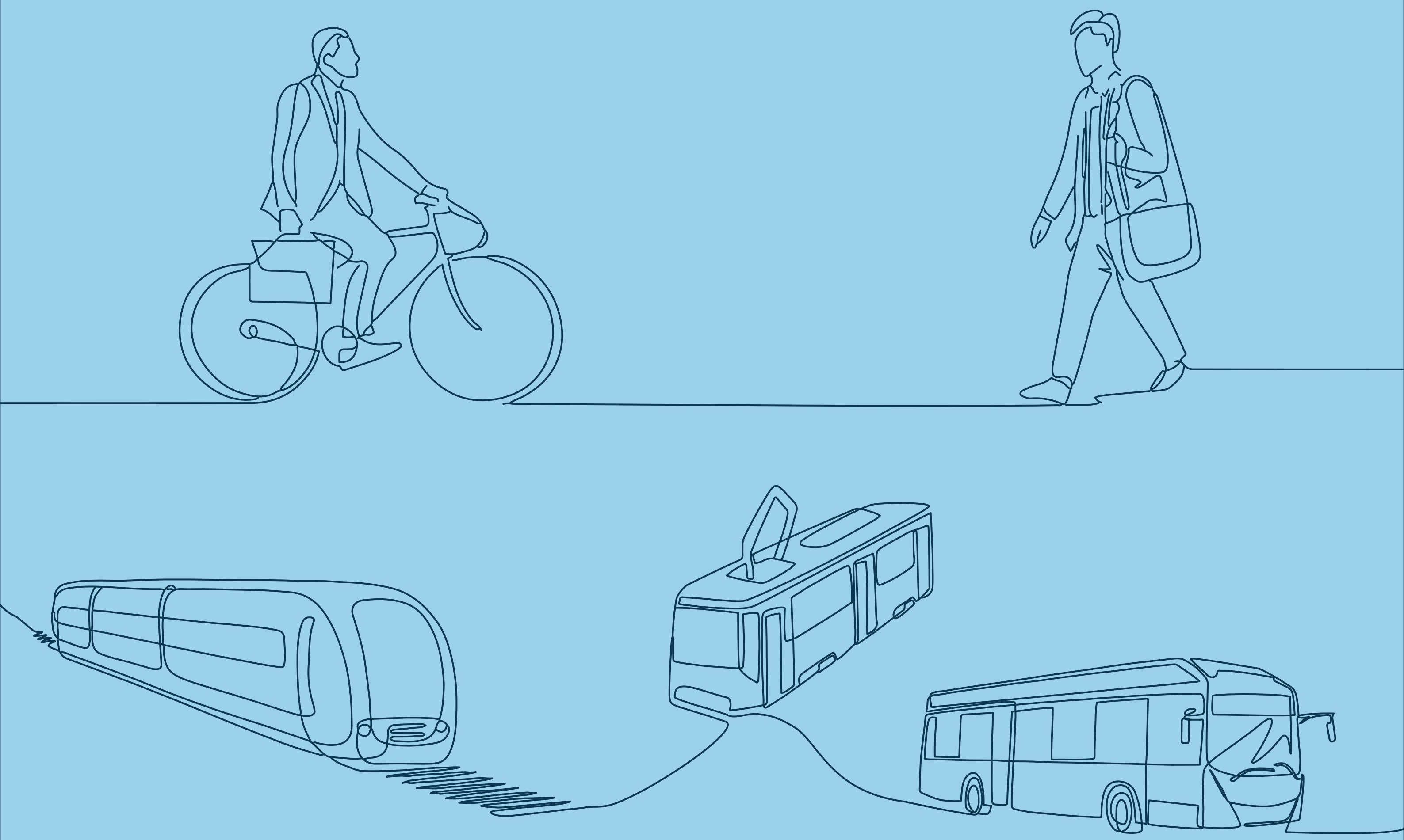

RETHINKING COMMUTING: SUSTAINABLE MOBILITY PRACTICES

A stated choice experiment exploring sustainable commuting modalities within the healthcare sector, given non-standard employment schedules

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MSc thesis Complex Systems Engineering & Management

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Rethinking Commuting:
Shaping Sustainable Mobility Practices

A stated choice experiment exploring sustainable commuting modalities within the healthcare sector given non-standard employment schedules

by

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Preface

This thesis marks the completion of my master's degree in Complex Systems Engineering & Management. Throughout this program, I have deepened my knowledge in the field of Transport & Logistics, which ultimately guided me to the topic I've focused on for the past six months. It was during my exchange at Instituto Tecnico Lisboa that I began to brainstorm ideas for my final project. Sustainability in the Transport & Logistics sector is an emerging area of interest, particularly for Pon, a company deeply committed to social responsibility and decarbonising mobility. The Living Lab Sustainable Transportation, on which Pon collaborated on with one of the largest academic medical centres in the Netherlands, presented the perfect opportunity for me to research the commuting behaviours of hospital employees. This unique partnership not only allowed me to complete my thesis but also gave me valuable insights into two distinctly different organisations, an experience I'm deeply grateful for. The findings from this research will hopefully be beneficial to both Pon and the academic medical centre, and I am proud to have contributed to this important work.

I am incredibly fortunate to have had a tremendous amount of support throughout this process, and I would like to take this opportunity to express my gratitude to those who made it possible. First, I would like to thank my first supervisor, Eric Molin, for his constant guidance and bi-weekly check-ins. Even during the times when I wasn't sure what to discuss, your advice and encouragement helped me refine my ideas and improve my thesis. To my chair, Bert van Wee, thank you for your thoughtful and inspiring feedback, and for always taking the time to thoroughly review my work. Your guidance was instrumental in helping me make critical decisions when I was at a crossroads. I would also like to thank Haiko van der Voort for your critical insights on the governance aspect of my research, which were invaluable.

A special thanks goes to my Pon supervisors, Kim Maas and Raymond Gense. Kim, I truly appreciate not only your academic support but also the care you showed for my well-being throughout this process. Raymond, I am grateful for the time you invested in helping me define the direction and goals of my research, and for your guidance along the way. The strategic team session at the farmhouse was an unforgettable highlight.

In addition to my academic and professional supporters, I owe a great deal to the people in my personal life. To my dear parents, Wessel, fellow graduate friends, roommates, and other close friends, thank you for your continuous encouragement, thoughtful advice, and for well-spent time away from my thesis. Your support allowed me to approach this project with very limited stress, and I can genuinely say that I've enjoyed the entire graduation process.

Looking back, I feel incredibly fortunate to have had six months of educational, enjoyable, and rewarding work, with lessons that will stay with me for years to come.

Noortje Charlotte van der Meulen
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Summary

Climate change is a critical global issue, with the transport sector contributing 24% of CO_2 emissions, largely from road traffic. In the Netherlands, commuting accounts for a significant portion of these emissions, with 70% of trips made by car. The healthcare sector, in particular, faces unique challenges, as hospitals operate 24/7, requiring employees to work non-standard hours. Shift work and irregular schedules often lead healthcare workers to rely on private vehicles, as they offer flexibility and convenience that public transport cannot provide, especially during off-peak hours. This reliance on cars makes it difficult to reduce commuting-related emissions within the healthcare sector.

This research focuses on employees of an academic medical centre in the Netherlands, participating in the 'Living Lab Sustainable Transport' pilot, which tracks commuting behaviours and tests interventions to encourage environmentally friendly transportation choices. The initiative aims to reduce the hospital's CO_2 emissions by 4.2% in 2024, as part of the healthcare sector's commitment to the Green Deal for Sustainable Care.

Located in a major science park, the hospital faces significant traffic congestion during rush hours, which increases emissions. The Living Lab, run by the academic hospital and Pon Mobility Nederland (Pon), offers sustainable commuting options like cycling, public transport, and shared mobility. Pon provides mobility solutions and helps the hospital understand individual commuting preferences and challenges, aiming to promote a modal shift toward more sustainable travel. Participants in the pilot can choose from various travel options, such as fully reimbursed public transport, 16 cents per kilometre for cycling, and access to shared e-bikes. While car use is not prohibited, parking authorisation is restricted during weekday mornings to encourage alternative modes.

This study investigates how hospital employees with irregular work schedules make commuting decisions and under what circumstances they would adopt more sustainable transportation modes. The goal is to identify how attributes of commuting modality, should be designed and implemented, particularly focusing on the constraints due to shift work and irregular schedules of employees and location-specific characteristics. Not only for the healthcare sector, this research's insights are relevant, but they could also inform other industries facing similar commuting challenges, such as the military, aviation or the entertainment business. The study seeks to provide both academic insights and practical recommendations for promoting environmentally friendly commuting options in healthcare settings. By addressing this research gap, the study aims to support the academic medical centre's and the Netherlands' efforts to reduce CO_2 emissions and meet national sustainability goals. The main research question is:

How can the attributes of sustainable commuting alternatives be effectively designed and implemented to maximise their adoption within the healthcare sector, considering the influence of non-standard employment schedules?

The first step of the research involved conducting a literature review to explore the consequences of shift work and irregular schedules on commuting behaviour. This review examined how non-standard employment conditions affect transportation choices, particularly focusing on the barriers these workers face when adopting sustainable commuting options. Additionally, key characteristics and barriers of sustainable transportation modes, such as public transport, cycling, and shared mobility, were identified. This review provided a foundation for understanding the constraints that influence commuting behaviour in standard employment settings and informed the attributes used in the Discrete Choice Experiment (DCE).

The design and implementation of the DCE focused on identifying the key commuting alternatives for hospital employees based on commuting distances and determining the most relevant attributes for each mode. These attributes included factors such as travel time, cost, delays, and parking availability, tailored to the real-world environment around the academic medical centre.

To capture variations in personal commuting preferences, socio-demographic and attitudinal questions were also integrated into the questionnaire. These included questions about travel habits, comfort, and

attitudes towards sustainability and health, structured using 5-point Likert scales. The DCE choice sets were generated using efficient design principles, ensuring that participants were presented with balanced and realistic commuting scenarios.

Finally, the questionnaire underwent a pilot test to assess its clarity and usability. Based on feedback, adjustments were made, ensuring that the final version was clear, concise, and aligned with the study's objectives. The questionnaire was distributed via Microsoft Forms, maintaining participant anonymity and ensuring smooth data collection for further analysis.

In the data preparation phase, a total of 183 valid responses were retained after addressing issues such as incomplete surveys, duplicate entries, and extreme outliers. The outliers, removed based on unusually long survey completion times, resulted in a recalculated average completion time of just under 10 minutes.

An important finding was the occurrence of non-trading behaviour, where respondents consistently selected the same alternative across all choice sets. This was particularly noticeable in Experiment 1, where 77% of respondents exhibited non-trading behaviour. While this could indicate extreme preferences or heuristic decision-making, such behaviour might also reflect strategic responses based on personal biases or strong preferences for certain commuting modes, such as car or bike use. Despite these challenges, the decision was made to retain the non-trading responses for further analysis.

The sample characteristics revealed a diverse distribution of respondents across gender, age, and work schedules. Experiment 1 had a high proportion of older respondents working irregular shifts, while experiments 2 and 3 had more regular schedules and a more balanced distribution across age and gender. These differences are essential in analysing how socio-demographic factors influence commuting choices.

Through exploratory factor analysis, six key factors were identified that shaped attitudes towards commuting. These factors included health consciousness, commuting habits, environmental consciousness, and attitudes towards specific commuting modes such as cars, public transport, and (e-)bike use. Interestingly, health consciousness was a strong theme across the sample, while environmental concerns were more neutral.

The traveller-related attitudes showed an overall positive perception of (e-)bike commuting, which was unexpected given the assumption that unfamiliarity with cycling might deter some respondents. Surprisingly, attitudes toward car and public transport commuting were similarly positive, with minor differences in reliability and comfort levels. When comparing the attitudes of employees with irregular schedules or shift work to those with standard work hours, the differences were minimal. However, car commuting was more positively perceived by shift workers, likely due to the flexibility it provides for non-standard working hours.

In the results section, the analysis of commuting choices begins with a breakdown of the modal split across the three experiments. It is notable that car commuting was consistently unpopular, even for longer distances. In experiment 1 (distances ≤10 km), no one chose to commute by car, with private (e-)bikes dominating the modal split. In experiment 2 (distances 11-30 km), car use remained low at 9%, while e-bike leasing and public transport combinations were much more popular. Even in experiment 3 (distances >30 km), car use was only 5%, with public transport options like train and bus/light rail dominating.

Due to the small sample size and a high level of homogeneity in the responses, the analysis focused on the Multinomial Logit (MNL) model, as the Latent Class Choice Model (LCCM) could not be estimated effectively due to non-trading behaviour. The MNL model was expanded with interaction effects, revealing several key findings. In experiment 1, the higher cost of leasing e-bikes reduced their appeal, making private (e-)bikes the preferred choice for shorter distances. In experiment 2, medium distances, travel allowances for e-bike leasing significantly boosted adoption, while increased parking costs and car delays further discouraged car use. In experiment 3, for longer distances, parking costs and travel allowances played a substantial role in reducing car use, with public transport emerging as the most preferred option.

Across all experiments, financial incentives like e-bike travel allowances and policies raising parking costs proved to be effective tools for promoting more sustainable commuting modes. Contrary to expectations, shift work and irregular schedules had minimal impact on commuting choices, with shift workers showing similarly positive attitudes towards public transport as regular workers. However, the safety concerns for cycling at night were a key consideration for shift workers, highlighting the need for additional support for these employees.

The analysis also showed that even modest financial incentives for e-bike usage could drastically increase cycling rates, with modal split rising to 55%. This demonstrates the strong potential of financial incentives to reduce car use, alongside parking restrictions and delays, which successfully discouraged car commuting. These findings suggest that financial incentives, alongside infrastructure improvements, can effectively promote a modal shift, even for employees with non-standard work schedules, provided that safety concerns and flexibility needs are addressed.

Based on these findings, several policy recommendations have been proposed to support a sustainable modal shift for hospital employees. Key recommendations include closely monitoring public transport capacity and the availability of shared e-bikes, especially as the full reimbursement of public transport costs is expected to increase demand. Promoting e-bike leasing schemes with financial allowances is also a crucial step, as even modest incentives significantly increase e-bike use. Providing a travel allowance of 18 cents per kilometre, similar to cycling reimbursement, would make e-bikes an attractive commuting option, particularly for the 74% of employees living within 30 kilometres of the hospital.

Additionally, parking authorisation for employees working irregular hours, especially night shifts, should be tailored to ensure safety and convenience while encouraging more sustainable commuting options for regular hours. Offering flexible, tailor-made commuting advice could further support employees in navigating sustainable alternatives, particularly during disruptions in public transport. The integration of health and environmental benefits into commuting recommendations would also help foster long-term behavioural changes toward more sustainable commuting.

A limitation of this research is the voluntary participation in the Living Lab which created a unique group of highly motivated and enthusiastic employees, possibly introducing bias into the findings. These individuals, likely more eager to adopt sustainable commuting options, may not represent the broader hospital employee base, including those less inclined to explore alternative commuting modes. This could result in a skewed, more optimistic outlook on the feasibility of implementing such alternatives across the entire workforce. Additionally, the strong financial incentives offered, such as full reimbursement for public transport, might have played a disproportionate role in driving the observed modal shift, making it unclear how much of the shift was due to other factors.

Future research should aim to include a more representative sample of the hospital's full employee population to provide a clearer picture of commuting preferences. Expanding the study to the entire employee base would help in understanding how varying levels of enthusiasm and readiness to change affect the adoption of sustainable commuting options. Furthermore, removing confounding factors like car costs and unlabelled alternatives would allow for more accurate reflections of actual commuting expenses and behaviours. By addressing these limitations, future studies could better inform policies aimed at achieving a wider modal shift towards sustainable commuting.

Contents

List of Figures

List of Tables

Nomenclature

The abbreviations used in this graduate thesis are presented in Table 1. Certain abbreviations are derived from their Dutch translations since they are frequently used acronyms in the healthcare industry. The symbols and definitions are displayed in Table 2.

Abbreviations

Table 1: Abbreviations used

Abbreviation	Definition
CoSEM	Complex Systems Engineering and Management
DCM	Discrete Choice Modelling
DCE	Discrete Choice Experiment
LCCM	Latent Class Choice Modelling
MaaS	Mobility as a Service
MNL	Multinomial Logit
PAF	Principal Axis Factoring
P+R	Park and Ride
PT	Public Transportation
RUM	Random Utility Maximisation
SDG	Sustainable Development Goal
WtP	Willingness-to-Pay

Symbols

Table 2: Symbols used

Symbol	Definition
U_{in}	Utility alternative i
V_{in}	Observed utility of alternative i
ε_{in}	Unobserved utility of alternative i
β_m	Taste parameter for attribute m
x_{im}	Attribute level of attribute m of alternative i

1 Introduction

Climate change poses an existential threat to our planet and way of life. Rising global temperatures are causing extreme weather events, sea level rise, biodiversity loss, and disruptions to ecosystems that provide food and water (UN, 2024a). The impacts are already felt through more frequent heatwaves, droughts, wildfires, flooding, and ecosystem collapse. If left unchecked, climate change will have devastating consequences for human health, food and water security, and economic stability, and has the potential to undo decades of improvement in world health (WHO, 2024). Urgent, transformative action is needed from governments, industries, and individuals to rapidly reduce greenhouse gas emissions and build resilience to the changes that can no longer be avoided.

Globally, the transport sector is a major contributor to CO_2 emissions, accounting for 24% of energy-related emissions, with 75% of these emissions originating from road transportation(Ritchie, 2020). Specifically, 29.4% of these emissions are from freight trucks and 45.1% from passenger traffic, making road transport responsible for 15% of total CO_2 emissions (IEA, 2018). The European Green Deal, including the 'Fit for 55' initiative under the European Climate Law, commits to reducing net greenhouse gas emissions by at least 55% by 2030 (European Council, 2023). Achieving European climate targets requires a transformation in transportation, a sector that poses a major challenge to meeting Sustainable Development Goal (SDG) 11 for sustainable cities and communities (UN, 2024b).

A modal shift toward more environmentally friendly transportation enhances sustainability and benefits public health and the environment. The Netherlands, in alignment with European climate goals, is committed to reducing CO_2 emissions from business and commuter travel, which represents over 50% of car travel in the country (Rijksdienst voor Ondernemend Nederland, 2024). In response, the Ministry of Infrastructure and Water Management (IenW) is studying these emissions and introduced legislation requiring companies with over 100 employees to report their CO_2 emissions from business and commuting activities starting July 1st, 2024.

In 2022, 16% of all movements made by Dutch residents had the purpose of covering the distance to and from work, with an average of 7.4 kilometre per resident (CBS, 2022). There is a notable difference in the average distance covered between full-time and part-time workers, with part-time workers travelling 8.3 km per day compared to 15.6 km per day for full-time workers (CBS, 2022). Commuting refers to the routine daily trip between home and work (Lyons & Chatterjee, 2008). Notably, 70% of these commutes were made by car rather more environmentally friendly modes. The National Government aims to enhance the appeal of all transportation modes, ensuring travel is quick, easy, and comfortable (Ministerie van IenW, 2024). Leveraging modern technology can make transportation safer, more efficient, and eco-friendlier.

As critical infrastructure, hospitals operate around the clock, necessitating shift work for their employees. Shift work, which often includes irregular hours, can significantly influence the commuting patterns of hospital staff. This irregularity poses unique challenges to creating sustainable commuting options, as the need for flexibility and reliability often leads to a reliance on private vehicles. Therefore, research is essential to gain insights into how shift work impacts hospital employees' commuting behaviours and identify strategies that can promote more sustainable travel choices among this workforce, ultimately contributing to broader environmental goals.

1.1 Knowledge gap

To encourage a shift toward sustainable transportation among shift workers, particularly in healthcare, it is crucial to understand the conditions under which employees are willing to adopt eco-friendlier commuting modes. Particularly in healthcare, it is critical to understand the effects of shift work and irregular schedules on employers, extending beyond just transportation issues. Much research has examined the attractiveness of different commuting options. This literature review further explores the characteristics and barriers that determine their (non-)attractiveness and, consequently, the circumstances under which commuters choose a particular mode. Various stakeholders —such as government agencies, environmental organisations, public transport operators, shared mobility providers, and employers— can play key roles in motivating shift workers to choose sustainable options.

In recent years, the increasing demand for flexible work schedules, particularly in the healthcare sector, has led to a rise in shift work and irregular work schedules (OECD, 2020). While this flexibility is critical for ensuring continuous and reliable services in hospitals, it poses significant challenges for employees, particularly concerning their health and well-being. Numerous studies have explored the negative impacts of shift work, especially irregular shifts, on workers, highlighting issues such as insomnia, sleep deprivation, daytime sleepiness, and elevated stress levels (Gu et al., 2023; Härmä et al., 2002; Setyowati et al., 2023). Moreover, research has shown that these irregular schedules are linked to serious long-term health risks, including gastrointestinal, metabolic, and cardiovascular disorders (D'ettorre et al., 2020; Khan et al., 2020).

Despite the growing body of research, there remains a notable gap in understanding the specific conditions under which shift work influences commuting behaviours among healthcare workers. While much attention has been given to the general health effects of shift work, there is limited knowledge about how these irregular schedules impact the daily commutes of hospital employees, particularly concerning their choice of transportation modes. This gap in the literature underscores the need for further research to explore how shift work and commuting intersect, potentially informing interventions aimed at promoting more sustainable and health-conscious commuting practices among healthcare professionals.

In support of this, Zadeits (2024) conducted qualitative research through in-depth interviews with hospital employees about their commuting behaviour, with specific focus on their level of fit to personal needs and perceived equity of the proposed travel alternatives. In total 17 employees were questioned about their commuting experiences with mobility challenges at the academic medical centre. Key obstacles include practical limitations and constraints that make sustainable transportation options unavailable or unfeasible in specific circumstances. The study revealed that public transport, although more environmentally friendly, is often perceived negatively due to high costs, longer travel times, and multiple transfers. Additionally, sustainable alternatives were deemed inadequate given the unique work circumstances of healthcare employees, who face irregular hours, high work pressure, and demanding physical and mental tasks. These challenges are not unique to healthcare but are also present in other sectors, such as the military, aviation, and entertainment industries.

Night-time mobility, in particular, presents unique challenges distinct from regular daylight travel. Poor lighting, limited public transportation, and increased feelings of insecurity are significant barriers to night travel, especially for women (Kapitza, 2022, 2024). Night travel also increases the likelihood of preferring cars due to time constraints and the need for flexibility (Kapitza, 2022). Given the necessity of arriving at and departing from work at specific times, often during rush hour, and the increased risk of traffic disruptions, Cass and Faulconbridge (2016) found that effective (re-)routing to maintain timeliness is a critical skill. Additional barriers to adopting more sustainable commuting modes include a strong reliance on private vehicles, entrenched in daily routines, as well as social practices such as parental responsibilities and shopping activities (Camilleri et al., 2022; Cass & Faulconbridge, 2016). Intrinsic motivation and how commuters use their travel time also play critical roles in transitioning to more sustainable modes (Meinherz & Binder, 2020).

Commuting decisions under normal circumstances are influenced by various mode-related attributes, such as travel time, cost, comfort, and perceived reliability. For instance, cars remain a dominant mode of transport, particularly for commuters prioritising convenience and flexibility. Research shows that car dependency is often tied to personal status, convenience, and a sense of control over the travel experience, particularly in areas with less accessible public transport or longer distances to cover (Li & Zhao, 2015; Molin et al., 2016). In contrast, active modes, such as cycling and walking, are typically favoured when infrastructure supports these modes and the journey is short (Esztergár-Kiss et al., 2021). Public transport, while environmentally friendly, is often perceived as less attractive due to factors such as transfer requirements and limited convenience for certain routes (Parmar et al., 2023).

Shared mobility options, like bike-sharing or ride-hailing services, are gaining popularity, particularly when integrated with public transport systems. However, their adoption is closely linked to affordability and perceived environmental benefits (Luo et al., 2023). These choices are often shaped by personal preferences and demographic factors, such as age, income, and lifestyle changes, all influencing the likelihood of choosing sustainable alternatives.

However, the unique demands of shift work, particularly in healthcare, present distinct challenges that disrupt these commuting norms. Shift workers often rely heavily on private cars due to the irregular hours and limited availability of public transport, especially at night. This reliance on cars is compounded by the need for flexibility and safety during off-peak hours and the perception that public transport is unreliable or inconvenient for their schedules.

