age	Gender	χ^2	4.8980	0.7684	8
Age	Occupation	χ^2	122.7798	< 0.0001	24
Age	Experience with Shared E-mopeds	χ^2	13.7345	0.0890	8
Age	Living Environment	χ^2	6.8286	0.5552	8
Education	Gender	χ^2	20.9891	0.0212	10
Education	Occupation	χ^2	109.7226	< 0.0001	30
Education	Experience with Shared E-mopeds	χ^2	15.6442	0.1103	10
Education	Living Environment	χ^2	11.0838	0.3510	10
Commute	Gender	χ^2	6.1521	0.4064	6
Commute	Occupation	χ^2	82.2078	< 0.0001	18
Commute	Experience	χ^2	5.8208	0.4436	6
Commute	Living Environment	χ^2	2.6481	0.8515	6
Errands	Gender	χ^2	2.2383	0.8965	6
Errands	Occupation	χ^2	16.7468	0.5406	18
Errands	Experience	χ^2	4.7673	0.5740	6
Errands	Living Environment	χ^2	20.4914	0.0023	6
Leisure	Gender	χ^2	4.2596	0.6416	6
Leisure	Occupation	χ^2	14.8359	0.6732	18
Leisure	Experience	χ^2	5.5488	0.4756	6
Leisure	Living Environment	χ^2	8.4500	0.2070	6