Living Lab Sustainable Transport

This research focuses on a unique target group, employees of an academic medical centre in the Netherlands, who participate in a pilot to explore sustainable commuting options. The pilot, 'Living Lab Sustainable Transport', involves 300 employees whose commuting behaviours are tracked, and interventions are tested to encourage more environmentally friendly transportation choices. The project was launched to address the hospital's goal of reducing CO_2 emissions from employee commuting as part of the healthcare sector's commitment to the Green Deal for Sustainable Care (Dutch Government, 2023). In particular, the academic hospital aims to reduce its carbon emissions by 4.2% in 2024.

Located in one of the largest science parks in the Netherlands, the hospital faces significant traffic congestion, especially during rush hours, contributing to CO_2 emissions. As the Green Deal outlines, a modal shift towards more sustainable commuting, such as cycling or public transport, is encouraged to reduce emissions and improve physical and mental health.

Two parties who have joined forces and are taking responsibility for the Living Lab are the academic hospital and Pon Mobility Nederland (Pon). Pon aids the academic hospital by sharing their expertise in mobility and providing a range of sustainable travel alternatives. They aim to comprehend individual travel preferences and the trade-offs involved in decision-making. Personal habits and characteristics are central to understanding commuting behaviour and crucial to promoting a modal shift and creating customised, inclusive mobility solutions for employees.

This study continues the research conducted by Zadeits (2024), exploring the travel behaviour of the academic medical centre's employees through interviews. The findings of Zadeits (2024) confirmed the complexity of available transportation for employees with irregular, emergency or night shifts. Another important outcome was the emphasis that employees put on how customised, inclusive, and well-communicated mobility solutions are essential to efficiently meeting the varied needs of healthcare workers.

1.2 Research objective and societal aim

The literature has thoroughly examined the general factors influencing commuting choices. However, there is a significant gap in understanding how irregular schedules and shift work specifically impact the adoption of sustainable transport modes. The combined challenges of flexibility, reliability, personal circumstances, and location-specific infrastructure have not been fully explored. This study addresses these gaps by examining how healthcare employees with irregular work schedules make commuting decisions and under what circumstances they are likely to adopt more sustainable options.

Building on the research by Zadeits (2024), which focused on a small sample of 17 participants, this study expands the analysis to the entire Living Lab population, with a sample size of 300. This expansion serves as an initial step toward scaling the research across the academic medical centre. While

Zadeits (2024) identified challenges related to irregular work schedules, this study further investigates how both irregular and standard schedules differently influence preferences for sustainable commuting alternatives. Additionally, it explores new options like the lease e-bike and shared e-bike hubs to reduce reliance on car-based commuting. While Zadeits (2024) focused on the level of fit and perceived equity, this research shifts to understanding how varying attributes of alternative commuting modes can drive adoption, addressing both preferences and the feasibility of implementing these solutions.

The primary goal of this research is to provide insights into these factors, contributing to both academic literature and practical interventions. The aim is to design tailored strategies that encourage a shift towards eco-friendly commuting in healthcare and other sectors facing similar challenges. The findings will inform policies that facilitate a transition to more sustainable transportation modes, ultimately contributing to reducing greenhouse gas emissions.

This research aligns with the CoSEM (Complex Systems Engineering and Management) programme by addressing the socio-technical complexity of commuting behaviours in healthcare and developing effective interventions. The study involves systems thinking to explore how individual behaviours, technological solutions, and institutional structures interact. By analysing these interactions, this research proposes practical strategies for stakeholders to foster sustainable transport modes within complex organisational settings like hospitals. The combination of systems engineering approaches with organisational science and policy-making demonstrates the multidisciplinary nature of the CoSEM programme, particularly within the Transport & Logistics track.

The societal objective of this research is to contribute to reducing CO_2 emissions in the Netherlands, particularly in the transport sector, where commuting accounts for 16% of all movements and 70% of those commutes are made by car. As a significant contributor to emissions, the healthcare sector has a unique responsibility to lead by example. This research, conducted within the context of the Living Lab Sustainable Transport, focuses on promoting a modal shift that will reduce the 27% of direct emissions caused by employee commuting at the academic medical centre (Academic Hospital, 2024).

This research addresses the urgent environmental challenge posed by transport-related emissions and aims to provide actionable insights for various stakeholders, including governmental agencies, environmental organisations, public transport operators, shared mobility providers, and employers. These findings can inform policies and interventions that support a sustainable modal shift, contributing to a more sustainable and resilient future for the Netherlands.

1.3 Research questions

This thesis addresses the primary research issue in light of the research gap and objective. The main research question and supporting sub-questions are outlined below.

Main Research Question:

How can the attributes of sustainable commuting alternatives be effectively designed and implemented to maximise their adoption within the healthcare sector, considering the influence of non-standard employment schedules?

A sequence of sub-questions has been designed to systematically explore different facets of this research question to guide the research process.

Sub-question 1

What is the impact of shift work and irregular schedules on hospital employees?

This sub-question seeks to understand the broader effects of non-standard employment in general. Insights from the literature and in-depth interviews, such as those conducted by Zadeits (2024), will help form hypotheses about how these factors shape decisions related to commuting modes.

Sub-question 2

What are the key characteristics and barriers of sustainable transportation modes that influence employees' commuting choices?

This question identifies specific characteristics and barriers of sustainable commuting options, such as public transport, cycling, and walking. The goal is to understand how these attributes influence decisions to shift from car-based commuting, particularly under standard employment conditions. A literature review will provide insights into the factors that motivate or hinder sustainable commuting.

Sub-question 3

What location-centered specifications pose challenges to the integration of sustainable commuting practices?

Location-specific factors, including infrastructure and accessibility challenges, play a crucial role in determining the feasibility of sustainable commuting options. This sub-question explores the unique challenges of the academic hospital's location, identifying barriers and enablers that affect the modal shift towards sustainable commuting. Based on exploring the academic hospital's surroundings, a hypothesis will be formed to identify potential challenges in promoting a modal shift towards sustainable transportation.

Sub-question 4

To what extent is it feasible to replace car commuting with sustainable commuting practices for employees with non-standard employment schedules?

This final sub-question assesses the feasibility of reducing car commuting by integrating sustainable alternatives for hospital employees. By examining various scenarios and considering the location-specific and schedule-related challenges identified earlier, this question evaluates the potential for a successful modal shift.

A combination of methods was employed to answer these research questions, starting with a literature review to develop hypotheses about the effects of non-standard employment on commuting choices. Discrete Choice Modelling (DCM), combined with a Discrete Choice Experiment (DCE), was used to explore commuters' trade-offs between different transport modes, grounded in Utility Maximisation Theory. The DCE allowed the testing of hypothetical scenarios to understand commuters' preferences and predict behaviour. Latent Class Choice Modelling (LCCM) was specifically chosen to capture heterogeneity in preferences, making it a suitable method for studying varied commuting behaviours under non-standard employment conditions, enabling more targeted insights and interventions.

1.4 Thesis layout

This thesis is structured to comprehensively address the research question regarding how non-standard employment schedules and location-specific challenges influence the commuting behaviour of hospital employees, particularly in the context of adopting sustainable commuting practices. Chapter 1introduces the topic, outlining the knowledge gap, research objective, societal aim, and the research questions guiding this study. The concept of the Living Lab Sustainable Transport initiative is presented in Chapter 2, explaining the participant group, interventions and data collection process, as well as a timeline. Then, in Chapter 3, the methodological approach is detailed, beginning with a literature review. This chapter also describes the Discrete Choice Modelling (DCM) technique, which was employed to understand decision-making processes related to commuting. The development, procedure, and analysis of the Discrete Choice Experiment (DCE), along with model estimation and fit criteria, are explained. Chapter 4 reviews relevant literature on shift work, commuting modalities, socio-demographic characteristics, and traveller-related attitudes. It also introduces the conceptual model that underpins the research. The operationalization of the DCE, detailing the development of commuting alternatives and attributes, as well as the generation of choice sets and the questionnaire structure is described in Chapter 5. This is followed by Chapter 6, which provides an analysis of the descriptive statistics, including data preparation and an overview of the sample's socio-demographic characteristics, with particular attention to the results of an exploratory factor analysis and traveller-related attitudes. All model estimation processes are fully described in Chapter 7, while Chapter 8 presents the results of the modal split across different commuting distances and the choice model estimations for each of the three experiments. It also explores the parameter estimates and the effects of various attributes on the modal split. The conclusions drawn from the study, comparing the results with the literature, and providing policy recommendations to promote sustainable commuting are all discussed in Chapter 9. It also outlines the study's limitations and suggests possibilities for future research. Finally, Chapter 10 offers a reflective gaze, providing personal insights into the research process, the governance aspect and the associated interplay of interests.

2
Living Lab Sustainable Transport

2.1 Concept Living Lab Sustainable Transport

Living Lab Sustainable Transport, in short, Living Lab, is an initiative of the academic hospital aiming to find suitable, effective, and executable solutions for employees' commuting. The academic hospital invites 300 employees to participate in this search with the primary aim of reducing CO_2 emissions and improving the accessibility of the hospital. The academic hospital invited employees to voluntarily sign up, and due to more than 300 registrations, a selection process was conducted. Those selected gave their consent to participate in focus groups and surveys and benefit from specific commuting arrangements, which are elaborated later on. Over six months, an enormous amount of data is gathered through logging, surveys are conducted, and the implementation of distinct interventions are tested. The academic hospital recognises the profound connection between human health and the vitality of the planet. Climate change and environmental pollution have a significant impact on human health. In 2023, the CO_2 emissions from employee commuting at the academic hospital amounted to 10,754 tonnes, accounting for 27% of their direct CO_2 emissions (Academic Hospital, 2024). The Living Lab encourages employees to make conscious choices about their commuting methods.

The healthcare sector has agreed on the 'Green Deal for Sustainable Care', drawn up between the Dutch government and other parties within this sector, to performance-oriented address five themes between 2023 and 2026 (Dutch Government, 2023). This agreement aims to address the paradox that by providing care, the sector is contributing to the climate crisis, environmental crisis and increasing demand for care. The three themes that apply to this issue are health promotion, knowledge and awareness, and CO_2 reduction amongst employees (Dutch Government, 2023). Specifically, the academic medical centre's KPI for 2024 is to reduce carbon dioxide emissions by 4.2%. As the academic medical centre contains over 12.000 employees, it is essential to consider carefully how employees can be incentivised, also considering the new law on CO_2 reporting.

Additionally, the academic medical centre is located in one of the Netherlands' largest science parks. A natural cause of this is the tremendous traffic jams during rush hours resulting in an enormous increase in CO_2 emissions. Research has shown that emissions rise by at least 50% during traffic jams when compared to free-flowing conditions; the severity of this increase varies based on the age and type of car (Zhang et al., 2011). Another theme included in the Green Deal for Sustainable Healthcare is the promotion of the physical and mental health of employees. Therefore the academic medical centre is encouraging a modal shift to more sustainable transportation modes, e.g. (e-)bikes or public transportation. An additional important side effect of a modal shift is that the collective accessibility of parking spaces and access routes is greatly improved.

For the Living Lab, the academic hospital collaborates with partners such as Shuttel and Hely, both Pon-owned companies. The Shuttle card grants participants access to all public transport and shared mobility options. To receive reimbursement, participants must register all their journeys, including work-from-home days, through the Shuttle app. Both the Shuttle card and app provide Pon and the academic hospital with extensive data from the Living Lab. At the nearest central station to the academic hospital, Hely has opened a bicycle hub providing access to shared city bikes and electric bikes, only accessible by employees from the academic medical centre. Through the Hely app, participants can book a bike to complete the last part of their journey, which they keep for the entire day.

Participants in the pilot project can choose from various daily travel options or a combination of several. Incentives are provided to promote sustainable commuting:

- Public transport usage is 100% reimbursed.
- Cycling is reimbursed at 16 cents per kilometre.
- Shared e-bikes free accessible at Hely hub.

Participants are not prohibited from using their private cars, yet they can no longer use their parking authorisation between 6 a.m. and noon on Monday through Friday and will lose their travel allowance.

The Living Lab gathers valuable insights from the experiences and travel behaviour of participants, shedding light on their motivations and obstacles related to commuting choices. These insights form the foundation for developing a new mobility policy that caters to the needs of employees while aligning with the academic hospital's sustainability objectives, including those outlined in the Green Deal Sustainable Care 3.0. For 2026, the targets have been set on a 30% CO_2 reduction and 55% by 2030. With the growing shortage of staff and the location of the academic medical centre on the border of one of the largest cities in the Netherlands, ensuring safe and accessible commuting for employees is a priority. This is especially important for those working irregular shifts and residing in the eastern part of the country, where there are fewer options for commuting to the academic medical centre. The Living Lab aims to better understand the motivations and barriers employees face, address traffic congestion, increase accessibility, and improve the overall commuting experience while collaboratively contributing to healthier employees and a more vital planet.

2.2 Data Collection & Interventions

To gain insights into employees' travel behaviour, the Living Lab has engaged participants in various data collection methods. At the outset, all employees were asked to complete a baseline survey, followed by an interim survey one month later, which focused on their experiences up to that point. In addition to surveys, focus groups were conducted with small groups of participants, delving into specific topics. The first focus group explored the use of park-and-ride (P+R) facilities, while the second focused on cycling as a mode of transportation.

The Living Lab itself can be considered an intervention, as participants are committed to lending their cooperation. However, further interventions were also implemented. These included a celebratory event held in mid-June and two interventions developed and implemented in collaboration with behavioural experts. The celebratory event was organised jointly by the academic hospital and Pon, featuring keynote speakers from both organizations and a pop-up exhibition showcasing the data collected until then. Appendix A provides visualisations of the event.

Regarding the interventions, the first one involved sending participants personalised feedback messages about their travel behaviour. To evaluate the effectiveness of this intervention, participants were divided into three groups: a control group, a group receiving message A, and a group receiving message A+B. Message A included information about the travel behaviour of other participants, while messaging B also incorporated the participants' predefined personal objectives, which were initially captured in the zero measurement survey. Due to the success of the Living Lab in general and the already reduced parking authorisations with 93%, it was decided not to implement the second intervention anymore.

The Sustainable Transport Living Lab runs from March 2024 to September 2024. Figure 2.1 visualises all activities during this running period. A distinction in processes is made between data collection, in the form of surveys or focus groups, and interventions implemented.

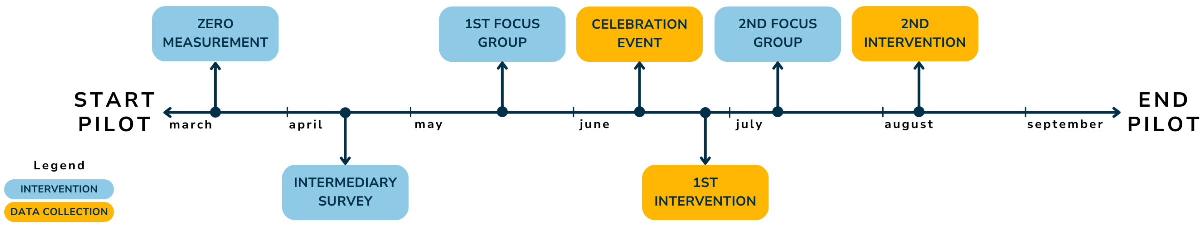

Figure 2.1: Timeline Living Lab Sustainable Transport

2.3 Mobility as a Service

As the demand for multimodal travel options has grown in the Netherlands, the central government has launched several Mobility as a Service (MaaS) pilot projects (Rijksoverheid, 2019). MaaS applications place the traveller at the centre, offering seamless planning, booking, and payment for various modes of transport—including shared bikes, cars, scooters, and public transport—through a single app. The goal is to provide door-to-door travel tailored to individual needs while improving the overall mobility system.

Despite infrastructure developments, congestion in and around cities is expected to increase, and public transport faces mounting pressure during peak hours. MaaS presents a potential solution by 'unburdening' travellers and encouraging a shift away from private vehicle use. In seven national MaaS pilots, including one around the academic hospital, MaaS apps were developed to address various policy objectives. The results showed that 55% of participants experienced some form of behavioural change, such as using different transport modes or travelling at different times (Ministerie van IenW, 2023). In the academic hospital area, car usage decreased by 40% (Ministerie van IenW, 2023). However, changing behaviour among personal vehicle owners proved more challenging.

Currently, several MaaS applications, including Shuttel, are integrated into the national mobility system. These initiatives aim to provide travellers with convenient, multimodal options while addressing congestion, public transport capacity, and accessibility challenges. By leveraging technology and personalised travel advice, MaaS seeks to promote sustainable commuting practices and reduce reliance on private vehicles.

Key highlights

Cause:	Employee commuting contributed to 27% of the academic hospitals direct CO_2 emissions.
Objective Living Lab:	Reduce CO_2 emissions with 4.2% in 2024, and improve hospital's accessibility through sustainable commuting solutions.
Participants:	300 academic hospital employees.
Incentives:	Full reimbursement for public transport, cycling reimbursement, and free access to shared e-bikes.
Data Collection:	Zero measurement, intermediary surveys, focus groups on park-and-ride facilities and cycling.
Interventions:	Personalised feedback messages and a celebratory event to engage and motivate participants.

3

Methodological approach

This chapter outlines the methodological approach to answer the sub-research questions and, ultimately, the main research question. The chapter starts with the literature study conducted in Section 3.1. As the methodological approach follows Discrete Choice Modelling with Latent Class Analysis, essential for understanding the decision-making processes in transportation under non-standard employment conditions, this mathematical tool is explained in Section 3.2. The chapter also covers the operationalisation of the Discrete Choice Experiment in Section 3.3. DCM, based on Utility Maximisation Theory, is used to predict choices between alternatives, while LCCM accounts for heterogeneity in preferences by segmenting the population into distinct classes. This DCE analysis process is elaborated in Section 3.4 through the model estimation and model fit methods.

3.1 Literature study

A comprehensive literature study was conducted to develop hypotheses for sub-questions 1 and 2, as well as defining the location-specific challenges of the academic medical centre to answer sub-question 3. This study aims to gather broad insights into the effects of shift work and irregular schedules under non-standard employment conditions. By understanding these effects, a stronger foundation is established upon which the conclusions of this research can be based. The second sub-question examines the characteristics and barriers that generally influence commuting choices. While the attractiveness of different commuting modalities is widely known, gaining insight into the tipping points that influence decisions helps in understanding the outcomes of this experiment within the specific context of this environment. Together, these research questions guide the formation of hypotheses on how various factors may shape adopting sustainable commuting modes.

The literature study primarily utilised the Scopus database to identify relevant research. This review compares the effects of standard and non-standard employment on commuting behaviours, helping to map out the differences in transportation choices under varying employment conditions. The hypotheses formed through this study are designed to be evaluated in light of the research results.

Chapter 4 presents the findings and insights from this literature study. Additionally, Appendix C provides a detailed account of the search process, including the search string and selection criteria.

3.2 Discrete Choice Modelling

Discrete Choice Modelling (DCM) is a powerful mathematical tool used to predict or explain decision-makers' choices when faced with two or more alternatives in a choice set (Calastri, 2020). Initially developed by McFadden, DCM has been widely applied in transportation to understand commuter mode choices (Bernasco & Block, 2013). The fundamental assumption underlying DCM is rooted in Utility Maximisation Theory, which posits that decision-makers will choose the alternative that provides the greatest utility (Train, 2009). Utility, in this context, can be thought of as a measure of the perceived satisfaction or benefit derived from a particular choice.

For hospital employees with non-standard work schedules, such as working shifts or on-call, this decision-making process becomes even more complex. These individuals are likely to wiegh certain commuting attributes (e.g. reliability, availability during late hours, and personal safety concerns) more heavily than others. The RUM framework allows us to model these trade-offs explicitly, capturing both the observable factors (e.g., commuting costs, travel time) and unobservable factors (e.g., attitudes toward cycling in the dark, safety concerns). This ensures that the specific challenges faced by hospital employees in choosing between commuting alternatives are taken into account.

In Random Utility Maximisation, the utility from a commuting alternative is typically composed of both observable and unobservable factors. Observable factors include measurable attributes of the alternatives, such as cost, time, and convenience. However, for hospital employees working irregular shifts, these observable factors might play a secondary role to unobservable factors such as safety, the inconvenience of multiple transfers during off-peak hours, or fatigue after long shifts (Train, 2009). These latent factors introduce an element of randomness into the model, which is captured by Random Utility Maximisation (RUM) models (Marschak, 1974). The Random Utility Maximisation theory and its mathematical model is further elaborated in Section 3.4.1.

RUMs are particularly useful in this research because they account for the fact that hospital employees, depending on their specific working schedules, may make different commuting choices even if the observable attributes remain constant. For instance, a worker with an evening shift may prefer a car due to safety concerns, whereas the same worker during a daytime shift may opt for public transport. By varying these attributes efficiently within a Discrete Choice Experiment (DCE), the study explores these trade-offs, estimating each attribute's relative importance in the decision-making process of hospital workers with varying schedules. Conducting this DCE contributes to answering the fourth sub-question focusing on the feasability of a modal shift, and concluding on the main research question how to design and implement sustainble commuting alternatives. Insights gathered from answering sub-questions one, two, and three were used to guide the design of the DCE.

In constructing a DCE, two main data collection paradigms are employed: revealed preference and stated preference. Revealed preference data is gathered from actual decisions made by individuals in real-world settings, providing insights into their behaviour under natural conditions. On the other hand, stated preference data is collected through surveys where individuals are presented with hypothetical scenarios and asked to make choices (Cox, 2015). The stated preference paradigm is particularly useful in exploring trade-offs in situations not frequently encountered in real life or when testing new products and services (Kroes & Sheldon, 1988). Stated preference data allows researchers to design experiments that isolate specific attributes and evaluate their impact on decision-making. This approach is well-suited for understanding commuting preferences, especially when evaluating new or hypothetical alternatives, such as leasing e-bikes (Cox, 2015).

Apart from the attributes of the alternatives, personal characteristics also play a significant role in shaping preferences (Polydoropoulou et al., 1994, 1996; Tsirimpa et al., 2007). In the context of this group, personal characteristics such as age and gender, household composition, but also attitudes toward comfort and reliability, and environmental- and health-consciousness play a significant role in shaping commuting preferences. The variation in preferences, known as heterogeneity, are captured using a Latent Class Choice Model (LCCM), which segments the population into distinct classes, each with its own taste preferences measured through a Multinomial Logit model (MNL). These classes are characterised by both observable attributes and latent factors, which are not directly measurable but influence the decision-making process (Greene & Hensher, 2003). By grouping respondents into classes, the goal is to maximise homogeneity within classes and heterogeneity between classes.

By including covariates such as socio-demographic variables and work-related characteristics, this study identifies unique commuter profiles within the hospital workforce. These segments allow for a deeper understanding of how hospital employees' preferences may differ from those in other employment sectors. LCCM also allows for the incorporation of both the rational decision-making process (Utility Maximisation) and the latent characteristics specific to hospital employees. For example, while cost minimisation might drive a rational choice, latent factors like perceived safety during night shifts or fatigue after long working hours might sway decisions in unexpected ways. This segmentation is key to developing targeted interventions that can promote a modal shift toward more sustainable commuting options tailored to the needs of not only this specific workforce, but also other workforces with comparable characteristics.

3.3 Development procedure DCE

To design the discrete choice experiment (DCE), a structured development strategy was employed. Abiiro et al. (2014) and Helter and Boehler (2016) both developed strategies to design a DCE, which were used to refine the strategy used for this research. This strategy involved several key steps: conducting in-depth interviews, performing a literature review, consulting with stakeholders, and piloting the DCE. Each of these steps informed the selection of alternatives, attributes, and attribute levels used in the experiment.

The DCE design was constructed to explore the trade-offs that participants make when selecting among commuting alternatives. An efficient design was chosen over a full factorial design due to the practical constraint that it would require approximately 1000 choice sets, making it infeasible. Efficient designs were preferred as they minimise the number of choice sets while avoiding dominant alternatives, thereby maximising the precision of parameter estimates and ensuring attribute balance. Before designing the questionnaire, the three generated designs are thus checked for dominant alternatives based on the MNL utilities and probabilities.

To ensure attribute balance, twelve choice sets were carefully constructed so that each attribute level appeared with equal frequency across the sets. A critical aspect of efficient design is the use of priors—predetermined estimates of parameter values. In this study, priors were incorporated from similar research (Arentze & Molin, 2013; Molin & Kroesen, 2023) to enhance the design's efficiency and accuracy further, thereby reducing standard errors and improving the overall reliability of the model.

Testing for linearity was particularly important for the attributes of car parking costs and delay time. These attributes were chosen because, intuitively, higher parking costs and longer delays should have increasingly negative impacts on utility. By testing for linearity, it could be confirmed whether respondents value these attributes in a proportional, linear fashion—as costs or delays rise, their disutility also increases.

The questionnaire is distributed among the 300 Living Lab participants, and therefore, the respondents will be recruited through the Living Lab communication channels. To participate in the Living Lab Sustainable Transportation, employees were able to voluntarily sign up, allowing those selected to benefit from the innovative commuting arrangements outlined in Chapter 2. Given participants' familiarity with the alternatives, labelled options were included in the DCE. The design process involved consultations with stakeholders and piloting with the project team, ensuring that the final design was both practical and robust. The detailed development procedure of the DCE is elaborated in Appendix B.1.

3.4 Analysis DCE

Due to the unique needs and therefore preference heterogeneity that is present among the participants of the Living Lab, a 'Latent Class Discrete Choice Model' is estimated. This provides the opportunity to include both utilising maximising attributes and including psychographic attitudes. This section provides an explanation on the model estimation process, the theory underlying the model, and on how the model fit is determined.

3.4.1 Model estimation

Random Utility Theory

As elaborated earlier, Random Utility Maximisation (RUM) models are widely used for determining individuals' preferences from data (Feng et al., 2022). RUM theory underpins the estimation process in this study by assuming that individuals choose the alternative that provides them with the highest utility. In this context, utility refers to the value or satisfaction derived from a particular alternative. Utility is composed of two elements: systematic utility, derived from observable factors such as the attributes of the alternatives, and a random error term that captures unobservable influences (Train, 2009; van Cranenburgh, 2023).

In a DCE, respondents are presented with alternatives, each associated with a utility function that reflects both the attributes of the alternatives and the individuals' characteristics. The goal is to estimate parameters, often referred to as β coefficients, that represent the relative importance, or weight, of these attributes. These parameters are estimated using the maximum likelihood method, which finds the set of parameters that maximises the likelihood of the observed choices.

The utility of an alternative consists of observed utility and unobserved utility. The unobserved utility of ε_{in} is captured by the included error term ε_{in}, e.g. everything else that affects individual decision-making (van Cranenburgh, 2023). The utility of an alternative:

$$U_{in} = V_{in} + \varepsilon_{in}$$

U_{in}	Utility alternative i
V_{in}	Observed utility of alternative i
ε_{in}	Unobserved utility of alternative i

The observed utility is a function of attributes in a linear-additive form:

$$V_in = \sum_m \beta_m \cdot x_{im}$$

V_i	Observed utility of alternative i
β_m	Taste parameter for attribute m
x_{im}	Attribute level of attribute m of alternative i

The choice probability of an alternative relative to the other alternatives j is given by:

$$P(Y = i) = \frac{e^{V_i}}{\sum_J e^{V_j}}$$

Data for RUM typically come from Stated Choice experiments, which allow for a complete exploration of attribute values and minimise correlation between attributes. However, these experiments can involve hypothetical bias and are subject to the bounded rationality of decision-makers, who are constrained by the provided choice sets and attributes.

Latent Class Choice Model

Latent Class Choice Models (LCCMs) are employed to capture individual taste heterogeneity in choice behaviour. Unlike traditional models that assume homogenous preferences across a population, LCCMs acknowledge that a population may be segmented into distinct groups, each sharing similar traits but differing from other groups. These groups, or latent classes, are defined based on similarities in choice behaviour, often influenced by socio-demographic and psychographic characteristics. The advanced version of the LCCM, known as the Latent Class Discrete Choice Model, combines these elements of person-related characteristics and the rational choice process, providing the highest utility.

LCCMs consist of two key components: the class membership model and the class-specific choice model. The class membership model estimates the probability that a decision-maker belongs to a particular class based on observable characteristics. This model allows for the identification of latent groups within the population, providing a person-centred approach rather than a variable-centred one.

The class-specific choice model describes the behaviour of each class based on the attributes of the alternatives presented. Each class has a unique estimated conditional choice probability, Willingness-to-Pay (WtP) and taste parameters, i.e. attribute weights β. These parameters indicate the importance of each attribute within the class and help in understanding the trade-offs that individuals in different classes are willing to make.

Panel and cross-sectional data can both be used, but panel data provides more information as multiple choices by one person yield more insight than a single choice by many. Cross-sectional data highlights differences between individuals at a specific point in time, whereas panel data tracks changes within individuals over time, thereby enhancing the predictive accuracy of travel behaviour models and deepening our understanding of travel behaviour (Kroesen, 2014). Personal characteristics data is typically collected through Likert scale questions, which capture varying degrees of agreement or disagreement on relevant statements (Anable, 2005).

LCCM uses a probabilistic model to maximize within-class homogeneity and between-class heterogeneity. Class membership probabilities and choice probabilities are combined to observe the choice for each class. In the model, the probability of observing the choice for alternative i of decision-maker n, is a weighted sum of choice probabilities across S classes:

$$P_n(i \mid \beta) = \sum_{s=1}^{S} \pi_{ns} P_n(i \mid \beta_s)$$

$P_n(i \mid \beta)$	Probability of observing that decision-maker n chooses alternative i with parameter β
$\pi_n s$	Class membership probability of decision-maker n belonging to class S

The log-likelihood function for panel data requires a function that calculates across all observations. The log-likelihood function for all observations is as follows:

$$LL(\beta) = \sum_{n=1}^{N} \ln \sum_{s=1}^{S} \pi_{ns} \left(\prod_{t=1}^{T} P_n(i_t \mid \beta_s) \right)$$

$\sum_{n=1}^{N}$	Sequence of chosen alternatives, across all n individuals
$\sum_{s=1}^{S}$	Sequency of chosen alternatives, for individual n

The conceptual model of a Latent Class Discrete Choice model is further specified with insights from the literature review, regarding this particular Living Lab and thus this specific group. Therefore, the theoretical framework is visualised in Figure 4.1 in Section 4.

3.4.2 Model fit

Determining the optimal number of latent classes is a critical step in the LCCM process. In latent class analysis, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are often recommended and have demonstrated good performance (Molin & Maat, 2015; Nylund et al., 2007). The goal is to select the number of classes that minimises the AIC and BIC value, thereby ensuring the best fit to the data. Appropriately determining the number of classes is performed without covariates, so that only the measurement model is assessed (Molin et al., 2016). First, an MNL model, a one-class model, is estimated assuming homogenous traveller preferences and, therefore, estimating one set of general preferences. Afterwards, LCCM is estimated, examining more than one class to find the best model fit.

Once the number of classes is determined, the next step is to estimate the attribute weights (β) for each class. These weights represent the relative importance of the attributes and random errors within each class and are estimated to make the observed data most likely (Molin, 2024). Larger β values indicate attributes that have a significant impact on choice behaviour within that class. Since attributes may have different units, direct comparison of β values can be misleading.

After estimating the (β) values, the class membership model is evaluated. This model determines the probability of each individual belonging to a specific class based on their socio-demographic and psychographic characteristics. These probabilities are derived from characteristics such as age, income, education, and attitudes (Boxall & Adamowicz, 2002). By averaging these individual class probabilities, the relative size of each segment within the population can be estimated.

Finally, the class membership probabilities, combined with the choice probabilities for each class, allow for the calculation of overall choice probabilities for the entire population. This segmentation process provides a nuanced understanding of traveller behaviour, which can be leveraged to design targeted strategies and interventions to stimulate a modal shift.

Key highlights

- A stated-preference method is chosen to allow easier engagement with hypothetical scenarios and the suitability for survey purposes identifying trade-offs.
- For the experimental design, an efficient design is chosen with priors based on the estimated parameters from similar context studies.
- The attributes delay and parking costs are tested for linearity.
- Latent Class Choice Modelling is used to capture heterogeneity in taste preferences.
- The conceptual model of Latent Class Discrete Choice Modelling, a combination of the econometric paradigm and mobility style paradigm, is included.
- Exploratory factor analysis is conducted to measure similar underlying factors for the attitudes.
- The model fit is determined based on the AIC and BIC criterion.

4
Literature review

As this research provides a unique insight into travel behaviour in which mode choices are constrained by shift work and irregular hours, it is of value asset to examine what mode choices travellers make without these conditions. This literature review is conducted first to identify the consequences for shift workers and irregular schedules, which is done in Section 4.1. Secondly, in Section 4.2, commuting behaviour is explored in standard employment situations to identify characteristics of modalities, their barriers and the circumstances under which travellers do or do not pick them. Section 4.3 discusses the traveller-related characteristics, such as socio-demographics and subjective attitudes, to include in the experiment. Since this experiment is conducted with the employees of the academic hospital, the potentially challenging aspects of this location are also examined in this section. Based on this analysis, the transportation modalities included in the research are then selected for the experiment.

4.1 Shift work & irregular schedules

Before delving into transportation and commuting modalities, this section addresses the first research question, which examines the impact of shift work and irregular schedules on employees. While much research has focused on the health risks associated with night work, this study aims to explore the broader context of non-standard work schedules. The Scopus database was used for the literature search, excluding non-English articles and those published more than ten years ago. The following search string led to a total of 112 results:

"shift work" AND (on-call OR irregular) AND (schedule OR shift OR duty OR service) AND NOT disease AND NOT night

In an era marked by rapid digitalisation, globalisation, and structural transformations, there is a common belief that labour markets must become more flexible. This increased flexibility is essential for employers to effectively respond to evolving market dynamics, with on-call work as an example to ensure a workforce can be available at short notice. Shift work is defined as "an organisation of daily working hours in which different teams work in succession to cover more or all of the 24 h" (Costa, 1997). Flexible work schedules are increasingly common in many professions, particularly healthcare. In line with this trend, the proportion of workers in regular full-time employment has decreased over the past decades, while there has been a notable rise in non-standard employment (OECD, 2020). This literature review seeks to gain a comprehensive understanding of the types of studies conducted on shift work and irregular work schedules, with a particular focus on understanding their impact on workers.

On-call and irregular shifts are critical in hospitals, allowing healthcare professionals to respond to emergencies and provide uninterrupted patient care. While this flexibility benefits the organisation and ensures reliable service, it also poses challenges for the workforce, affecting work-life balance, job satisfaction, and well-being (Bamberg et al., 2012). Among shift work, particularly irregular shift work is considered particularly harmful due to its strong association with a higher incidence of insomnia, sleep deprivation, daytime sleepiness, concentration issues, and elevated stress levels (Gu et al., 2023; Härmä et al., 2002; Setyowati et al., 2023). Additionally, it is linked to an increased risk of gastrointestinal, reproductive, metabolic, and cardiovascular disorders (D'ettorre et al., 2020; Khan et al., 2020).

Gu et al. (2023) concluded that the level of burnout amongst rotating shift workers, especially those with irregular shifts, was higher than that of other workers. Shift workers showed signs of cynicism, which were mainly due to inadequate sleep or depression, while poor professional efficacy was a result of their stressful work environment (Gu et al., 2023). Härmä et al. (2019) distinguished between shift work with and without night shifts, which showed that long-term exposure to shift work involving night shifts is linked to increased fatigue on days off and extended sleep duration. Specifically focusing on medical interns, Arora et al. (2008) found that a higher on-call workload led to more significant sleep loss, extended shift durations, and reduced participation in educational activities. As a result of consecutive night shifts, Kosmadopoulos et al. (2024) discovered that police officers experienced circadian disruption, resulting in impaired sleep and waking function. Additionally, Sardadvar and Reiter (2023) addresses that circadian disruptions are linked to general cognitive decline, as seen by executive function and memory assessments.

Suleiman et al. (2021) gained insights into workers' perspectives on non-standard work schedules and concluded that long work hours and irregular schedules are the most limiting factors to their well-being. Specifically, physical health impacts such as a lack of exercise, weight gain, and exhaustion were mentioned. Adding this to the effects, as mentioned earlier, of irregular and on-call shifts highlights the critical need to develop and implement interventions that mitigate these negative health impacts and simultaneously promote healthier behaviour.

Insights into the effects of shift work among this population were gathered through interviews conducted by Zadeits (2024). Interviewees highlighted that working irregular shifts often makes it impossible to commute to the academic hospital by public transport, especially during certain times. Additionally, some noted that cycling is not viable due to poorly lit and inadequately maintained areas, particularly at night. The habitual use of cars was also emphasized, as employees are frequently compelled to drive during evening and night shifts. Childcare responsibilities were frequently mentioned as a constraint, with employees needing to drop off children at specific times, which public transport schedules or routes often fail to accommodate. Moreover, despite the high parking fees, some employees accept these costs, particularly during cold winter months, as they prefer not to use other modes of transportation.

Based on the literature, it is hypothesised that *hospital employees working under shift schedules, particularly those with irregular or on-call shifts, are less likely to adopt sustainable commuting modes compared to employees with standard work schedules*. This reluctance arises from their need for flexibility and reliability in transportation, which is often better met by private vehicles than public or active modes, especially during non-standard hours. Additionally, the health impacts associated with shift work — such as increased fatigue, sleep deprivation, and stress — may lead these workers to prioritise more comfortable and convenient transportation options that minimise travel time and physical exertion. The disruption caused by irregular schedules further exacerbates the preference for private vehicles, as they offer the consistency and comfort necessary to cope with their work's physical and mental demands. Consequently, the likelihood of a modal shift towards eco-friendly commuting practices is significantly reduced among this group.

4.2 Commuting modalities

After exploring shift work and irregular schedules generally, this literature review section delves further into travel behaviour and sustainable commuting practices. First, the possible commuting alternatives and their attributes are explored before scoping them along the location-centered challenges. As this research is two-fold and focuses on mode-related attributes and traveller-related characteristics, both preferences and attitudes are also included.

The literature review focused on identifying commuting modalities and attributes that come with modalities. Following the second research question, the aim is to identify the key characteristics and barriers of sustainable transportation mode. Also preferences and attitudes are included to include traveller-related characteristics. The search string that was entered into Scopus, resulting in 235 documents, is as follows:

(travel OR transport) AND behavio* AND commut* AND (choice OR decision) AND (attractive OR preference OR attitude) AND (sustainab* OR environment*)*

It is acknowledged that by adding the concepts of attractive, preference, attitude, sustainab* and environment*, strongly limits the search string. This is a well-considered choice since without these concepts, the string resulted in 1500 documents. After applying exclusion criteria the final search led to a result of 65 articles. The full literature search process with all inclusion and exclusion criteria is described in Appendix C.1, together with Table C.2 presenting the findings in an overview. Section 5.3 elaborates on the traveller-related characteristics identified with this search process.

As already introduced, sustainable commuting practices include modalities such as public transport, walking, and cycling, which generally have a less negative environmental impact than, usually compared with, commuting by private car (Lind et al., 2015). It is widely acknowledged that promoting sustainable travel choices benefits humans by mitigating the negative effects of mobility. Yet, car commuting is represented by the majority of 70% compared to all other modalities. This section, therefore, delves into the characteristics of commuting modalities, the barriers to adopting them and the circumstances under which commuters choose them.

Car

Car commuting remains one of the most prevalent modes of transportation, especially among those who prioritize convenience and control over their travel experience. Research conducted by Li and Zhao (2015) points out that higher-status travellers tend to travel by car. This preference is often linked to the perceived status and convenience associated with car use. De Vos et al. (2016) adds that urban commuters value car transportation more negatively than suburban commuters, which might be due to issues such as traffic congestion, limited parking in urban areas, and larger distances to be covered.

An outcome from the research Kamruzzaman et al. (2015) conducted is that car travellers find themselves strongly dependent on a car and do not manage well without one. This dependency underscores the critical role cars play in the daily routines of many commuters, particularly in areas where alternative modes of transportation are less accessible or convenient. ICT systems and applications often promote car travel by providing travellers with real-time traffic information, which typically suggests the quickest travel time (Gössling, 2018). However, it's important to note that these applications only report the in-car travel time and often omit the egress time—such as parking and walking to the final destination—which is included in the travel times for other modalities. Such an overview can create a skewed perception of the car's efficiency compared to other modes.

Esztergár-Kiss et al. (2021) found that the car is perceived negatively and as a disadvantage compared to other modes in its research, primarily because all associated costs have been fully accounted for, and a realistic travel time, including parking time, has been presented. Yet, the same research showed that in most cases, car travellers do not value travel costs and health as being very important. This suggests that despite the drawbacks, the perceived convenience and necessity of car use often outweigh the associated costs for many commuters. Molin et al. (2016) concluded that if car commuters would switch to more sustainable modes, it would mostly be towards sustainable cars rather than PT or cycling.

Demographic factors also play a significant role in car commuting patterns. Research by Lee et al. (2020) showed that car use strongly increases between the ages of 36 and 41 due to significant life events such as marrying, having children, and moving to the suburbs, making it challenging to maintain environmentally beneficial behaviours. These life events often require greater flexibility and convenient transportation, which the car uniquely provides. Comfort is generally valued greatly by car commuters, or at least private vehicles (Parmar et al., 2023). This emphasis on comfort makes the car particularly attractive to those who prioritize a stress-free and controlled travel experience.

The car remains a preferred mode of transportation for several reasons, particularly among employees who live more than 30 kilometres from the academic medical centre (Zadeits, 2024). These individuals find that the options offered, such as public transport subscriptions and financial allowances for (e-)bikes, are not more advantageous than driving in terms of cost and effort. The car offers the fastest, most convenient door-to-door option, which is especially important for those with appointments or plans before or after work. Practicality and convenience are key factors that make the car an indispensable choice for many employees.

Active modes

Active modes of transportation, such as walking and cycling, are often discussed collectively in the literature rather than as separate modes. Esztergár-Kiss et al. (2021) reported that the majority favours the bicycle due to its efficiency, particularly when considering factors like travel time, cost, and environmental impact. Additionally, for shorter trips, Li and Zhao (2015) highlights that bicycles are often the most important mode of transport. This is especially true for students, who tend to use active modes and public transport for trips to city centres. However, bicycles become the preferred choice when adequate infrastructure is available (Hasnine et al., 2018).

Contributing to this, Esztergár-Kiss et al. (2021) found that individuals who place a high value on their health strongly prefer walking or cycling. This finding is further supported by Parmar et al. (2023), who identified a positive relationship between health concerns and the use of non-motorized vehicles. Molin et al. (2016) also noted that those who regularly bike are more likely to engage in other forms of sustainable transportation, such as public transit, and generally have a strong aversion to car commuting.

This aligns with the findings of Brand et al. (2021), who state that cyclists have significantly lower overall life cycle CO_2 emissions compared to non-cyclists. However, regarding comfort, Parmar et al. (2023) concluded that travellers who place less importance on comfort also tend to have a negative view of active modes.

Active modes of transportation are favoured by some employees interviewed by Zadeits (2024), due to avoiding traffic jams at the Science Park at the end of the day. Those who commute using e-bikes or speed pedelecs are particularly positive about the facilities and alternatives provided by the academic medical centre. Compared to public transport and car users, these individuals find active modes to be more appealing and efficient, highlighting the benefits of the current infrastructure for cyclists. Cycling is a very attractive, yet only a feasible option within 25-30 kilometres from the medical centre and for the majority strongly depends on the weather conditions.

Public transportation

Public transportation is often the mode of choice for individuals who either lack access to a private vehicle or need to enter city centres where parking is costly or limited. In these cases, PT offers a practical and accessible alternative to other motorised modalities. Additionally, it is favoured by those who place a high value on environmental sustainability. Esztergár-Kiss et al. (2021) concludes that travellers who prioritise environmental concerns are more likely to choose PT over other modes of transport. PT is particularly popular among younger travellers with lower incomes, who may anticipate shifting to car travel once they have the financial means (Molin et al., 2016).

Research by Lee et al. (2020) shows that younger commuters prefer using PT for their daily commutes but tend to switch to active modes for non-commuting purposes. This group of travellers does not typically exhibit a strong pro-exercise attitude, which could be because they do not view PT as an opportunity to incorporate more physical activity into their routines. This limited engagement in physical activity might reduce the overall health advantages typically associated with public transport use.

Furthermore, Parmar et al. (2023) found that the attractiveness of PT significantly decreases as the access and egress distances increase. Additionally, last-mile connectivity is crucial to enhancing the overall appeal of PT (Parmar et al., 2023). Zimmerman and Fang (2015) also highlights that the effective integration of PT—through coordinated schedules, fare structures, and an increased number of stops—significantly boosts ridership. Such improvements enable public transit to compete more effectively with private car use, offering many travellers a viable and sustainable alternative.

From the interviews conducted by Zadeits (2024) with employees from the academic medical centre, it can be concluded that PT is often viewed as less attractive due to several factors. For some employees, the number of required transfers and the incomplete commute reimbursement make it a less viable option. Even for regular public transport users, the cost can be as high as driving, particularly when their hometown falls just outside the offered public transport subscription. Additionally, the need to leave early and the lack of familiarity with public transport routes contribute to hesitation and discourage its use. A stimulance that was pointed out for PT use is the possibility to read a book or start working.

Shared mobility
One aspect of the MaaS pilot in the Netherlands was the inclusion of shared mobility options. Over the past decade, shared mobility has gained significant popularity worldwide as a key component of sustainable transport networks. Luo et al. (2023) explored perceptions of various forms of shared mobility and found that e-scooters are generally preferred over shared bikes and ride-hailing services. Another notable finding was the critical importance of travel costs, with the study suggesting that more affordable services could not only attract a larger user base but also reduce car trips (Luo et al., 2023). For shared mobility to effectively replace car trips, there is a need to strengthen its synergy with public transit, particularly in terms of affordability, to make it accessible to lower-income groups (Luo et al., 2023). Health factors also play a role in shared mobility, especially bike sharing, which requires physical activity. However, travel time considerations strongly influence the decision to choose this mode due to the physical activity (Luo et al., 2023). Additionally, the study found that travellers with a positive attitude toward shared mobility tend to prioritise social values, particularly the environmental impact of their chosen modes (Luo et al., 2023).

Based on the literature review on the general perception of sustainable commuting practices, the earlier hypothesis regarding the effects of shift work can be more precisely formulated. The initial hypothesis stated: *hospital employees working under shift schedules, particularly those with irregular or on-call shifts, are less likely to adopt sustainable commuting modes compared to employees with standard work schedules.* This review highlights additional factors that should be considered. Firstly, it is assumed that habitual car commuting is likely to develop more easily among shift workers, leading them to rely more heavily on car travel and to be less inclined to switch to other modes. Additionally, it is expected that shift workers may have a particular aversion to public transport, whether or not combined with shared mobility options, due to the inconvenience of multiple transfers.

4.3 Traveller-related characteristics

Understanding travel behaviour extends beyond the mode of transportation and includes who is travelling and their underlying attitudes. This section combines insights from the literature presented in Table C.2 with the specific characteristics of the target group: hospital employees. First, the focus is on socio-demographics, followed by a discussion on attitudes.

4.3.1 Socio-demographic characteristics

Socio-demographic variables have been found to significantly influence various dimensions of travel behaviour (Kattiyapornpong & Miller, 2006). These factors can act as both constraints and enablers in travel choices and activities. Twelve of the studies in Table C.2 include socio-demographics such as age, gender, education level, and income. A less common but relevant factor is household composition. Zadeits (2024) found that, for example, dropping off children at daycare is a significant constraint when selecting a commuting modality. Similarly, other household-related limitations may impact travel choices.

Specific socio-demographics relevant to the hospital setting include personnel number, function family (which groups similar activities), regular or irregular work schedule (changing every week), and shift type (day, evening, night, weekend, or on-call). These factors influence commuting patterns as different shifts pose unique challenges for travel options. The socio-demographics included in the conceptual model in Figure 4.1, with Dutch translations provided in Appendix C.2.

4.3.2 Traveller-related attitudes

In recent years, more attention has been paid to the psychological traits of individual travellers, often referred to as subjective attitudes. Studies show that behaviour is shaped by psychological factors such as values, attitudes, subjective norms, and perceptions (Abrahamse et al., 2009; Paulssen et al., 2014). Paulssen et al. (2014) developed a model demonstrating that attitudinal factors like flexibility, comfort, and convenience have a greater impact on travel choices than traditional mode-specific variables. Understanding these attitudes is crucial in determining when hospital employees may shift to sustainable commuting alternatives.

Habits & norms

Travel behaviour is closely tied to personal habits and norms. Individuals who exhibit a strong preference for routine are more likely to stick to familiar commuting choices (Gao et al., 2019). To measure habit strength and the extent to which behaviour has become habitual, this research draws upon the Self-Report Habit Index (SRHI) developed by Verplanken and Orbell (2003). The SRHI can be employed as a dependent variable or as a tool to assess and monitor the strength of a habit without relying solely on behavioural frequency measures.

Reliability

Reliability of transport modalities is a key concern for hospital employees, especially those working shifts, as they must arrive on time for handovers (Zadeits, 2024). Also, in the case of on-call or standby shifts, employees must report to the location within a certain time, stressing the importance of the reliability of their modality. Research has shown that uncertainty in public transport leads to its avoidance (Eagling & Ryley, 2015; Guo et al., 2020; Kamruzzaman et al., 2015). The statements used in Guo et al. (2020) directly questioned the reliability of public transport. In contrast, Parmar et al. (2023) and Molin et al. (2016) rephrased it to worrying, which is perceived as a more careful approach that indirectly measures the same aspects.

Comfort

Comfort is another important factor, particularly for employees with physically demanding jobs (Zadeits, 2024). Several studies examined comfort, with variations in perception ranging from general perception to seat availability, avoidance of congestion, transfers and waiting time (Guo et al., 2020; Molin et al., 2016; Parmar et al., 2023).

Annoyances delay

While maximising satisfaction is generally seen as the primary motivation, there is evidence that minimising annoyance, frustration or other negative feelings can drive some decisions. An example is the "Status Quo Bias" of Samuelson and Zeckhauser (1988), stating that people sometimes make decisions to avoid the annoyance of changing routines or dealing with uncertainties, even if a change could be more satisfying. Molin et al. (2016) contradicted the concept of PT acceptability with statements including annoyances, and Parmar et al. (2023) addresses the annoyance of bus waiting time and number of transfers.

Environmental importance

While convenience and comfort are key factors in commuting, environmental concerns increasingly influence behaviour. For example, Esztergár-Kiss et al. (2021) found that those who prioritise environmental impact often choose cycling. Parmar et al. (2023) also highlighted the link between private vehicle use and pollution, showing that this awareness can encourage shifts to greener options. Similarly, Van et al. (2014) categorised different travel modes based on their perceived environmental friendliness, with cycling and public transport viewed as more eco-friendly than cars. Moreover, Luo et al. (2023) discussed how growing environmental concerns drive changes in commuting behaviour, whereas Dunlap (2008) introduced the 'New Environmental Paradigm Scale,' a tool to measure environmental attitudes and their effect on travel decisions.

Health importance

Health benefits are another major factor influencing the shift to sustainable commuting options. Active modes like walking and cycling are environmentally friendly and promote physical and mental well-being. Parmar et al. (2023) noted the link between walking or cycling and better health outcomes, while Brand et al. (2021) found that active commuters often have lower BMI and better fitness. Mental health is also a consideration, as commuting via active modes can reduce stress and improve mood. Esztergár-Kiss et al. (2021) emphasised the need to promote both the mental and physical health benefits of active commuting, especially for workers in high-stress environments like healthcare.

4.3.3 Location-specific characteristics

As this research is based on a case study focusing on the academic hospital, the commuting options are limited to the surroundings. This section answers the third sub-question by connecting the literature and the hospital's surroundings to determine the alternatives, attributes and attribute levels. The academic hospital is located on the eastern side of the city centre of one of the top five largest cities in the Netherlands. It is part of the largest Science Park and shares this park with the city's university, university college, and University of Applied Sciences. In addition, the science park offers student housing, botanical gardens, supermarkets, sports facilities, and the main university library. Approximately 85,000 people travel here daily, necessitating a highly efficient and well-maintained infrastructure (USP, 2024). The last-mile infrastructure facilities are as follows:

- *Cycling:* the bike lane infrastructure surrounding the hospital is exceptionally well-maintained. Despite the high volume of visitors, particularly during rush hours, the presence of multiple routes helps to distribute traffic and reduce congestion. The areas to the north, east, and south of the hospital are largely open meadows with few buildings, offering an extensive network of bike lanes.
- *Light rail:* the increasing number of visitors to Science Park has spurred the construction of a new light rail line, which connects two southern municipalities directly to the city's central train station. From there, the light rail departs every five minutes to the Science Park, passing through a smaller train station on the way. The journey from the central station to the academic hospital takes approximately 15 minutes, with the light rail stop just a few minutes from the main entrance.
- *Bus:* in addition to the light rail, the academic hospital is serviced by seven bus routes, all of which stop at the exact location as the light rail, providing convenient access for commuters.
- *Motorised vehicles:* the hospital is strategically positioned at the junction of two highways, with the nearest highway exit just one kilometre from the hospital's parking garage, ensuring easy access for those travelling by car. However, due to the enormous activity in the Science Park, it is very crowded during rush hours causing long delays.

The location-specific characteristics of the academic hospital, particularly its high daily traffic volume and the diverse modes of last-mile infrastructure, may pose challenges to achieving a significant modal shift toward sustainable transportation. Despite the well-maintained cycling infrastructure and the introduction of a new light rail line, which is very well connected to the central train station in the city centre, this advantage primarily benefits those who travel via that station. However, some individuals may prefer to avoid the city centre due to crowdiness, reinforcing their reliance on motorised vehicles. The hospital's strategic location near major highways, along with the convenience and accessibility of car commuting, is likely to maintain a strong preference for car commuting. Additionally, the high demand on existing public transport and road infrastructure due to the large number of daily commuters may lead to congestion and limit the effectiveness of alternative, more sustainable commuting options.

4.4 Conceptual model

The conceptual model presented in Figure 4.1 summarises all literature review findings from research questions one, two and three, and connects it to the methodological conceptual model for a latent class discrete choice model as presented in Section 3.4.

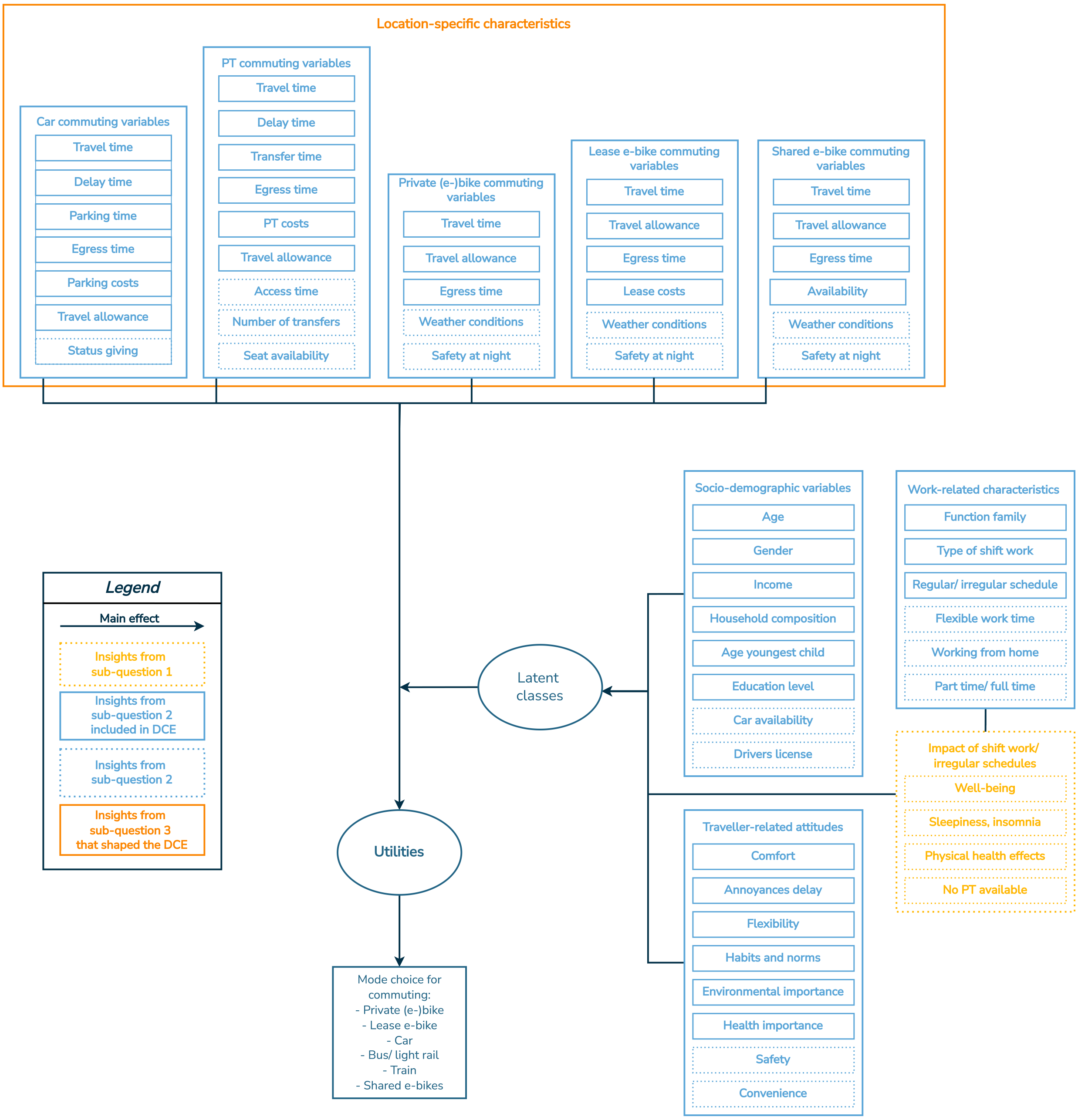

Figure 4.1: Conceptual model 'Living Lab Sustainable Transport'

5

Operationalisation

This chapter outlines the operationalisation phase of the DCE and questionnaire, covering both its design and test phase. Section 5.1 discusses the development of alternatives and the selection of commuting modalities for each experiment, based on commuting distances. Section 5.2 addresses the development of attributes and attribute levels for each modality, considering commuting distances, travel times, and the real-world environment around the academic medical centre. In Section 5.3, the operationalisation of socio-demographic and attitudinal questions is detailed, highlighting how these aspects are integrated into the DCE. Section 5.4 explains the choice set generation using efficient design principles, followed by Section 5.5, which presents the overall questionnaire structure. Finally, Section 5.6 covers the testing and finalisation of the questionnaire, ensuring its readiness for distribution.

5.1 Commuting alternative development

During the pilot at the academic medical centre, the 300 participants can access a limited range of commuting alternatives. While these options are provided, this research is not confined to only these modalities. Therefore, this section connects the literature review with the location-specific challenges. Details on the literature findings regarding alternatives are presented in Table C.2 in Appendix C.

The available alternatives include private (e-)bikes, private cars, public transport, and shared e-bikes. It is important to note that (e-)bike and car commuting is only possible for those with a private vehicle, as no lease contracts are provided. Participants can use all public transport modes in the Netherlands, but buses and light rail are the only last-mile options. A partnership with Hely provides shared electric and city bikes at a hub at the central train station (Hely, 2024). These bikes are exclusively accessible to all academic hospital employees. Additionally, participants carry a Shuttle mobility card, granting access to public transport and shared (e-)bikes.

Due to the Netherlands' cycling culture, private (electric) bicycle commute is included in the experiment. A variation is Lease a Bike, an emerging concept providing bike lease schemes for companies to offer their employees. This concept makes electric bicycles more financially accessible; thus, it is included as a research alternative (Lease a Bike, 2024). Since the goal of this research is to determine the circumstances under which employees switch from using a private car to a more eco-friendly mode of transportation, car commuting is included.

Some studies include public transport as a general term, while others specify the type. Since different PT modalities have distinct characteristics, it is decided to include them separately. For last-mile PT to the hospital, bus and light rail use the same stops, so they are combined as one alternative. For longer distances, the train is added, resulting in the following two alternatives dependent on commuting distance: bus/light rail or train + bus/light rail.

Other last-mile options include Hely's shared (e-)bikes are included in the experiment, with combinations of car or train travel. Car commuting with a last-mile shared (e-)bike uses a P+R location. Interviews by Zadeits (2024) suggest P+R locations could be attractive, prompting their inclusion for further research. Although the Hely hub is only at the central train station near the hospital, five hypothetical P+R locations around the hospital are considered, assuming a Hely hub at each.

5.1.1 Commuting distances

The choice of commuting modality strongly depends on the commuting distance. Similar to the research by Molin and Kroesen (2023), categories have been established based on commuting distance. As previously mentioned, the Netherlands is a cycling country, and bike commuting is common, though distances vary significantly among employees. Molin and Kroesen (2023) set a 15-kilometre limit for regular cycling, noting that many employees commute beyond this distance. Zadeits (2024) suggested extending the e-bike commuting range to 25-30 kilometres due to the growing use of speed pedelecs, which can reach speeds of up to 45 km/h (Gazelle, 2024). Therefore, this research sets the cycling distance limit at 30 kilometres.

For this study, commuting distance categories have been defined as <=10 km, 11-30 km, and >30 km, with each category matched to suitable alternatives. An overview of these categories and their corresponding alternatives is presented in Table 5.1. Note that the P+R locations are named location 1 to 5, due to its anonimity. Living Lab participants were presented actual P+R locations in the surroundings of the academic medical centre. The Dutch translations of the alternatives are provided in Appendix C.2, and the alternatives' coding used for model estimation is presented in Appendix D.1.

Table 5.1: Commuting distances per experiment with modal alternatives

Assignment criteria			Modal alternatives in the experiment						
Exp	*Commuting distance*	*Most attractive P+R location*	*(E-)bike*	*Lease e-bike*	*Car*	*Bus/ light rail*	*Train + bus/light rail*	*Train + shared (e-)bike*	*Car (P+R) + shared (e-)bike*
1	<= 10 km	No	X	X	X	X			
2	11-30 km	P+R location 1		X	X		X	X	X
	11-30 km	P+R location 2		X	X		X	X	X
	11-30 km	P+R location 3		X	X		X	X	X
	11-30 km	P+R location 4		X	X		X	X	X
	11-30 km	P+R location 5		X	X		X	X	X
3	> 30 km	P+R location 1			X		X	X	X
	> 30 km	P+R location 2			X		X	X	X
	> 30 km	P+R location 3			X		X	X	X
	> 30 km	P+R location 4			X		X	X	X
	> 30 km	P+R location 5			X		X	X	X

5.2 Attributes and attribute level development

To determine the attributes and levels of the commuting alternatives, a combination of factors from the hospital's surroundings and the literature was considered. Travel time and costs are the primary attributes in this experiment, but they vary based on different aspects of each alternative. Therefore, travel time and cost are broken down by alternative to identify the relevant attributes. When designing attribute levels, the concept of equidistance — ensuring equal intervals between levels — was applied to maintain orthogonality or statistical independence between attributes (Molin, 2024). An overview of the attributes and their levels is presented in Table 5.4, with Dutch translations provided in Appendix C.2.

Travel time

Each alternative has a different travel time based on the commuting distance. For the three experiments, distinct travel distances were used to calculate the minimum travel time. The average commuting distance of academic hospital employees, provided by the hospital from a mobility study, was used to determine these times. Key commuting distances are shown in Table 5.2. For car and public transport, distances were calculated using Google Maps (2024) and Nederlandse Spoorwegen (2024b), while bike and e-bike times were based on average speeds, 17 km/h for bikes and 25 km/h for e-bikes (Fietsersbond, 2024). The shared (e-)bike alternative also uses the electric bike speed. Total travel times for each experiment and P+R locations are displayed in Table 5.3 with three P+Rs in the same city averaged into a single value. While the minimum travel times remain constant, attributes such as congestion determine additional time. Note that the five P+R locations are grouped into three locations, as three P+Rs are in the same city, for which an average travel time is included. Only the travel times for alternatives including the P+R location differ within the same experiment, the other travel times such as for lease e-bike, car and train + bus/light rail stay the same. For each alternative, the minimum travel time stays the same as noted in 5.3, yet attributes determine extra time added due, for example, to congestion.

Table 5.2: Commuting distance per category

Category	No. of employees	Avg. commuting distance per employee [km]	Total commuting distance [km]
<=10 km	3,972 (33.4%)	6.45	25,603
11-30 km	4,793 (40.3%)	18.97	90,910
>30 km	3,125 (26.3%)	56.60	176,705
Total	*11,890*	-	*293,218*

Table 5.3: Travel times per experiment

Exp	P+R	(E-)bike	Lease e-bike	Car	Bus/light rail	Train + bus/light rail	Train + shared e-bike	Car + shared e-bike
1	-	20 min	15 min	10 min	15 min			
2	Loc. 1		44 min	20 min		36 min	35 min	34 min
	Loc. 2		44 min	20 min		36 min	32 min	25 min
	Loc. 3		44 min	20 min		36 min	40 min	33 min
3	Loc. 1			40 min		60 min	50 min	55 min
	Loc. 2			40 min		60 min	50 min	52 min
	Loc. 3			40 min		60 min	55 min	59 min

(E-)bike & Lease e-bike

The (e-)bike is a relatively straightforward door-to-door modality. A standard addition of five minutes is factored into the travel time to account for parking the bike and reaching the entrance, as it is assumed that bicycle parking is conveniently located near the entrance. For the lease e-bike alternative, an additional attribute is the monthly lease price. After consulting with Pon, the attribute levels for the monthly lease price are set at €38, €48, and €58 per month, reflecting Lease a Bike's actual leasing programs.

Car

The private car, being the most complex alternative, offers numerous options for attributes. Despite the proximity of highway access, the area around the academic hospital is known for congestion and poor accessibility. Consequently, delay due to congestion is an important attribute to include, as supported by five identified articles. Using Google Maps (2024) and planning a departure time of 8 a.m. on a Tuesday, the travel time ranges between 15 and 30 minutes. Based on this range, the delay attribute levels are set at 5, 10, and 15 minutes.

Upon reaching the destination or parking facility, additional time is required to find a parking spot, park the car, and walk to the entrance. As identified in the literature, added travel time is categorised into two attributes: parking time (covering both searching and parking) and egress time (walking from the car park to the entrance). In consultation with the academic hospital and Pon, parking time levels were set at 2, 4, and 6 minutes, while egress time levels were set at 5, 10, and 15 minutes. The parking costs reflect the actual rates at parking facilities near the academic hospital, corresponding to €2, €4, and €7 per day.

Bus/light rail

When travelling the last mile by bus or light rail, delays are possible. The attribute levels for this delay are determined based on the light rail option. Since bus delays are highly unpredictable and bus and light rail are considered as one alternative, it is assumed that light rail delays apply to buses as well. The central train station nearest to the academic hospital serves as the reference point for departure times. According to the actual schedules from 9292 (2024), the light rail departs every 5 minutes. Therefore, the delay attribute levels are set at 0, 4, and 8 minutes. For egress time, a standard factor of 5 minutes is included in the travel time to reflect the actual situation at the academic hospital.

Train + bus/light rail

The train alternative can only be used in combination with bus/light rail or the shared (e-)bike. When combined with bus/light rail, the train option may experience delays. According to NS's half-year report, 91.5% of trains run on time or with delays of less than five minutes, which is considered within the permissible range (Nederlandse Spoorwegen, 2024a). Although there are ten train routes with the most delays, the central station nearest to the academic hospital is not among them (Nederlandse Spoorwegen, 2024a). Therefore, the delay attribute levels are set at 0, 4, and 8 minutes, representing no delay, a delay within the permissible range, and an official delay.

In addition to delay time, transfer time from train to bus/light rail is included with this alternative. Based on NS's travel planner for routes to the academic hospital, the minimum transfer time is 5 minutes for the train to light rail (Nederlandse Spoorwegen, 2024b). The average transfer time ranges between 5 and 10 minutes, and to maintain equidistance, the attribute levels are set at 5, 8, and 11 minutes.

Train + shared (e-)bike

When combining the shared (e-)bike with the train, the transfer time becomes fixed, so a standard transfer time of 5 minutes is included in the travel time. As this alternative is subject to train delays, the same delay attribute levels as the train + bus/light rail option are used: 0, 4, and 8 minutes. Additionally, an extra attribute is considered for the shared (e-)bike due to its nature as a shared mobility service. There may be instances when no (e-)bikes are available at the hub. Although bikes can be reserved in advance, the possibility of unavailability is included to examine whether this uncertainty influences travellers' choices. The levels for this attribute are unavailability of 0, 1, or 2 times per month. Parking for the (e-)bike is available at the designated Hely hub located at the academic hospital, with a 5-minute walk to the hospital entrance included in the travel time.

Car + shared (e-)bike

The final alternative involves combining a private car with a shared (e-)bike for last-mile travel. Since the (e-)bike covers the last mile, the delay attribute is excluded. Parking costs differ as this option uses a P+R facility, where parking for the entire day costs €2.70 (U-OV, 2024). The attribute levels are set at 0, 1, and 2 €/day to distinguish between standard and P+R parking and to assess the attractiveness of P+R as an option. Like the train + shared (e-)bike alternative, this option includes the unavailability attribute with levels of 0, 1, or 2 times per month, along with a standard 5-minute walking time. Parking time at P+R locations is assumed to be negligible, as these areas are expected to be less crowded.

Travel allowance

In addition to modality-specific attributes, there is a general attribute that applies to all modalities: travel allowance. These allowances, ranging from 0 to 30 cents per kilometre, are based on current collective bargaining agreements and were determined in consultation with the academic hospital and Pon. The levels are designed to discourage less sustainable and encourage more sustainable options. Public transport and the lease e-bike have exceptions. Public transport is fully reimbursed, reflecting the pilot's current allowances. For the lease e-bike, current regulations state that employees lose their travel allowance. To assess whether this discourages leasing an e-bike or if retaining the allowance encourages it, the levels are set at 0, 10, and 20 cents per kilometre.

An overview of all attributes and attribute levels corresponding to one of the three experiments is presented in Table 5.4. Attribute and attribute level coding used for model estimation is presented in Appendix D.1.

Table 5.4: Attribute and attribute levels per experiment

Experiment 1: <= 10 km	*Bike*	*Lease e-bike*	*Car*	*Bus/light rail*
Travel time from central station	22 min	15 min	20 min	18 min
Parking time	-	-	2, 4, 6 min	-
Egress walking time	5 min	5 min	5, 10, 15 min	5 min
Delay time	-	-	0, 5, 10 min	0, 4, 8 min
Transfer time	-	-	-	-
Parking costs	-	-	2, 4, 7 €/dag	-
Travel allowance	20, 25, 30 ct	0, 5, 10 ct	10, 15, 20 ct	100% reimb.
E-bike lease costs	-	€38, €48, €58	-	-

Experiment 2: 11 - 30 km	*Lease e-bike*	*Car*	*Train + Bus/light rail*	*Train + shared e-bike*	*Car + shared e-bike*
Travel time from central station	Table 5.3	Table 5.3	Table 5.3	Table 5.3	Table 5.3
Parking time	-	2, 4, 6 min	-	-	-
Egress walking time	5 min	5, 10, 15 min	5 min	5 min	5 min
Delay time	-	0, 10, 20 min	0, 4, 8 min	-	-
Transfer time	-	-	5, 8, 11 min	-	-
Parking costs	-	2, 4, 7 €/day	-	-	0, 1, 2 €/day
Travel allowance	0, 10, 20 ct	10, 15, 20 ct	100% reimb.	0, 10, 20 ct	0, 10, 20 ct
E-bike lease costs	€38, €48, €58	-	-	-	-
	-	-	-	0, 1, 2x/mo	0, 1, 2x/mo

Experiment 3: >30 km	*Car*	*Train + Bus/light rail*	*Train + shared e-bike*	*Car + shared e-bike*
Travel time from central station	Table 5.3	Table 5.3	Table 5.3	Table 5.3
Parking time	2, 4, 6 min	-	-	-
Egress walking time	5, 10, 15 min	5 min	5 min	5 min
Delay time	0, 10, 20 min	0, 4, 8 min	0, 4, 8 min	-
Transfer time	-	5, 8, 11 min	-	-
Parking costs	2, 4, 7 €/day	-	-	0, 1, 2 €/day
Travel allowance	10, 15, 20 ct	100% reimb.	0, 10, 20 ct	0, 10, 20 ct
E-bike lease costs	-	-	0, 1, 2x/mo	0, 1, 2x/mo

5.3 Traveller-related socio-demographics and attitudinal statements

The traveller-related socio-demographics are questioned through categorical questions. Their variable name and coding per category is listed in Table D.4, in Appendix D.1. While studying travel behaviour the focus also lies on other aspects such as who is travelling and what are their attitudes. Section 4.3.2 determined which attitude categories are applicable in this experiment and which leaves the question how to query these. All statements are categorised using a notation system, similar to Molin et al. (2016). Positively worded statements, expressing a favourable or agreeable sentiment, are marked with a (+) symbol. Conversely, negatively worded statements, conveying an unfavourable or disagreeable sentiment, are denoted with a (-) symbol. Translations of the attitudinal statements to Dutch are listed in Appendix C.2.

Habits and norms

Combining the guidelines of Self-Report Habit Index (SRHI) with the statements of Gao et al. (2019), the following statements are included questioning habits and norms:

- Choosing a mode of travel for commuting is something I do without thinking. (+)
- I am open to a sustainable way of travelling for commuting, even if it is different from how I usually travel. (+)

Reliability

Worrying about something is perceived as the more careful approach and therefore is used for questioning reliability. Since this research aims to discover under what circumstances employees alter their mode choices, the same statement questioning reliability is asked thrice, namely for bike/e-bikes, cars and public transport:

- Travelling by (e-)bike makes me worry about whether I will be at the academic hospital on time. (-)
- Travelling by car makes me worry about whether I will be at the academic hospital on time. (-)
- Travelling by public transport makes me worry about whether I will be at the academic hospital on time. (-)

Comfort

The concept of comfort is very broad and personal, i.e. one might perceive seat availability as comfort, while others might perceive no congestion/waiting time as comfortable. Thus, it is decided to include the general concept of comfort, for the same three modality categories similar to the reliability concept:

- After a work day, I find travelling by (e-)bike comfortable. (+)
- After a work day, I find travelling by car comfortable. (+)
- After a work day, I find travelling by public transport comfortable. (+)

Annoyances delay

Whether commuting choices are driven by minimising annoyance or frustration is questioned through the following statements, focusing on delay:

- I am annoyed by waiting for delayed PT during my commute. (-)
- I am annoyed by traffic jams during my commute. (-)

Environmental importance

The statements included in this research questioning environmental importance are refined based on the literature, so that their applicability and relevance in this context is enhanced:

- The “environmental/ecological crisis” facing humankind has been greatly exaggerated. (-)
- I think that humans are seriously abusing the environment. (-)

Health importance

Based on the literature, to what extent Living Lab participants value their health is questioned through these three statements:

- Physical activity is important to me. (+)
- Being outside helps me clear my mind. (+)
- I seriously take my health into account in my life. (+)

Measuring scale

To measure the stated attitudes, a common measurement scale is required. Among the reviewed articles in Table C.2, the 5-point Likert scale is widely used. While studies show that reliability improves with a 7-point scale and validity increases with six or more options, 5-point, 7-point, and 10-point scales are easy to use. Shorter scales are quicker to complete, while longer scales better capture nuanced feelings. A 5-point scale is less confusing and can boost response rates. Based on these considerations and common practice, a 5-point Likert scale was chosen for this research, ranging from strongly agree to strongly disagree (Taherdoost, 2019).

5.4 Choice set generation

The choice sets for the discrete choice experiment were generated using Ngene software, with a separate design created for each of the three experiments based on participants' commuting distances. As a efficient design is used, priors are thus required to be incorporated in the Ngene code. This approach ensured that each experiment had a tailored set of alternatives suited to its respective group. The designs were checked for dominance by calculating utilities and probabilities to ensure that no alternative had an expected probability exceeding 0.90, which would indicate dominance. This process helped maintain the validity of the experiment so that all alternatives were considered equally viable. The final choice sets, generated through this procedure, were then used as the basis for visualising the choice experiment. Details on the Ngene code, the full procedure, including utilities and probabilities, are provided in Appendix D.

5.5 Questionnaire structure

The questionnaire was constructed within the Microsoft Forms environment and distributed by the academic hospital to all pilot participants through email and the Microsoft Teams platform. The academic hospital's project team collected all data responses, which were then anonymised before any further analyses were performed.

Questionnaire Invitation

Participants received an invitation to take part in the choice experiment. The invitation briefly explained the aim of the questionnaire, what a choice experiment entails and that it was part of a master's thesis research at TU Delft. Little light is put on the sustainability aspects since this might create information bias and aversion (Saija et al., 2023). The invitation addresses the anonymity of the participants, mitigating social desirability bias for respondents (Denisova-Schmidt et al., 2022; Nederhof, 1985). The invitation also included an example image of the choice set. The full invitation text, provided in both Dutch and English, can be found in Appendix D.4.

Personnel Number

The questionnaire commenced with personnel numbers, which were translated into anonymised respondent IDs by the project team. These coded IDs uniquely identified respondents while protecting actual personnel numbers. The IDs enabled linking survey responses and DCE data to employee records of other surveys and data, without exposing real personnel numbers, maintaining anonymity while allowing data connection for analysis.

Objective Covariates

Person-related characteristics (covariates) were divided into two sections for two reasons: to maintain respondents' attention by varying question types and to minimise bias in the choice experiment. Questions on health, environmental concerns, reliability, comfort, and delays could influence responses toward more sustainable options. Therefore, the section before the choice experiment focused on habits and norms, and raising awareness of the alternatives to reduce bias and keep participants engaged.

Choice Experiment

Before starting the choice experiment, the respondents are presented with an allocation question determining which of the three experiments is presented. The respondents are asked to which category they belong for commuting distance. For the two distance categories 11-30 km and >30 km, the follow-up question states which P+R location they would choose in case they must use one, after which respondents are routed towards the choice sets including that P+R. In the case that non of these listed P+R locations is perceived as attractive, respondents could choose 'not applicable', still routing towards the choice experiment. The choice experiment is introduced with elaboration and an example choice set in which the varying attributes are highlighted.

To provide participants with a clear overview of the choice set, a visualisation approach was adapted from research on ASML employees' commuting behaviour (Molin & Kroesen, 2023). The goal was to simulate real-world conditions and reduce hypothetical bias, as people's actions often differ from what they claim. Icons from the 'NS Reisvergelijker,' a Dutch Railways tool for comparing travel options, were used for consistency, with a self-developed shared e-bike icon in the same style (Nederlandse Spoorwegen, 2023). A brief explanation accompanied each question to clarify the alternatives and attributes, tailored for the academic participant group. While the term "hypothetical" was used, this was a conscious choice to distinguish the study's focus on commuting modalities rather than future alternatives. An example choice set in experiment 3 is shown in Figure 5.1. Although some researchers recommend including a "none of the above" option in DCEs to avoid bias, it was excluded here because participants must commute to work, making real-world options the focus. Excluding this option also increased the significance of the beta parameters by boosting response rates.

Subjective Covariates

Following the choice experiment, participants were asked about subjective covariates. These questions focused on the factors: reliability, comfort, annoyances related to delay, the importance of environmental considerations, and the importance of health-related aspects.

Closing

At the end of the questionnaire, participants were thanked for their participation. It was disclosed that feedback would be provided after the results were analyzed. Additionally, participants had the opportunity to leave any questions or to contact the researchers directly via email.

5.6 Testing the questionnaire

In the final phase of the DCE development, a pilot study was conducted with the academic hospital's project team to assess the questionnaire's length, clarity, and overall comprehension. Feedback suggested presenting total travel time and costs in a separate overview to improve clarity. For cost-related attributes, an orange colour was recommended for costly, and green for break-even or cost-saving alternatives to improve visibility. Travel time from the P+R location was added for the shared bike option, although it remained consistent across sets. As car costs were not directly included, the statutory travel allowance of 0.23 cents/km was used, with other alternatives calculated similarly. Parking costs were halved since the experiment focused on one-way trips. The team responded positively to the covariate questions and understood the purpose of the choice experiment. After implementing these suggestions, the questionnaire was deemed ready for distribution.

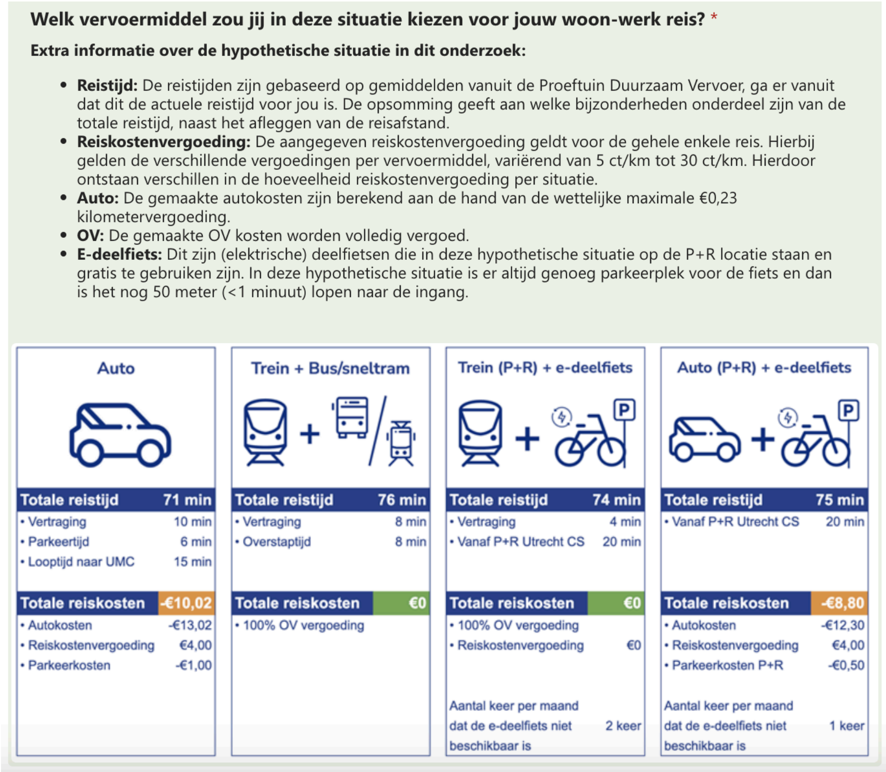

Figure 5.1: Example choice set for experiment 3

Key highlights

- The research includes three experiments, which differ in commuting distances. The three categories are <=10 km, 11-30 km and >30 km. The choice sets were generated using Ngene software, with efficient design principles and the inclusion of priors for utility calculations. Each experiment had its own design, with alternative dominance checks performed based on utilities and probabilities.
- Is concluded from research that commuters use e-bikes for distances up to 30 kilometres, so the lease e-bike alternative is included in experiments 1 and 2.
- The visual design for the choice set was based on real-world commuting scenarios using consistent icons to mitigate hypothetical bias, despite mentioning "hypothetical" in explanations to clarify the focus on commuting modalities based on the real-world situation around the academic medical centre.
- Travel times per modality are based on the average commuting distances of all hospital employees, within the three commuting distance categories.
- The attitudes topics, all measured on 5-point Likert scales, are habits and norms, modality reliability, modality comfort, annoyances delay, environmental importance, and health importance.
- Objective covariates were divided to minimise bias and maintain attention, while subjective covariates were addressed post-choice experiment focusing on reliability, comfort, and environmental considerations.
- The questionnaire was distributed via Microsoft Forms by the academic hospital, ensuring participant anonymity and linking responses with anonymised IDs.
- Feedback from the pilot study led to presenting travel time and costs separately, adjusting attribute colours for clarity, and refining cost calculations for car and parking alternatives. After the pilot study suitability was confirmed.

6 Descriptive statistics

6.1 Data preparation

A total of 201 responses were collected for this study. After an initial review, nine respondents were excluded since they did not complete either the baseline or interim survey, and thus, data on their type of work shift was lacking. Five additional responses were excluded due to missing socio-demographic data. Furthermore, two respondents filled in the survey twice, leading to the exclusion of their second entry. This left a final dataset of 183 valid responses.

These 183 responses are distributed over three experiments therefore leading to a relatively small sample size per experiment. Unfortunately, it was not possible to gather collect more respondents from the whole academic hospital population, due to the advantages for Living Lab participants concerning travel costs and reimburshments summed up in Section 2.1. Including respondents outside the Living Lab participants, thus without these benefits, would lead to incorrect outcomes due to the different starting points.

The average time to complete the survey was initially recorded at 22 minutes and 43 seconds. However, 10 outliers who took an unusually long time to complete the survey, often several hours, were identified and removed. The extended completion times for these outliers could be attributed to factors such as respondents reaching out for clarification or pausing the survey due to interruptions. After removing these outliers, the average completion time was recalculated to 9 minutes and 39 seconds, which is only slightly longer than the expected duration of 7 minutes.

In analysing the data, it was important to account for the multiple observations per individual, which provides greater insight into how decision-makers respond to varying choice situations. One particular area of focus was the phenomenon of non-trading behaviour, where respondents consistently choose the same alternative across all choice sets (Hess et al., 2010). Hess et al. (2010) stated that this behaviour is often observed in labelled choice situations and can arise for several reasons:

1. *Extreme preference*: Non-trading may indicate a respondent's strong preference for a particular alternative, reflecting their believe that their utility is maximised when choosing that alternative.
2. *Heuristic decision-making*: Alternatively, it may result from heuristic (non-utility maximising) decision-making caused by misunderstanding, boredom, or fatigue during the survey.
3. *Strategic behaviour*: Non-trading could also reflect a form of political or strategic behaviour, where respondents consistently choose the same option due to their stance on a particular issue.

It can be expected that some respondents have an extreme preference for a particular modality or certain characteristics of that alternative. Yet, strategic behaviour could also be the case when, for example, respondents are in favour of full reimbursement, or the concept of leasing e-bikes. Given the difficulty in definitively determining the cause of non-trading behaviour, it was decided to retain these responses in the dataset.

The data was also checked for consistency between the commuting distance category chosen in the survey by respondents and those recorded in the database. In some cases, discrepancies were found, which may be due to recent changes in the respondents' addresses. These responses were included in the analysis under the distance category, which the respondents chose themselves since they participated in that experiment.

The number of responses per experiment, non-trading cases and discrepancies for the commuting distance are all reported in Table 6.1. For the number of responses, the percentage is calculated based on the total number of responses. For non-trading and commuting distance discrepancy cases, the percentage is calculated based on the responses specific to that experiment.

Table 6.1: Data preparation

	Responses		Non-trading behaviour		Commuting distance discrepancy	
	Frequency	*Percentage*	*Frequency*	*Percentage*	*Frequency*	*Percentage*
Experiment 1	13	7%	10	77%	3	23%
Experiment 2	83	45%	28	34%	12	14%
Experiment 3	87	48%	31	36%	4	5%
	183		**69**		**19**	

Notably, the amount of respondents per experiment is not equally distributed. Only 13 respondents in experiment 1, together with the high percentage of 77% of non-trading behaviour, suggest the strong homogeneity of that respondent group. As for experiments 2 and 3, more than one-third of the respondents still showed non-trading behaviour, giving limited insights into trade-offs between attributes. It cannot be stated with certainty what the reasons were for the non-trading behaviour, yet it is important to remember this during the analysis.

6.2 Sample characteristics

The sample characteristics provide an overview of the socio-demographic profile of the respondents across the three experiments. This includes variables such as age, gender, job function, and work schedules, which are crucial for understanding commuting patterns. Additionally, exploratory factor analysis was applied to identify key latent factors influencing participant attitudes towards commuting, and differences were examined between those with regular and irregular working schedules.

6.2.1 Socio-demographic variables

All socio-demographic variables have been coded to facilitate analysis during the LCCM estimation. The socio-demographics are organised separately for each experiment to provide a clear overview of the sample population. While age is treated as a continuous variable during LCCM estimation, it is divided into age groups for the purpose of this overview, following the categories used by Gao et al. (2019). A summary of the socio-demographic characteristics of the sample and their coding is presented in Table 6.2. All nominal socio-demographic variables were integrated into the analysis based on the provided coding, with the exception of the continuous variable, age. Age categories are only presented to give an overview of the age distribution for each experiment.

The academic hospital supplied function family classifications, with translations into Dutch in Appendix C.2. Additionally, two variables were included to measure the type of shift work and whether participants have irregular schedules. The levels of shift work were defined based on their potential impact on commuting. All commuting modalities are typically available during day shifts or in the absence of shift work. However, evening, night, and weekend shifts pose similar challenges for public transport. On-call shifts primarily focus on travel time, with distinctions made between only on-call shifts, on-call shifts combined with day shifts, and those combined with evening, night, or weekend shifts.

Interestingly, the respondent group of experiment 1 comprises 77% older (>40 years) people and the other 23% of people below 30 years old. Within this group, the majority works in nursing and care, together with physician assistants and basic physicians, and clinical (co-treatment), which also might account for the relatively high amount of evening, night, weekend and on-call shifts and irregular schedules. Notably, experiment 2 is predominantly composed of females and respondents aged 50 and above, while experiment 3 shows a more balanced distribution across both gender and age. Regarding shift work, the majority in both experiments are working day/no shifts. The other 30% has evening, night and/or weekend shifts, some with and others without on-call shifts. As for irregular schedules, the distribution of one-fourth in the second experiment with an irregular schedule, and a small one-fifth in the third experiment is comparable.

Table 6.2: Sample's socio-demographic characteristics

			Experiment 1		Experiment 2		Experiment 3	
Socio-demographic	*Coding*		*Frequency*	*Percentage*	*Frequency*	*Percentage*	*Frequency*	*Percentage*
GENDER	0	Male	7	54.0%	15	18.1%	35	40.2%
	1	Female	6	46.0%	68	81.9%	52	59.8%
AGE		<30 years old	3	23.0%	15	18.1%	17	19.5%
		30 - 40 years old	0	0.0%	10	12.0%	26	29.9%
		41 - 50 years old	1	8.0%	17	20.5%	23	26.4%
		>50 years old	9	69.0%	41	49.4%	21	24.1%
FFAMILY	0	Analytical personnel	2	15.4%	7	8.4%	6	6.9%
	1	Physician assistants and basic physician	0	0.0%	1	1.2%	5	5.7%
	2	Facility	2	15.4%	7	8.4%	3	3.4%
	3	In training	0	0.0%	2	2.4%	6	6.9%
	4	Clinical (co-)treatment	1	7.7%	8	9.6%	12	13.8%
	5	Clinical support	2	15.4%	10	12.0%	7	8.0%
	6	Management	1	7.7%	5	6.0%	12	13.8%
	7	Medical specialist	0	0.0%	0	0.0%	1	1.1%
	8	Staff, administration and secretariat	0	0.0%	20	24.1%	18	20.7%
	9	Nursing and care	5	38.5%	17	20.5%	6	6.9%
	10	Scientific research and education	0	0.0%	6	7.2%	11	12.6%
SHIFT	0	Day, no shift	5	38.5%	56	67.5%	62	71.3%
	1	Evening, night, weekend shift	3	23.1%	14	16.9%	13	14.9%
	2	On-call shift	1	7.7%	1	1.2%	0	0.0%
	3	On-call + day shift	0	0.0%	1	1.2%	2	2.3%
	4	On-call + evening, night, weekend shift	4	30.8%	11	13.3%	10	11.5%
IRREGULAR	0	No	6	46.2%	62	74.7%	71	81.6%
	1	Yes	7	54.0%	21	25.3%	16	18.4%
AVER. COM DIST			9.31 km		21.88 km			53.51 km
TOTAL RESPONSES			13		83			87

6.2.2 Exploratory factor analysis

To identify underlying latent factors that influence participants' attitudes, an Exploratory Factor Analysis was conducted on the questionnaire data collected from the Living Lab participants. The questionnaire included fifteen questions designed to measure various attitudes, i.e. latent variables as they cannot be directly observed but can be inferred from responses to indicator variables.

A Principal Axis Factoring (PAF) method with oblique rotation was chosen for this analysis. Oblique rotation was selected because it allows for the possibility of correlations between the underlying factors, which is often more realistic in social science research compared to the orthogonal rotation that assumes no correlations between factors. The detailed steps of the PAF method, including the criteria for removing indicators and assessing the number of factors, are documented in Appendix E.1.

Five factors were retrieved using the PAF method. The two statements questioning habits were eliminated since their communalities were too low. As interviewees pointed out the concept of habitational commuting, it was decided to include *habit1*, with an individual measurement scale, to examine the presence of habitational commuting (Zadeits, 2024).

Note that all items in Table E.1 marked with an asterisk (*) are reverse coded so that it complies with the factor names.

Table 6.3: Factors obtained through PAF

Factor 1: Health conscious		
health1	Physical activity is important to me.	0.88
health2	Being outside helps me clear my mind.	0.75
health3	I seriously take my health into account in my life.	0.66
Factor 2: Pro (e-)bike commuting attitude		
comf1	After a work day, I find travelling by (e-)bike comfortable.	0.73*
reliab1	Travelling by (e-)bike makes me worry about whether I will be at the academic hospital on time.	0.67
Factor 3: Pro car commuting attitude		
reliab2	Travelling by car makes me worry about whether I will be at the academic hospital on time.	0.71
annoy2	I am annoyed by traffic jams during my commute.	0.50
comf2	After a work day, I find travelling by car comfortable.	0.45*
Factor 4: Pro PT commuting attitude		
reliab3	Travelling by PT makes me worry about whether I will be at the academic hospital on time.	0.59
annoy1	I am annoyed by waiting for delayed PT during my commute.	0.55
comf3	After a work day, I find travelling by PT comfortable.	0.47*
Factor 5: Environmentally conscious		
env1	The "environmental/ecological crisis" facing humankind has been greatly exaggerated.	0.67
env2	I think that humans are seriously abusing the environment.	0.66*
Factor 6: Commuting as usual		
habit1	Choosing a mode of travel for commuting is something I do without thinking.	+

6.2.3 Traveller-related attitudes

The responses to the questioned attitudes are grouped based on the retrieved factors from the exploratory factor analysis. Figures 6.1 and 6.2 show the distribution of the responses, where a distinction is made between general attitudes and modality-related attitudes. These graphs are not grouped according to experiment since there were minimal differences in attitudes across the three experiments. The exact response amount per factor, per experiment, along with the coding, are listed in Appendix E.2.

Figure 6.1 reveals that the majority of the respondents identify as health-conscious, with most either agreeing or strongly agreeing with statements related to their health awareness. This reflects that the participants of the Living Lab are generally health-conscious, raising the question to what extent this awareness influences their commuting decisions. In contrast, responses regarding environmental consciousness are largely neutral, with a small yet significant portion disagreeing with environmentally friendly statements, indicating that not all respondents are strongly environmentally motivated. Commuting as a habitual activity also stands out, with a substantial portion of respondents either neutral or agreeing that commuting is a routine part of their daily lives. Very few respondents disagree with this idea, suggesting that this group thinks carefully about their commute and may use different means of transport/ routes.

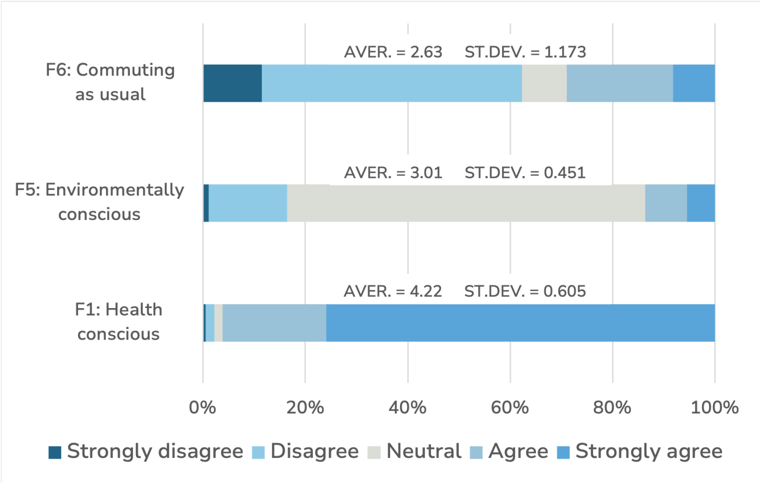

Figure 6.1: General attitudes

Highlighting modality-related attitudes, Figure 6.2 shows the overall positive attitude towards (e-)bike commuting, evaluating it as reliable and comfortable. This is an interesting result to notice since it contradicts the assumption that unfamiliarity might discourage the usage. It's particularly surprising that many find cycling comfortable, which could encourage wider adoption. Finally, the attitudes toward car and PT commuting are surprisingly similar regarding reliability and comfort. Both modes also reflect some level of annoyance among respondents regarding delays. Still, the close alignment between car and PT preferences was unexpected, suggesting neither mode stands out significantly over the other in terms of satisfaction.

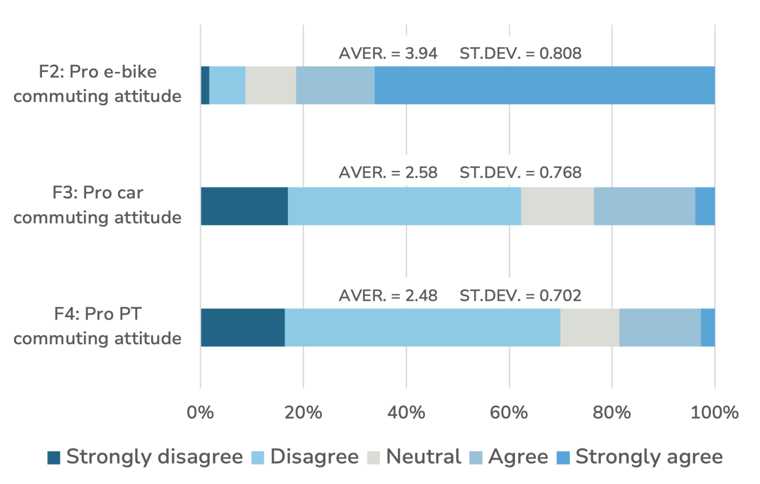

Figure 6.2: Modality related attitudes

Besides general attitudes, differences in modality-related attitudes were also examined between employees with irregular schedules, shift workers, and those with regular schedules. The results of this comparison are visualized in Figure 6.3. he exact numbers are provided in Appendix E.2. These insights help to better comprehend the commuting preferences among employees with non-standard working hours.

The results in Figure 6.3 show minimal differences in attitudes between shift workers, employees with irregular schedules, and those on standard schedules. This notable consistency suggests that non-standard working hours do not significantly influence general modality preferences.

Shift workers have a more positive perception of car commuting than employees with standard schedules, who tend to have a slightly more negative view. This difference could be attributed to the limitations of public transport during late-night hours and safety concerns, making car commuting more attractive for non-standard workers.

Public transport attitudes are overall very positive, with more than three-quarters of all types of workers expressing support. Contrary to the expectation that shift workers would be more reliant on cars due to limited public transport options during off-peak hours, this group shows an even higher positive perception of public transport.

(E-)bike commuting shows the most pronounced difference, whereas there are employees with non-standard schedules that hold a negative view compared to the standard schedule employees. The non-standard workers show a clear division, with fewer neutral opinions and no strong positive responses at all. This suggests that e-bike commuting may be less convenient or appealing for those with irregular schedules.

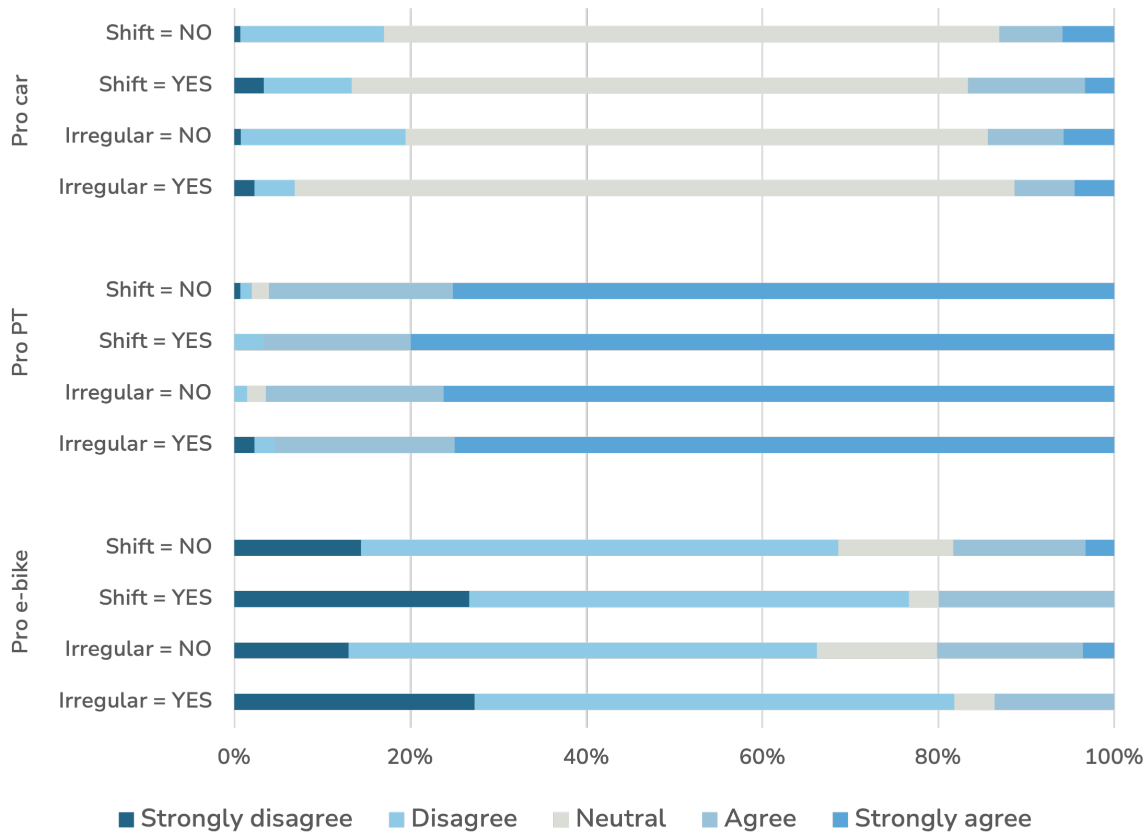

Figure 6.3: Modality-related attitudes in case of irregular schedules and shift work

Key highlights

- Data cleaning and preparation: A total of 183 valid responses were retained after excluding incomplete, duplicate, and outlier responses. Outliers were removed based on unusually long survey completion times, resulting in a recalculated average time of 9 minutes and 39 seconds.
- Non-trading behaviour: A significant portion of respondents exhibited non-trading behaviour, particularly in Experiment 1, where 77% consistently chose the same alternative. This behaviour may indicate extreme preferences, heuristic decision-making, or strategic responses.
- Sample characteristics: The socio-demographic profile of respondents was uneven across the experiments, with notable differences in gender, age, and work schedules. Experiment 1 had a higher percentage of older respondents, while experiment 2 was predominantly female, and experiment 3 had a balanced distribution across gender and age. A significant portion of respondents in Experiments 2 and 3 worked regular schedules, with fewer employees working irregular shifts. This balance is crucial for understanding commuting patterns in relation to work schedules.
- Exploratory factor analysis: Six key factors were identified through exploratory factor analysis, highlighting important attitudes like health consciousness, commuting habits, and attitudes towards different modes of transport (car, public transport, and (e-)bike commuting).
- Traveller-related attitudes: General attitudes showed strong health consciousness among respondents, while attitudes toward environmental consciousness were more neutral. Modality-related attitudes revealed an overall positive view of (e-)bike commuting and similar satisfaction levels for car and public transport commuting, which was surprising given assumptions about discomfort with certain modes.

7 Model estimation

7.1 MNL estimation process

As part of the LCCM estimation process, a one-class MNL model is first estimated. While LCCMs account for taste heterogeneity, MNL models assume homogenous preferences, resulting in one set of taste parameters for all respondents. As outlined in Chapter 3, LCCMs address heterogeneity by segmenting the population into distinct classes, aiming to maximise homogeneity within classes and heterogeneity between them. These classes can then be profiled based on socio-demographics and attitudes, which are also included in the questionnaire.

The one-class model serves as a baseline comparison to evaluate which model provides the best estimates. Four statistical criteria are used to assess the model fit: Log-Likelihood (LL), the adjusted McFadden's ρ^2, AIC, and BIC. Together, these criteria describe how well the model fits the observed data. Log-Likelihood reflects the model's ability to describe the data, with higher (less negative) values indicating a more accurate representation of the choices made by individuals (Hauber et al., 2016). The adjusted McFadden's ρ^2 measures the proportion of initial uncertainty explained by the model, where values between 0.2 and 0.4 indicate a good fit. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) focus on evaluating the plausibility of the models by minimising the loss of information. Unlike McFadden's ρ^2 measures, lower AIC and BIC values are preferred, as they indicate a more efficient model with reduced complexity while still explaining the data (Hauber et al., 2016).

After estimating the MNL model, the LCCM is assessed using the same four statistical criteria to determine the optimal number of classes, starting with two and increasing gradually. However, due to the small sample size per experiment, meeting the guideline of 30 respondents per class was difficult. As noted by Weller et al. (2020), balancing sample size with model fit is key.

7.2 LCCM estimation process

While the application of LCCMs was theoretically aligned with the research's objectives to uncover heterogeneity in preferences across this specific group of hospital employees with non-standard work schedules, the empirical data from the Living Lab proved to be less accommodating. The most significant challenge in estimating the LCCM was the high level of observed homogeneity in the data. As visualised in Table 6.1, a large number of respondents exhibited non-trading behaviour, consistently choosing the same commuting alternative across all choice tasks, despite the diversity in work schedules and job functions.

This non-trading behaviour, as discussed in Section 6.1, occurs when respondents consistently choose the same alternative across multiple choice sets, often due to either an extreme preference, heuristic decision-making, or strategic behaviour (Hess et al., 2010). For instance, many participants may have strongly preferred the PT, likely driven by institutional policies like restricted car parking authorisations and full reimbursement. Another explanation could be the strategic preference for lease e-bikes, since participants would like to see this option realised. This contributed to a lack of variation in responses, which can make it difficult for the LCCM to distinguish between latent classes.

Another significant outcome from the Living Lab data is the 93% reduction in car parking authorisations. This drastic decline can likely be attributed to the parking restrictions in place between 6 a.m. and noon. While some employees may still park their cars elsewhere, the reimbursements submitted for commuting expenses further support the reduction in car usage. The distribution of these reimbursements reveals that 71% were for public transport, 14% for cycling, and 15% for car commuting. However, it's important to note that not all trips were recorded or claimed, meaning these figures may not fully represent the complete commuting behaviour of participants.

The limited variation in commuting mode choices further reduced the model's ability to detect heterogeneity. The small sample size per experiment compounded these issues, making it difficult to meet the '30 respondents per class' guideline for LCCM estimation. This issue was compounded by the limited number of respondents and high rates of non-trading behaviour, leading to the failure of the model to converge in all three experiments. In this context, where hospital policies might have heavily influenced commuting behaviour, the homogeneity in responses is understandable. Some participants may have chosen for the alternatives they would like to see being reasiled by the academic medical centre, such as leasing e-bikes, rather than making diverse trade-offs between attributes. As such, the decision-making process captured by the model reflected this policy-driven behaviour rather than revealing a natural heterogeneity in preferences.

7.3 MNL with interaction effects

Given the non-convergence of the LCCM, the MNL model was expanded with interaction effects to assess the impact of covariates such as gender, age, shift work, and irregular schedules. The MNL with interaction effects was compared to the main-effect MNL model using the same statistical criteria. The Apollo syntax of the MNL model with interactions can be found in Appendix F. Tables 8.1, 8.2 and 8.3, present the statistical criteria of the main effect MNL and the interaction MNL per experiment, together with the estimated taste parameters, standard deviation, t-values and p-values.

Of all choice sets in experiment 1 (<=10 km), no respondent chose car commuting as an alternative, which is thus removed from the model. After removing, the main-effect MNL model performs slightly better than the interaction MNL, as reflected in the marginally better values across three statistical criteria. This is likely due to the simplicity of the main model despite the interaction model having a slightly higher LL. The differences between the two models, however, are minimal.

In experiment 2 (11-30 km), the interaction model demonstrates a clear advantage in terms of goodness of fit. It has a higher log-likelihood, indicating a better model fit, and a higher ρ^2, suggesting it explains more variance. Additionally, lower AIC and BIC values indicate a better trade-off between fit and complexity than the main-effect model.

For experiment 3 (>30 km), the commuting option of car and shared e-bike was chosen in 0.77% of cases, and was therefore also eliminated from the model. After elimination, the results from the model were mixed. The interaction model has a higher LL, a higher ρ^2, and a lower AIC, indicating it is superior to the main-effect model. However, the slightly higher BIC suggests that the increased complexity of the interaction model may negatively impact its fit.

8

Results

This chapter presents and analyses the results of the choice model estimation. The Chapter starts with a visualisation in Section 8.1 of the modal split in the three experiments. Section 8.2 continues with the analysis of the parameter estimates for the MNL models, with additional insights into the effects of covariates such as gender, age, shift work, and irregular schedules. Also, the relative importance of each attribute is examined. Finally, Section 8.3 visualised the effects of attribute on the modal split across the different experiments, highlighting key insights for interventions aimed at promoting sustainable commuting behaviours.

8.1 Modal split

It is surprising to see that car commuting is chosen very sparingly across all experiments, despite being a common mode of transport. In experiment 1, commuting distance until 10 km, no respondents selected car commuting, which is likely influenced by the shorter distances involved, where private (e-)bikes dominate at 72%, and bus/light rail use stands at 23%. The limited use of the car here is understandable as alternative modes like cycling suffice for such short distances.

In experiment 2, where commuting distances range from 11 to 30 km, car use remains relatively low at 9%. Instead, e-bike leasing emerges as a popular choice at 41%, and train + bus/light rail combinations account for 38%, indicating that respondents are willing to explore sustainable alternatives for medium-distance commuting. Only 4% chose the car + shared e-bike combination, which is in line with the feedback from focus groups where many respondents expressed that switching between driving and cycling at a Park + Ride (P+R) location was inconvenient. The locations of the P+R stations were also perceived as unsuitable for a significant portion of participants, further reducing the attractiveness of this mode.

In experiment 3, where commuting distances exceed 30 km, car use increases but remains modest at 5%. Train + bus/light rail becomes the dominant mode at 58%, with train + shared e-bike following at 36%. However, the car + shared e-bike option remains extremely unpopular at just 1%, substantiating the sentiment from focus groups that this combination of transport modes is not practical for most respondents.

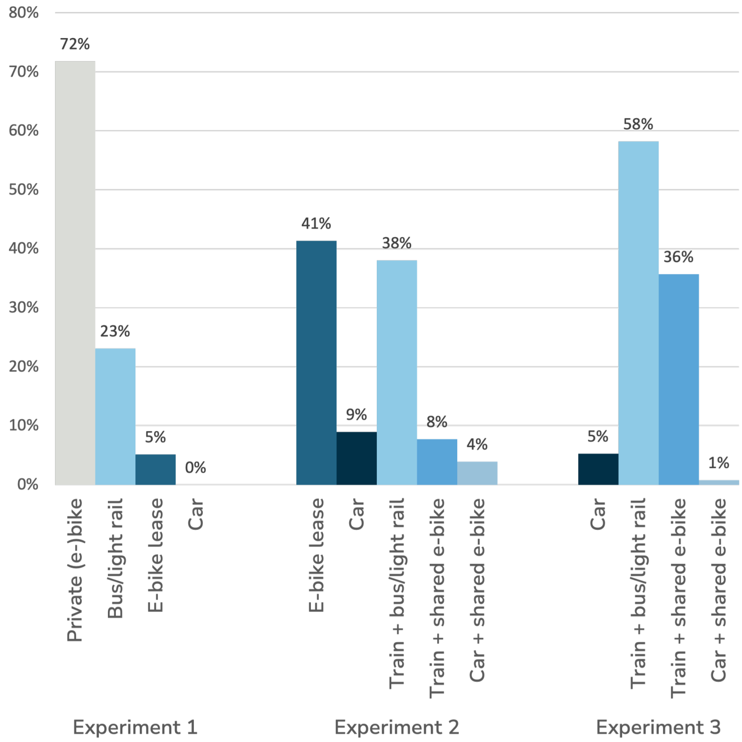

Figure 8.1: Modal split per experiment

8.2 Parameter estimates

8.2.1 Experiment 1: <10 km

In experiment 1, the interpretation focuses on the main effects MNL model, as the interactions model has a lower McFadden's ρ^2. Among all the parameters, only the monthly lease cost for e-bikes is statistically significant at the 95% confidence level. Not only is this parameter significant, but it also has the strongest influence on utility. The estimate of e-bike lease costs suggest that higher leasing costs significantly reduce utility, which is intuitively reasonable as higher costs make leasing less attractive. Other parameters, such as allowances and delay times for bus and tram services, show expected signs but do not strongly influence the choice in this model. Their lack of significance is not surprising, given the small sample size of 13 respondents in this experiment.

Table 8.1: Experiment 1: Statistical criteria MNL model

	Experiment 1			
LL	-112,23			
Adjusted McFadden's R^2	0,310			
AIC	236,47			
BIC	254,77			
	Estimate	*Rob. s.e.*	*Rob. t. rat. (0)*	*p(1-sided)*
Parameters				
a_bike	0,002	0,037	0,046	0,482
a_ebike	0,034	0,137	0,056	0,402
c_ebike_lease	-0,621	0,263	-2,357	0,009
t_delay_bustram	-0,054	0,056	-0,957	0,169
Alternative specific constants				
C_BIKE	-	*NA*	*NA*	*NA*
C_EBIKE	-2.269	1,071	-2,12	0,017
C_BUSTRAM	-0.885	1.106	-0.801	0.212

To evaluate the extent to which each alternative delivers the highest utility when attribute levels align with the real-world conditions at the academic medical centre, a base scenario was developed that closely mirrors the current commuting situation. The strength of this preference is determined by calculating the utility under that base scenario.

The following utility values were calculated for the most realistic scenario:

$$U(BIKE) = 0 + 0.002 \cdot 20 = 0.040$$

$$U(EBIKE\_LEASE) = -2.269 + 0.034 \cdot 0 - 0.621 \cdot 1 = -2.890$$

$$U(BUSTRAM) = -0.885 - 0.054 \cdot 4 = -1.101$$

From these results, it can be concluded that the private (e-)bike provides the highest utility, followed by bus/tram, while leasing an e-bike results in a significantly negative utility. This outcome is primarily driven by the alternative-specific constants (ASCs), which have the greatest influence in determining the baseline preferences.

The ASCs reveal important insights into the inherent preferences for each commuting option when other attributes, like cost and travel time, are set to zero. In this case, the ASC for leasing an e-bike is much lower than that for bus/tram, which implies that respondents have a stronger inherent preference for public transport over leasing an e-bike. However, both options are viewed less favourably than private (e-)bikes, which reflect the highest utility.

The lower ASC for leasing e-bikes might stem from respondents' unfamiliarity with leasing schemes, concerns about maintenance, safety, or the general inconvenience compared to owning a private bike. In contrast, the ASC for bus/tram, while higher than leasing an e-bike, still indicates a lower baseline preference relative to private bikes. This may be explained by the general perception of public transport as less reliable or comfortable compared to personal commuting modes, though it remains a more familiar and accessible option compared to leasing.

These findings emphasize that ASCs play a critical role in explaining baseline preferences and reflect underlying perceptions of each transport mode. Even before considering specific attributes, respondents show a clear preference for modes like private bikes, reflecting their control, familiarity, and convenience.

The socio-demographic characteristics of the respondents in Experiment 1 reveal a group largely composed of older individuals (77% aged over 40), with many working in roles such as nursing, care, and clinical co-treatment. These professions are typically associated with evening, night, weekend, and on-call shifts, being confirmed by the 54% working irregular schedules and 60% shift workers, which might explain their commuting preferences. The commuting distance in this experiment is also less than 10 km, which further influences the choice of transport mode.

Given the short distance, a regular city bike may suffice for many respondents, contributing to the significant negative baseline preference for leasing e-bikes. Leasing may be perceived as unnecessary or inconvenient for such short trips, especially when coupled with the irregular and demanding schedules these professionals face. The strong preference for private (e-)bikes over leasing could be linked to the flexibility and reliability needed for non-standard working hours and the practicality of using a personal bike for shorter commutes. Yet, the small sample size, combined with the high amount of non-trading behaviour, makes it difficult to generalise these findings.

Lastly, the relative importance of each attribute per experiment is examined. This tells us how much influence or weight a particular attribute has in the decision-making process compared to other attributes. This is calculated as follows:

$$\text{Relative importance of attribute A} = \frac{\text{Utility range of attribute A}}{\text{Total utility range of all attributes}}$$

The sum of the relative importance values equals 100%, allowing for easy comparison across attributes. For experiment 1, this is visualised in Figure 8.2, where insignificant attributes are shown in grey. The e-bike lease cost emerges as the most influential attribute, followed by delay time for bus/light rail travel and e-bike allowance. In contrast, private (e-)bike allowance had little influence on this experiment.

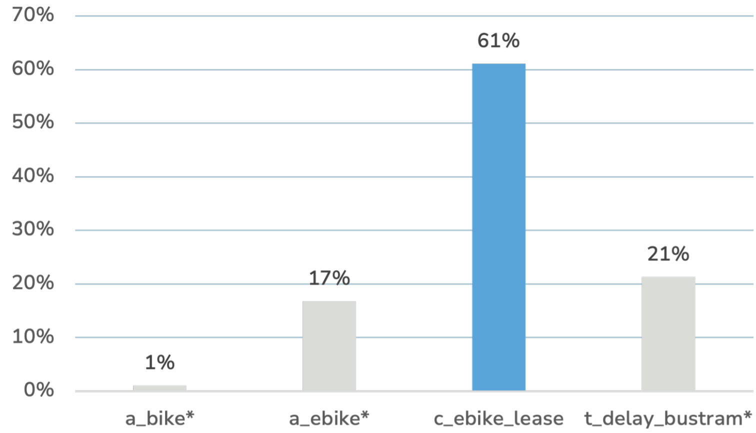

Figure 8.2: Experiment 1: Relative importance attributes

8.2.2 Experiment 2: 11-30 km

In experiment 2, the interaction model reveals several important relationships between factors and commuting mode choices. One of the most significant findings, consistent with Experiment 1, is the negative effect of e-bike leasing costs on utility. As expected, delays for cars and train + bus/light rail combinations also have a significant negative impact on utility, showing that travel delays consistently reduce the attractiveness of these options. The model also highlights the importance of allowances. The allowance for leasing e-bikes is significant, indicating a higher base preference for leasing e-bikes than other options. Allowances for cars and train + shared e-bike options are also significant, but they have a much smaller influence on utility than the allowance for leasing e-bikes.

To evaluate the utility values for the most realistic attribute levels at the academic medical centre in experiment 2, complementary to the base scenario in experiment 1. This scenario closely mirrors the current commuting conditions for hospital employees between 11 and 30 kilometres. The utility calculations under this base scenario are as follows:

$$U(EBIKE\_LEASE) = 5.620 + 0.132 \cdot 0 - 0.176 \cdot 1 = 5.444$$

$$U(CAR) = 0 - 0.032 \cdot 2 - 0.065 \cdot 5 - 0.061 \cdot 5 - 0.145 \cdot 4 + 0.048 \cdot 20 = -0.314$$

$$U(TR\_BUSTRAM) = 4.675 - 0.040 \cdot 4 - 0.077 \cdot 5 = 4.132$$

$$U(TR\_SBIKE) = 5.013 + 0.010 \cdot 4 + 0.022 \cdot 20 - 0.093 \cdot 0 = 5.493$$

$$U(CAR\_SBIKE) = 3.940 - 0.319 \cdot 1 + 0.025 \cdot 20 - 0.172 \cdot 0 = 4.121$$

From these results, it can be concluded that the train + shared e-bike combination delivers the highest utility, followed by car + shared e-bike and leasing an e-bike. On the other hand, car commuting has the lowest utility under the base scenario, reflecting a strong preference against this mode.

Table 8.2: Experiment 2: Statistical criteria MNL model

	Experiment 2							
	Main effects				*Interactions*			
Statistical criteria								
LL	-1211.22				-1135.74			
Adjusted McFadden's R^2	0.233				0.270			
AIC	2460.44				2341.48			
BIC	2553.61				2513.11			
	Estimate	*Rob. s.e.*	*Rob. t. rat. (0)*	*p(1-sided)*	*Estimate*	*Rob. s.e.*	*Rob. t. rat. (0)*	*p(1-sided)*
Parameters								
a_ebike	0.125	0.020	6.185	0.000	0.132	0.022	6.050	7.24E-10
c_ebike_lease	-0.168	0.062	-2.715	0.003	-0.176	0.065	-2.708	0.003
t_park_car	-0.040	0.036	-1.109	0.134	-0.032	0.037	-0.868	0.193
t_egress	-0.061	0.026	-2.348	0.009	-0.065	0.026	-2.552	0.005
t_delay_car	-0.057	0.021	-2.727	0.003	-0.061	0.021	-2.957	0.002
c_park_car	-0.137	0.071	-1.930	0.027	-0.145	0.072	-2.015	0.022
a_car	0.045	0.021	2.183	0.015	0.048	0.021	2.251	0.012
t_delay_train_bustram	-0.038	0.014	-2.762	0.003	-0.040	0.015	-2.747	0.003
t_transfer	-0.075	0.020	-3.716	0.000	-0.077	0.021	-3.622	1.46E-04
t_delay_train_sbike	0.012	0.026	0.469	0.320	0.010	0.027	0.381	0.352
a_train_sbike	0.021	0.008	2.762	0.003	0.022	0.008	2.826	0.002
u_sbike_train	-0.073	0.158	-0.459	0.323	-0.093	0.162	-0.576	0.282
c_park_car_pr	-0.326	0.138	-2.355	0.009	-0.319	0.141	-2.265	0.012
a_sbike_car	0.023	0.028	0.817	0.207	0.025	0.029	0.885	0.188
u_sbike_car	-0.177	0.212	-0.836	0.202	-0.172	0.215	-0.800	0.212
Alternative specific constants								
C_EBIKE	0.032	0.436	0.073	0.471	5.620	1.697	3.311	4.65E-04
C_CAR	-	NA	NA	NA	-	NA	NA	NA
C_TRAIN_BUSTRAM	1.174	0.522	2.248	0.012	4.675	1.583	2.953	0.002
C_TRAIN_SBIKE	-1.363	0.532	-2.562	0.005	5.013	1.979	2.533	0.006
C_CAR_SBIKE	-1.769	0.651	-2.719	0.003	3.940	1.870	2.107	0.018
Interactions								
C_EBIKE_I_gender					-3.485	1.147	-3.038	0.001
C_TR_BUSTRAM_I_gender					-2.572	1.080	-2.381	0.009
C_TR_SBIKE_I_gender					-3.734	1.297	-2.878	0.002
C_CAR_SBIKE_I_gender					-3.067	1.477	-2.077	0.019
C_EBIKE_I_age					-0.044	0.018	-2.423	0.008
C_TR_BUSTRAM_I_age					-0.012	0.017	-0.733	0.232
C_TR_SBIKE_I_age					-0.051	0.027	-1.884	0.030
C_CAR_SBIKE_I_age					-0.049	0.029	-1.683	0.046
C_EBIKE_I_shift					-0.040	0.240	-0.169	0.433
C_TR_BUSTRAM_I_shift					-0.220	0.272	-0.809	0.209
C_TR_SBIKE_I_shift					-0.048	0.299	-0.162	0.436
C_CAR_SBIKE_I_shift					-0.345	0.382	-0.904	0.183
C_EBIKE_I_irregular					-0.863	0.694	-1.243	0.107
C_TR_BUSTRAM_I_irregular					-0.736	0.843	-0.873	0.191
C_TR_SBIKE_I_irregular					-2.387	1.551	-1.539	0.062
C_CAR_SBIKE_I_irregular					-1.245	0.877	-1.421	0.078

*Not statistically significant estimates

The utility results are significantly influenced by the alternative specific constants (ASCs), which capture the baseline preferences for each mode of transport when all other attributes, such as cost and time, are set to zero. In this case, leasing an e-bike shows a strong ASC, which aligns with its high utility, suggesting a positive inherent preference for this mode despite potential practical barriers like cost. Interestingly, the train + shared e-bike option, which was only chosen by 8% of respondents, shows the highest utility, which is largely driven by its ASC.

It is important to note that this high utility for train + shared e-bike is somewhat surprising, as the attribute for delay in this mode has a positive direction, though it is insignificant. This could indicate that delays are not perceived as strongly negative for this mode compared to others, though this result should be treated with caution due to its insignificance.

Additionally, the availability of shared bicycles is crucial for maintaining the utility of this option, as seen in the negative utility associated with the unavailability of shared bikes. Ensuring there are enough shared bicycles available is therefore essential to avoid driving down the utility of this option.

On the other hand, car + shared e-bike shows a relatively low inherent preference, with respondents likely perceiving this mixed mode as overly complicated due to the need to park the car and then transition to a shared bike for the last leg of the journey. This is reflected in both the low ASC and the fact that it was chosen by only 4% of respondents.

Socio-demographic factors, particularly gender, play a crucial role in transportation choices. Gender significantly affects preferences for e-bikes, train + bus/light rail, and train + shared e-bike options. This likely indicates that, relative to men, women have lower utility or preference for these options. Age also plays an important role, particularly for leasing e-bikes, where older respondents tend to have lower utility for this option than younger respondents.

When it comes to the effects of shift work and irregular schedules, it is noteworthy that these factors have minimal influence, as none of these interactions are statistically significant. This suggests that while demographics like gender and age are key determinants of commuting choices, work-related factors like shift work and irregular schedules do not strongly affect commuting preferences. This could be because participants completed the choice experiment with a typical workday in mind, or it may simply be that these factors do not significantly impact commuting decisions.

The socio-demographic characteristics for experiment 2 highlight a predominantly female respondent group, with most participants aged 50 and above. This age profile, combined with the fact that a significant portion of participants work regular day shifts, suggests a more stable commuting routine than those with irregular or on-call schedules. The commuting distance in this experiment is between 11 and 30 km, a range where leasing an e-bike becomes more practical for many participants, reflected in the significant preference for this mode of transport.

The older age group and predominantly female respondents show a lower utility for e-bikes, which could be linked to perceptions of effort or unfamiliarity with the leasing option. Nevertheless, the higher base preference for leasing e-bikes compared to car commuting aligns with the idea that leasing offers a practical alternative for moderate distances, especially for those less inclined to drive. The relatively low percentage of participants with irregular schedules also suggests that the negative utility of car commuting and the strong preference for more sustainable options, such as e-bikes and public transport, may stem from a more structured, predictable work-life routine. Since most participants in this group work regular day shifts, they likely have better access to these transport options, making them more appealing for daily commuting. Therefore, non-standard working hours, which might complicate commuting choices, seem to impact their preferences less in this experiment.

When examining the relative importance of the attributes in the second experiment, as shown in Figure 8.3, it is clear that the most significant attribute is the allowance for lease e-bikes, followed closely by delay time during car commutes. Rounding out the top five most important attributes, in order of ranking, are car parking costs, egress time, and parking costs at the P+R facility.

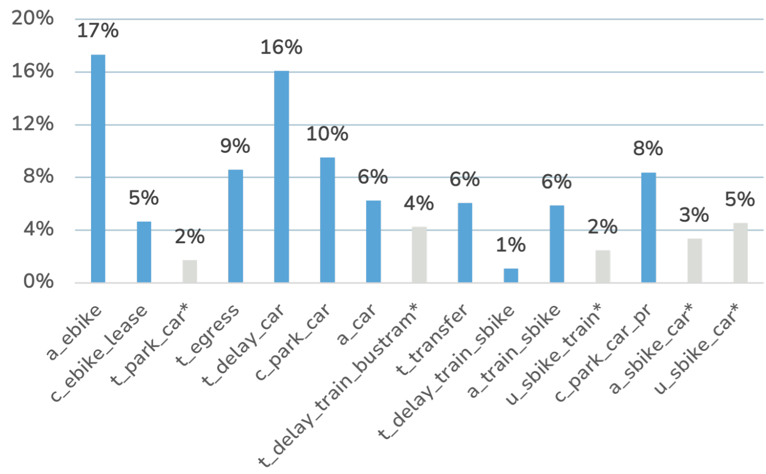

Figure 8.3: Experiment 2: Relative importance attributes

8.2.3 Experiment 3: >30 km

In experiment 3, the MNL interactions model uncovers key insights into the factors influencing commuting mode choices over 30 kilometres. The commuting option of car + shared e-bike was eliminated during the estimation process. One notable finding is the significant negative effect of parking time for cars on utility, suggesting that longer parking times reduce the attractiveness of car commuting. Similarly, delays for train + shared-bike combinations significantly reduce utility, indicating that people are sensitive to delays when using this transportation mode. The allowance for car commuting is the only allowance that is significant and has a positive effect on utility. This could be explained since public transport is already reimbursed 100%, and thus the effect of extra allowance for the last mile travel with a shared e-bike is insignificant.

To evaluate the utility values for the most realistic attribute levels at the academic medical centre in Experiment 3, a base scenario was developed that closely mirrors the current commuting conditions for hospital employees travelling distances over 30 kilometres. The utility calculations under this base scenario are as follows:

$$U(CAR) = 0 - 0.364 \cdot 2 - 0.051 \cdot 5 - 0.018 \cdot 5 - 0.309 \cdot 4 + 0.099 \cdot 20 = -0.329$$

$$U(TR\_BUSTRAM) = 2.540 + 0.011 \cdot 4 + 0.028 \cdot 5 = 2.724$$

$$U(TR\_SBIKE) = 2.904 - 0.033 \cdot 4 + 0.000 \cdot 20 + 0.205 \cdot 0 = 2.772$$

From these results, it can be concluded that the train + shared e-bike option delivers the highest utility, followed closely by train + bus/tram, while car commuting results in significantly lower utility. This reflects a strong preference against car use in this commuting distance scenario.

The alternative specific constants (ASCs) reveal that train + shared e-bike and train + bus/tram are significantly preferred over car commuting, with the highest utility for the shared-bike combination. Interestingly, train + shared e-bike was chosen by 36% of respondents, and its high utility is largely driven by the ASC. However, despite the high utility, the parameter for shared-bike allowance is 0.000 and not significant. This suggests that while shared bikes are generally perceived positively, increasing the allowance for this mode does not significantly enhance its attractiveness.

For train + bus/light rail, the moderately high utility reflects its appeal for long-distance commuters, though it is slightly less preferred than the shared-bike alternative. This may be due to the perceived convenience of a flexible last-mile option like a shared e-bike, compared to relying entirely on public transport.

On the other hand, car commuting delivers the lowest utility, as captured by its lower ASC and corresponding parameters. The strong negative utility reflects respondents' inherent preference to avoid car use for longer commuting distances, likely due to factors such as parking difficulties and increased travel times, particularly in comparison to the smoother, more predictable public transport alternatives.

The socio-demographic factors play a less crucial role in shaping preferences compared to the second experiment. Only gender shows a significant effect on preferences for both train + bus/light rail and train + shared-bike options. Similar to experiment 2, these negative coefficients suggest that, relative to men, women have lower utility for these combined transportation options. Yet, the effect is much weaker than observed in experiment 2. Age has a marginally significant effect (p=0.07) for the train + bus/light rail option, indicating that older respondents may slightly prefer this mode, while age is insignificant for other modes.

When looking at work-related factors, such as shift work and irregular schedules, these interactions are not significant, indicating that irregular work patterns have minimal influence on commuting preferences, similar to the second experiment. This suggests that while demographic factors like gender play an important role, work schedule irregularities do not have a major impact on transportation choices in this model.

In the third experiment, respondents are evenly distributed across gender and age, with no irregular schedules reported. This demographic balance allows for the observation of commuting preferences without the influence of irregular work patterns, aligning with the model's findings, which show that socio-demographic factors like age and gender have less impact compared to earlier experiments.

The absence of irregular schedules and reduced influence of shift work suggests that respondents have more flexibility in choosing public transport. However, parking costs and time emerge as critical factors, with longer parking times reducing the appeal of car commuting. Given the over 30-kilometre commuting distance, alternatives to car use are limited, likely driving the strong preference for train + shared e-bike and train + bus/light rail combinations.

The relative importance of attributes for the third experiment are visualised in Figure 8.4. Here, car parking costs emerged as the most important attribute, followed closely by parking time, which ranked second. This is a significant difference compared to experiment 2, where parking time was insignificant and thus indicating that when covering a bigger commuting distance, also parking time becomes more important. The third most influential attribute was the car allowance, also a logical result in case of longer distance travels. It is notable that more parameters have little impact in this experiment, suggesting that fewer attributes play a significant role in the decision-making process for longer distances.

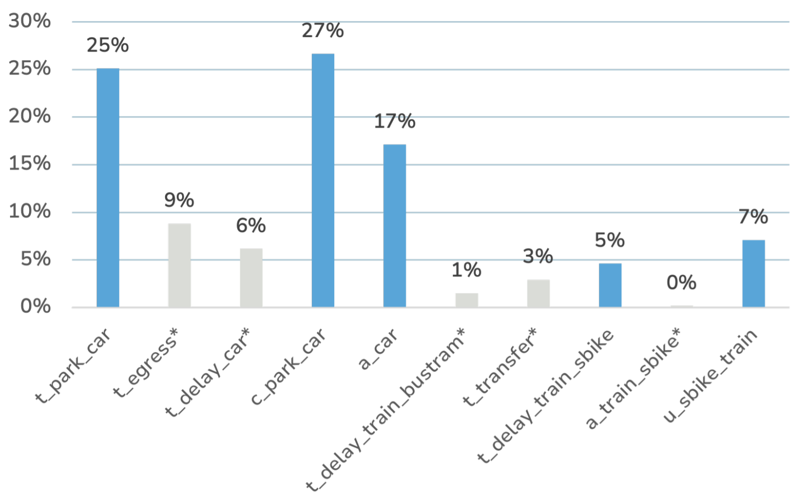

Figure 8.4: Experiment 3: Relative importance attributes

Table 8.3: Experiment 3: Statistical criteria MNL model

	Experiment 3							
	Main effects				*Interactions*			
Statistical criteria								
LL	-844,3				-832,49			
Adjusted McFadden's R^2	0,253				0,257			
AIC	1712,61				1704,97			
BIC	1772,02				1803,99			
	Estimate	*Rob. s.e.*	*Rob. t. rat. (0)*	*p(1-sided)*	*Estimate*	*Rob. s.e.*	*Rob. t. rat. (0)*	*p(1-sided)*
Parameters								
t_park_car	4,05E-04	0,129	2,773	0,003	0,364	0,129	2,828	0,002
t_egress	0,114	0,042	-1,155	0,124	-0,051	0,043	-1,179	0,119
t_delay_car	0,209	0,016	-1,166	0,122	-0,018	0,016	-1,116	0,132
c_park_car	0,001	0,059	-5,105	1,65E-07	-0,309	0,059	-5,230	0,000
a_car	0,006	0,028	3,406	3,30E-04	0,099	0,029	3,438	0,000
t_delay_train_bustram	0,309	0,015	0,693	0,244	0,011	0,015	0,730	0,233
t_transfer	0,178	0,022	1,246	0,106	0,028	0,022	1,267	0,103
t_delay_train_sbike	0,059	0,012	-2,764	0,003	-0,033	0,012	-2,787	0,003
a_train_sbike	0,481	0,006	-0,065	0,474	0,000	0,006	-0,079	0,468
u_sbike_train	0,008	0,064	3,176	7,48E-04	0,205	0,065	3,168	0,001
Alternative specific constants								
C_CAR	-	NA	NA	NA	-	NA	NA	NA
C_TRAIN_BUSTRAM	0,001	1,283	2,725	0,003	2,540	1,631	1,558	0,060
C_TRAIN_SBIKE	0,003	1,272	2,528	0,006	2,904	1,735	1,674	0,047
Interactions								
C_TR_BUSTRAM_I_gender					-0,906	0,514	-1,762	0,039
C_TR_SBIKE_I_gender					-0,918	0,547	-1,676	0,047
C_TR_BUSTRAM_I_age					0,036	0,025	1,474	0,070
C_TR_SBIKE_I_age					0,022	0,026	0,848	0,198
C_TR_BUSTRAM_I_shift					0,178	0,240	0,743	0,229
C_TR_SBIKE_I_shift					0,113	0,237	0,477	0,317
C_TR_BUSTRAM_I_irregular					0,229	0,948	0,242	0,405
C_TR_SBIKE_I_irregular					0,201	1,028	0,196	0,422

*Not statistically significant estimates

8.2.4 Willingness-to-Pay

When interpreting beta parameters or model estimates in transportation research, it is important to note that they cannot be compared directly with each other. This is due to differences in the units of measurement and the fact that these estimates are not standardised. In order to derive deeper insights into how individuals value certain attributes, the concept of Willingness to Pay (WTP) can be used.

WTP represents the monetary value that a person is willing to pay for a one-unit increase or decrease in a given attribute. In transportation research, a common application of WTP is the Value of Time (VoT), which represents the price travellers are willing to pay to save travel time. However, in this study, there is no single, direct measurement of total travel costs because, for example, public transport is fully reimbursed and not varied within the experiment. Instead, there are indirect cost factors such as parking costs and e-bike lease costs, both of which are attributes with high relative importance.

Given the importance of these cost-related factors, they are taken into account when calculating WTP, which allows us to understand how respondents value these attributes.

WTP Lease e-bike commuting

In the case of e-bike lease costs, the WTP is calculated by dividing the parameter estimate for the e-bike travel allowance by the parameter estimate for the e-bike lease cost. The formula for this is:

$$\text{WTP}_{\text{ebike}} = \frac{0.132}{-0.176} = -0.75\,\text{€/km}$$

This result indicates that respondents would need €0.74 of e-bike travel allowance to compensate for each €1 increase in e-bike lease costs. In other words, for every €1 increase in lease costs, respondents expect an additional €0.74 in allowance to maintain the same level of utility.

This is outcome is intriguing, but it is difficult to compare directly to previous studies since e-bike leasing is a relatively new concept. Consequently, there is limited literature for validating this number. However, to provide some context, if a person commutes 20 days per month and covers 20 km/day (400 km per month), the following allowances per kilometre would account for a monthly allowance of:

- 5 ct/km: $0.05 \cdot 400 = 20$€/month
- 10 ct/km: $0.10 \cdot 400 = 40$€/month
- 18 ct/km: $0.18 \cdot 400 = 72$€/month

This suggests that respondents are still evaluating e-bike allowances quite highly relative to lease costs, making them a potentially attractive option if further incentivised. Interestingly, the Living Lab provides 18 ct/km reimburshment for cycling, meaning that for a leased e-bike, an individual would actually earn money by cycling every day. Additionally, the business case could be made regarding potential health benefits and reduced medical costs for the academic medical centre, resulting from the improved well-being of employees who cycle daily.

WTP Car commuting
In the case of car commuting, the WTP can be derived for various factors related to the last mile of the journey. These include parking time, egress time (the time spent after parking and reaching the destination), and delay time. Each of these attributes is compared to car parking costs to understand the monetary value respondents place on reducing these travel inconveniences. Calculating these attributes in €/minute is appropriate because we are focusing on the last-mile, which is measured in minutes rather than hours.

The WTP for reducing parking time is calculated as:

$$\text{WTP}_{\text{parking}} = \frac{-0.032}{-0.145} = 0.22\,\text{€/min}$$

This result suggests that respondents are willing to pay around €0.22 per minute to reduce their parking time. In practical terms, this means that for every minute saved on parking, respondents value this reduction at €0.22.

As for the reduced egress time, the WTP is:

$$\text{VoT}_{\text{egress}} = \frac{-0.065}{-0.145} = 0.45\,\text{€/min}$$

Respondents are willing to pay around €0.45 per minute to reduce egress time. This shows that transitioning from the car park to the hospital or other final destinations is seen as an inconvenience, and respondents place a higher value on reducing this time compared to parking time.

The reduction in car delay time, which mainly occurs at the Science Park and thus also within the last mile of the journey, is calculated as:

$$\text{VoT}_{\text{delay}} = \frac{-0.061}{-0.145} = 0.42\,\text{€/minute}$$

Respondents are willing to pay €0.42 per minute to avoid delays in their car commute. This WTP could indicate that delays are a source of frustration, particularly in the last mile of the commute.

For the last mile of car commuting, respondents thus place significant value on reducing egress time and delays, with €0.45 per minute for egress and €0.42 per minute for delays, compared to €0.22 per minute for parking time. This demonstrates that respondents are more concerned with the time spent after parking or dealing with delays than with the actual time it takes to find parking.

8.3 Attribute effects on modal split

Different attributes can significantly influence the modal split. As previously discussed, this analysis focuses on the four attributes with the highest relative importance. These attributes offer valuable insights and can serve as a foundation for developing interventions that promote a shift toward more sustainable commuting modes. Due to the limited sample size of only 13 respondents in experiment 1, it is excluded from this section, as it provides insufficient data to form a reliable basis for intervention strategies. Therefore, only the results from experiments 2 and 3 are considered for developing actionable insights.

To analyse the impact of attributes with the highest relative importance, the modal split was calculated for each of the three attribute levels. For instance, when evaluating the travel allowance for lease e-bikes, the modal split was first calculated by applying a filter for a lease e-bike allowance of 0 cents per kilometre. Next, the filter was adjusted to 5 cents per kilometre, and the modal split was recalculated. Finally, the same process was repeated for an allowance of 10 cents per kilometre. This approach was followed for each attribute, ensuring a consistent analysis across different levels.

8.3.1 Experiment 2: Lease e-bike travel allowance

Figure 8.5 illustrates a clear shift in the modal split towards leasing e-bikes as the travel allowance increases. With zero allowance, public transportation dominates, but with an increase to 5 cents per kilometre, the lease e-bike share dominates. Even with 'only' 10 cents per kilometre, the modal split for lease e-bikes is more than 50%. Considering the commuting distance of 11-30 kilometres, this experiment demonstrates the great potential to incentivise commuters to lease e-bikes.

Note: it is important to note that the relatively high alternative-specific constant for leasing e-bikes suggests that there is more at play than just the financial allowance as a stimulus. This implies that factors such as convenience, personal preferences, or the perception of e-bikes as a viable commuting mode also contribute significantly to choosing e-bikes, reinforcing that simply increasing financial incentives may not be the sole driver of behaviour change.

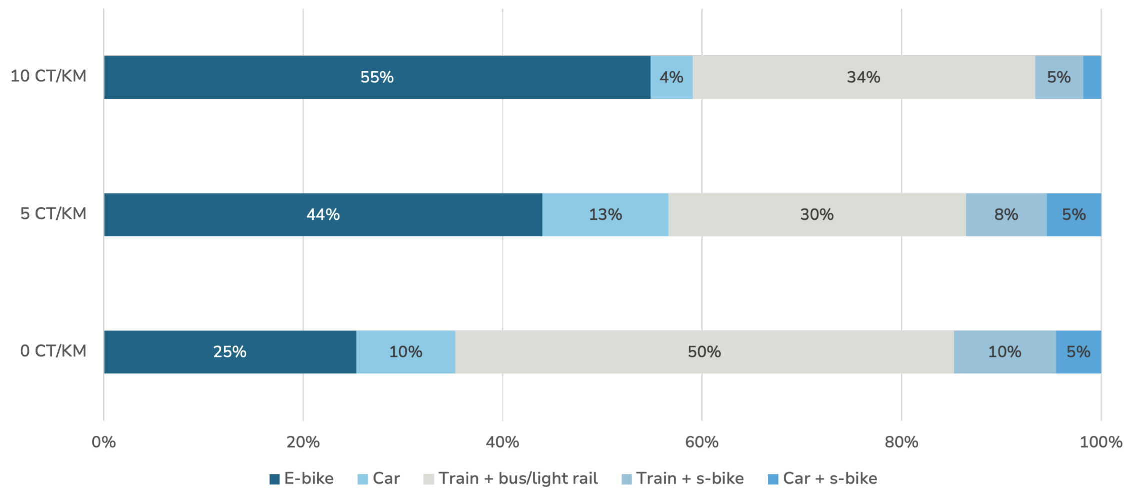

Figure 8.5: Effect of travel allowance for lease e-bikes on modal split

8.3.2 Experiment 2: Car delay

A strong effect is visualised in Figure 8.6 of the delay on the modal split. With zero car delay, the mode share of the car is much higher than with a ten or twenty-minute delay time. In the case of car delays, both ten and twenty minutes, there is a noticeable shift toward train and e-bike commutes. This indicates that longer car delays encourage individuals to switch to more sustainable modes of transport as the inconvenience of car travel grows.

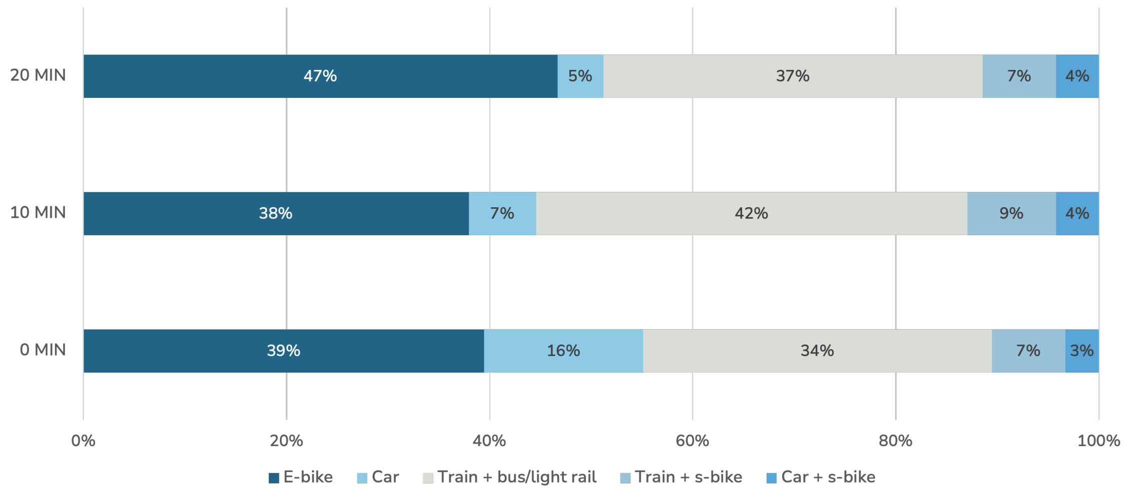

Figure 8.6: Effect of car delay on modal split

8.3.3 Experiment 3: Car parking costs

Figure 8.7 illustrates how varying car parking costs strongly influence the modal split for longer-distance commuting. Car commuting dominates at the lowest parking cost, with train options being far less popular. As parking costs rise to €4/day and €7/day, there is a significant shift towards train commuting, especially the train combined with bus/light rail. This indicates that higher car parking costs discourage car use and encourage a modal shift towards public transport.

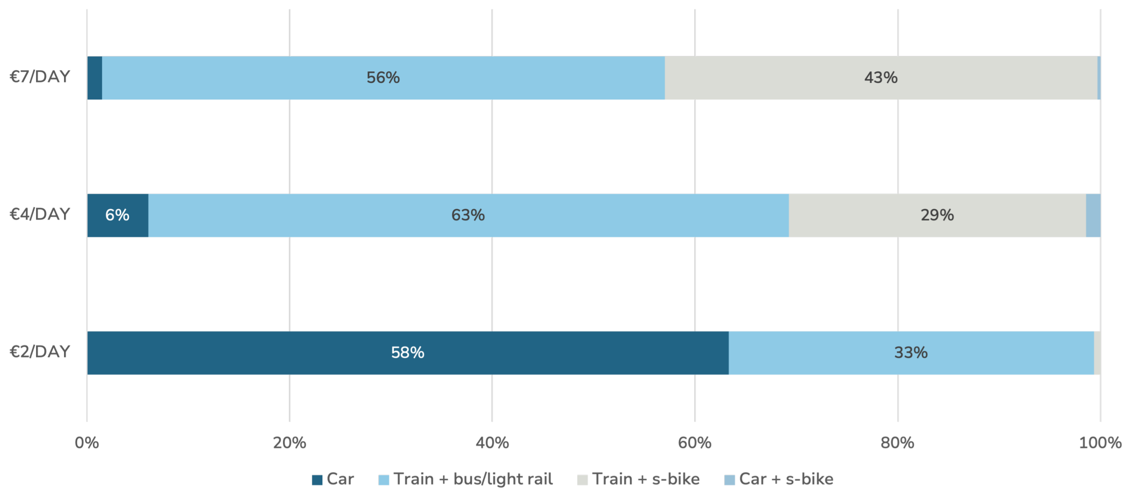

Figure 8.7: Effect of car parking costs on modal split

8.3.4 Experiment 3: Car travel allowance

A remarkable effect of car travel allowance on the modal split, can be observed in Figure 8.8. Surprisingly, there is a decrease in car commuting between the 10 and 15 cent/km allowance levels, followed by an increase when the allowance reaches 20 cent/km. This pattern could be due to the relatively low parameter estimate for the travel allowance. The low value suggests that small changes in the allowance have a limited initial impact on car commuting. Still, once the allowance surpasses a certain threshold, its influence becomes more noticeable. This suggests that interventions aiming to discourage car commuting could be more effective if the travel allowance is kept below that threshold.

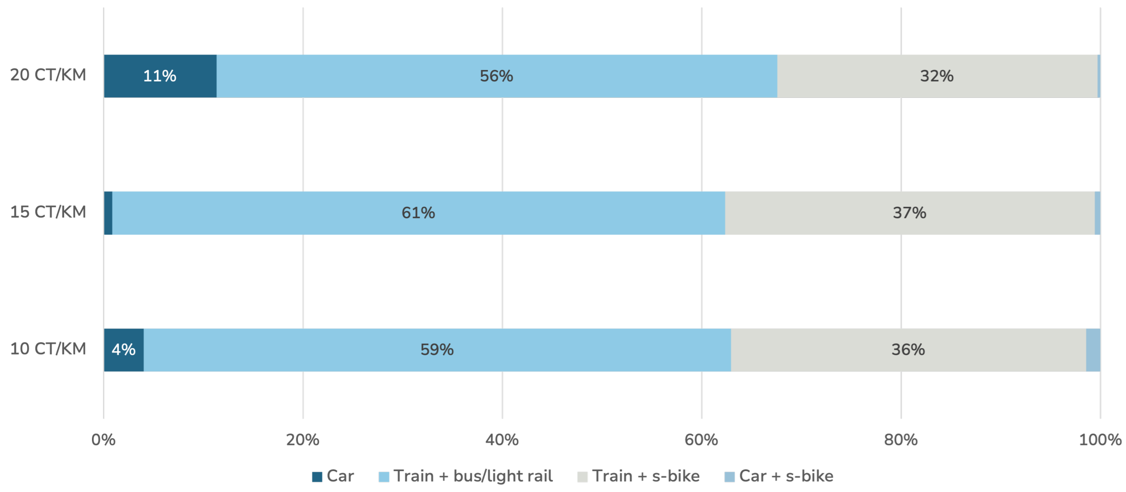

Figure 8.8: Effect of travel allowance for cars on modal split

To reinforce the shift towards sustainable commuting modes, the four most important attributes —lease e-bike allowance, car delays, parking costs, and car travel allowance— can be leveraged to make alternatives more attractive. The experiment results indicate that increasing e-bike lease allowances and implementing higher car parking costs or delays can incentivise people to shift away from car commuting. This transition can lead to new habits being formed, as participants from the Living Lab reported that, after experiencing the benefits of alternative modes, they no longer wanted to revert to car commuting.

However, for employees with irregular schedules, where public transport options may be unavailable during late or early hours, car parking authorisation should be reinstated with a limited number of free passes, allowing them to park for free a few times a month. Similarly, participants who feel unsafe cycling in the dark should have flexible commuting options and not be penalised for choosing to drive because of safety concerns. During the focus group discussions, participants suggested providing every employee with two free parking passes per month, a number that was generally agreed upon as reasonable. It was also proposed that these passes should not roll over to the next month to prevent employees from driving simply because they had unused passes.

Moreover, participants highlighted the need for better information about alternative routes in case of public transport disruptions. Providing tailored travel advice or creating a network where employees from the same area can share travel experiences could further encourage a shift toward sustainable commuting, even in less predictable scenarios.

The analysis shows that the initial hypothesis regarding shift workers and employees with irregular schedules being less likely to adopt sustainable commuting modes is not fully supported. The initial hypothesis stated: *Hospital employees working under shift schedules, particularly those with irregular or on-call shifts, are less likely to adopt sustainable commuting modes than employees with standard work schedules.* Contrary to expectations, these employees do not demonstrate a significant aversion to sustainable commuting options such as public transport. In fact, shift workers displayed a positive attitude towards public transport, even though it was assumed that the inconvenience of multiple transfers might deter them. While habitual car use was noted, it did not overwhelmingly prevent these workers from considering alternative modes, suggesting that shift schedules do not heavily influence a reluctance to adopt sustainable commuting modes.

Key highlights

- The MNL model was used as the baseline, as the LCCM failed to converge due to homogeneity and small sample size. MNL interaction models showed a better fit for experiments 2 and 3.
- Experiment 1 (<= 10 km): E-bike leasing costs significantly reduced utility as they increased, with private (e-)bikes being preferred over leased e-bikes and public transport. Car commuting was never chosen. However, insights from this experiment are limited due to the small sample size.
- Experiment 2 (11-30 km): E-bike leasing allowance had a significant positive effect on utility, making e-bikes a highly preferred mode of transport. Car delays and parking costs also significantly reduced the attractiveness of car commuting, encouraging shifts to public transport and e-bike options.
- Experiment 3 (<30 km): Parking time and costs for cars were the most influential attributes, with longer parking times and higher costs strongly discouraging car use. The allowance for car commuting showed a mixed effect, with a noticeable impact once it exceeded a certain threshold, reinforcing the idea that travel subsidies can influence commuting mode choices. The option train + shared e-bikes was limitedly chosen and eliminated from the analysis.
- Gender and age played notable roles in influencing transportation preferences, with women and older respondents generally less likely to prefer e-bikes and public transport combinations. At the same time, shift work and irregular schedules had minimal impact.
- Increasing e-bike allowances and car parking costs shifted preferences toward sustainable modes, while car delays also encouraged alternative transport. Financial incentives, particularly larger travel allowances, can significantly influence commuting choices.

9 Conclusion & discussion

The academic medical centre, located in one of the Netherlands' largest science parks, faces significant challenges from traffic congestion and CO_2 emissions related to employee commuting. In line with the Green Deal for Sustainable Care, the centre aims to reduce CO_2 emissions by 4.2% in 2024, promote employee health, and raise awareness of the links between human activity and environmental health. To achieve these goals, the Living Lab Sustainable Transport was launched, a collaboration between the academic medical centre and Pon Mobility Nederland, to explore tailored mobility solutions for hospital workers with specific needs, such as evening, night, and on-call shifts. With employee commuting contributing 27% to the medical centre's direct emissions, transitioning from car-based commutes to more sustainable modes is critical. This research's insights are not only relevant to the healthcare sector but can also inform sustainable mobility practices in other industries facing similar commuting challenges.

Participants in the Living Lab benefited from special commuting incentives, including fully reimbursed public transport, a 16 ct/km cycling reimbursement, and free access to shared e-bikes. Although car commuting was not prohibited, parking authorization was restricted during weekday mornings. The voluntary nature of participation, combined with these benefits, contributed to a unique commuting environment that incentivised a modal shift towards more sustainable options.

A mixed-methods research approach, beginning with a literature review, examined how shift work and irregular schedules influence commuting choices and explored barriers to adopting sustainable transport. A Discrete Choice Model (DCM) was developed to evaluate the trade-offs between commuting alternatives, considering the specific location and infrastructure challenges of the academic medical centre. Initially, a Latent Class Choice Model (LCCM) was considered to account for heterogeneity in preferences. However, due to significant non-trading behaviour observed in the data, the LCCM could not be effectively estimated. As a result, the Multinomial Logit (MNL) model, expanded with interaction effects, was used to capture variations in commuting preferences, such as age, gender, and shift work. The MNL model with interactions performed better than the main-effect model in several cases, particularly for mid-range commuting distances (11-30 km), where the inclusion of interaction terms significantly improved the model's goodness of fit. For shorter and longer commutes, the differences between the main-effect and interaction models were less pronounced, but the interaction model still provided valuable insights into how different factors influence commuting decisions.

When reflecting on the conceptual model visualised in Figure 4.1, a lot has changed. Due to limitations imposed by the academic hospital, only socio-demographics, age and gender, work-related characteristics, type of shift work, and regular or irregular schedules could be integrated into the model. Besides this, the findings will be discussed in alignment with the literature, and the contrasting findings will be elaborated. All elements are concluded in a final conceptual model visualised later on in Figure 9.1.

9.1 Alignments with literature

The findings of this study align closely with existing literature on sustainable commuting practices, particularly in relation to the challenges faced by hospital employees with non-standard schedules and the location-specific constraints of the academic medical centre. One key insight is the impact of the high congestion levels at the Science Park, which made car commuting less attractive for employees. This aligns with previous studies that show how congestion in areas with limited parking options discourages car use, especially when there are viable public transport alternatives. In this case, the introduction of a fast and efficient light rail service, particularly for employees commuting via the central train station, became an attractive alternative to driving. The data support this, with 70% of employees in the Living Lab shifting to public transport, a significant modal shift compared to previous patterns.

For shift workers and employees with evening or night shifts, public transport, although attractive during standard hours, remains impractical due to its unavailability during off-peak times. This group expressed concerns about the safety of cycling at night, and as such, car commuting still served as a critical mode. These insights are consistent with literature that highlights the limitations of sustainable commuting options for shift workers who require reliable, flexible transportation for early or late shifts. Additionally, those balancing work with personal responsibilities, such as childcare, echoed the need for flexible commuting options, reinforcing the importance of door-to-door transport that cars provide. While sustainable alternatives like cycling or public transport have their appeal, the need to integrate personal schedules, makes car use more convenient for many.

The importance of reimbursement policies, as highlighted in both the literature and this study, remains a key factor in shaping commuting decisions. Incomplete reimbursement for public transport costs was a significant deterrent for many respondents, reinforcing the findings of Zadeits (2024), who identified financial support as a crucial incentive for adopting sustainable commuting practices. The financial incentives offered in the Living Lab, particularly the full reimbursement for public transport, played a fundamental role in shifting behaviour. The reimbursement made public transport affordable, resulting in 70% of respondents opting for this mode. Cycling also saw an increase, which could be explained by the 16 cents travel allowance, with 14% of employees choosing to bike to work. Although it is important to consider the seasonal effect, as the study took place during the summer when weather conditions were favourable for cycling. Also, the good cycling infrastructure on the Science Park can be a stimulance as adressed by Esztergár-Kiss et al. (2021), active modes of transport are viewed favourable when infrastructure supports them.

In contrast, only 15% of participants continued to rely on car commuting, leading to a drastic 93% reduction in parking movements. When looking at increase parking costs, it is clear that with and increase from 2 €/day to 7 €/day, the modal shift reduces from 58% to 1%. This shift highlights the powerful influence of financial incentives and restrictions on car parking in driving the adoption of more sustainable commuting modes, a finding that is well-supported by existing research on the role of cost and convenience in commuting decisions.

The relationship between car commuting and age, however, aligned with existing studies, as older respondents were more likely to favour car use. Life events such as having children and moving to suburban areas, which often require greater flexibility, likely contribute to this preference (Lee et al., 2020). In contrast, younger employees were more likely to choose cycling, a finding that matches the general literature which highlights the connection between younger demographics, health-conscious behaviour, and a preference for sustainable commuting options (Esztergár-Kiss et al., 2021). This trend also reflects the importance placed on health by this younger group, supporting earlier studies that link active commuting to better physical and mental well-being (Parmar et al., 2023).

9.2 Contrast with literature

The most striking contrast between this study's findings and the existing literature is the exceptionally low rate of car commuting observed among Living Lab participants. In the Netherlands, car commuting accounts for around 70% of all trips, but in this study, less than 5% of the participants chose car commuting as their preferred mode of transport. This is totally the opposite to the superior belief of cars due to their reliability and control, but also their level of comfort, convenience, privacy and reduced physical exertion (De Vos et al., 2016; Parmar et al., 2023). In line with this is the surprising finding of a minimal difference in attitudes towards cars and public transport, namely 0.1 difference in averages on a scale of one to five. The positive reception of public transport may be linked to the full reimbursement offered during the Living Lab, which encouraged at least 70% of participants to shift from car to public transport, and led to a absurd reduction of 93% in car parking movements. This drastic reduction can also be attributed to the specific conditions of the Living Lab, such as restricted car parking authorisations, creating a unique commuting environment where cars became significantly less attractive.

Additionally, while previous studies have suggested that shift workers and those with irregular schedules tend to rely more on cars due to the flexibility and control they offer, this study found that their commuting preferences were surprisingly similar to those of regular workers. Despite facing challenges such as stress, fatigue, and safety concerns during night shifts, shift workers demonstrated a generally positive attitude toward public transport and a neutral stance toward car commuting. Moreover, despite the well-researched and interview insights from Zadeits (2024), physical strain and health challenges associated with shift work, the majority of respondents, even those working irregular hours, expressed a pro-bike commuting attitude, suggesting a growing recognition of the health benefits associated with active commuting. This is a significant difference from expectations, as literature often points to comfort and convenience as primary concerns for those dealing with health-related issues such as fatigue and stress (Gu et al., 2023). Interestingly, the only notable difference was that shift workers were slightly less positive about (e-)bike commuting, though this can also be explained by their specific concerns about safety, especially when cycling at night.

The study's findings on cycling, particularly electric bicycles (e-bikes), reveal some unexpected insights. While logical reasoning suggests that cycling is feasible for shorter commutes, the data show that employees are willing to cycle distances over 30 kilometres on e-bikes, particularly when incentivised. The lease e-bike emerged as a promising new alternative, even though under Dutch regulations, cyclists with lease e-bikes do not receive standard cycling reimbursements. However, the introduction of e-bike travel allowances—ranging from 0 to 5 to 10 cents per kilometre, resulted in a significant increase in e-bike use, with modal split rising from 25% to 44% and then to 55%. This demonstrates the strong potential of financial incentives in shifting commuting preferences toward e-bikes.

The calculated willingness to pay (WTP) for e-bike allowances indicates that respondents would require €0.74 in travel allowance to compensate for each €1 increase in lease costs. This suggests that even modest reimbursements can cover a large portion of the lease costs, making e-bikes an attractive daily commuting option. With the Living Lab providing an 18 ct/km reimbursement, many employees would effectively earn money by cycling daily on a leased e-bike. Additionally, from a business perspective, increased cycling offers the potential to reduce employer costs related to insurance and illness, as regular cycling improves employee health and reduces absenteeism. This creates a compelling case for further promoting e-bike leasing schemes as a sustainable commuting option.

A final unexpected outcome involved the non-elected of Park & Ride (P+R) facilities. While interviews conducted by Zadeits (2024) had highlighted P+R as a potential solution to encourage public transport use, only 4% of participants chose P+R in experiment 2, and just 1% in experiment 3. This could be explained by the fact that the P+R locations were situated near the hospital, but many participants showed an overall aversion to car commuting altogether. Therefore, P+R locations close to home might have been more attractive, as commuters seem to prefer avoiding cars for their entire journey rather than only part of it.

To conclude, the feasibility of replacing car commuting with sustainable modes can be significantly enhanced through a combination of financial incentives and policy measures. For shorter commutes, incentivising e-bike leasing through allowances has clearly increased e-bike usage. Additionally, policies like car delays and higher parking costs effectively reduced car use. However, employees with non-standard schedules require additional support, such as free parking passes for occasional car use during early or late shifts when public transport is unavailable. Safety concerns, especially for those cycling at night, must also be addressed to make sustainable modes a practical alternative. Overall, while financial incentives and infrastructure improvements are promising strategies to promote a modal shift, the needs of employees with irregular schedules must be met with flexible and safe commuting options to ensure the sustainability of these solutions.

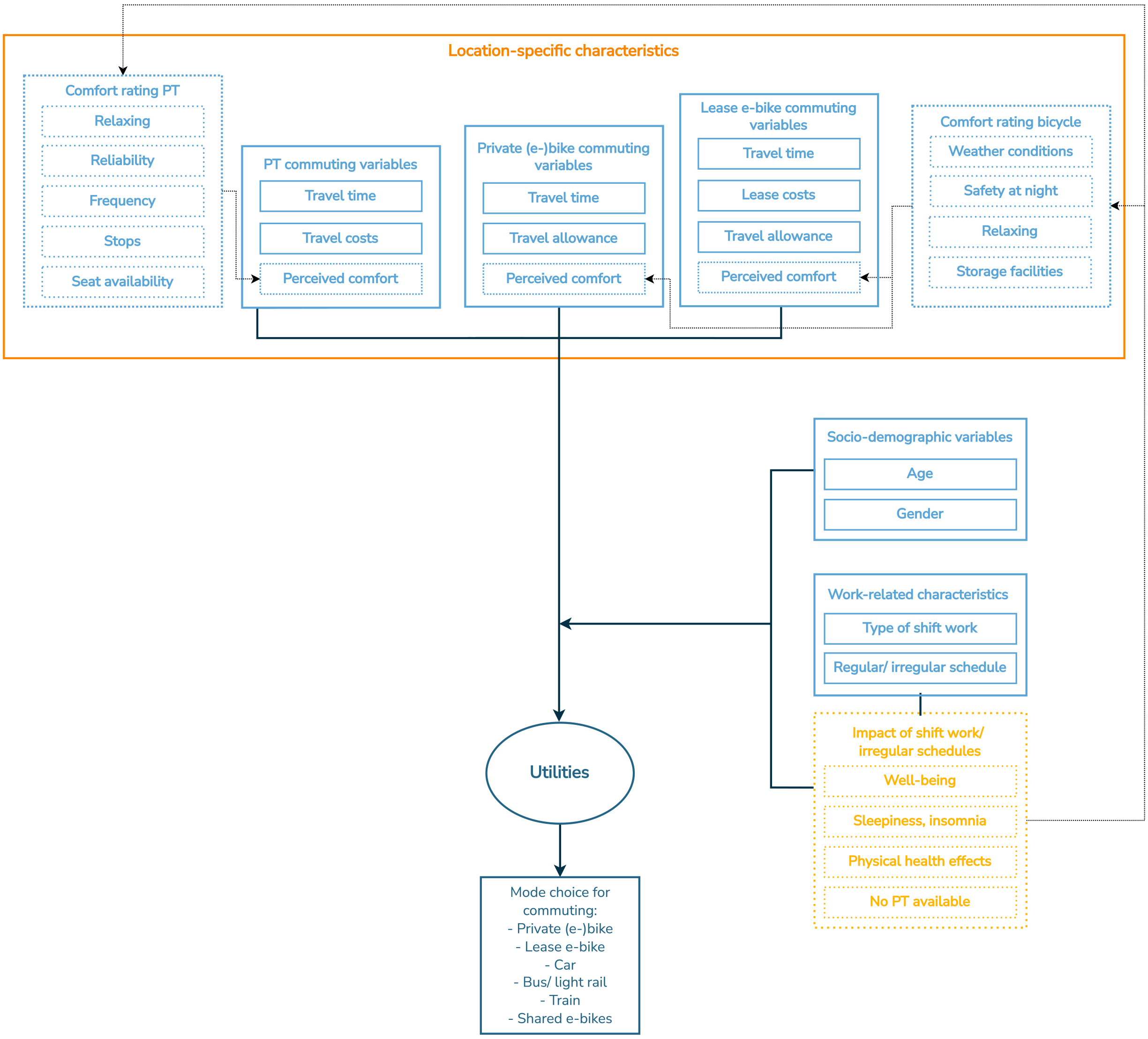

Figure 9.1: Final conceptual model

Building on the conceptual model presented in Chapter 4, Figure 4.1, the feasibility of a particular mode of transport strongly depends on various personal factors, especially in the case of non-standard employment. These factors are primarily related to perceived comfort or ease. For example, employees working night shifts may not feel safe cycling home, while those with childcare responsibilities may find public transport impractical. Furthermore, these factors differ for each individual, sector, and location, reflecting specific work-related and location-specific characteristics. The decision-making process involves a complex interplay between travel time, travel cost, and perceived comfort, with all these aspects affecting the choice of commuting mode. These findings culminate in an updated version of the conceptual model, as shown in Figure 9.1, which integrates the key insights from this research.

9.3 Policy recommendations and implications

In light of the findings from the Living Lab interventions and the upcoming changes to the collective bargaining agreement, several policy recommendations can help support a modal shift towards sustainable commuting for hospital employees. These recommendations are designed to address the unique challenges employees face with irregular hours and shift work while encouraging more environmentally friendly commuting practices.

1. Monitoring Public Transport Use and Shared E-bike Alternatives
As of October 1st, the collective bargaining agreement will introduce significant changes, including the 100% reimbursement of public transport for all employees. This adjustment, combined with the findings from the Living Lab, which showed a positive response to full reimbursement for public transport interventions, is likely to increase demand, particularly for the already limited light rail and bus services. With more employees potentially choosing public transport as their primary commuting mode, location-specific challenges could reach their limits, e.g. the tram system could face overcrowding during peak hours. Therefore, it is crucial to closely monitor the shared e-bike system regarding supply and demand as an alternative for employees who cannot use the light rail or bus services.

From January 1st, employees can change their commuting allowance based on their daily travel mode, introducing greater flexibility. This shift offers a unique opportunity to encourage sustainable options during regular times and to choose the modality that suits personal needs. The hospital should carefully track the extent to which employees switch between modes of transport and how often they utilise the flexibility offered by this new system. By closely monitoring these trends, it will be possible to adjust policies or interventions to better support employees in making sustainable commuting choices.

2. Promote e-bike leasing with travel allowance
To further promote sustainable commuting, implementing a travel allowance for lease e-bikes could be a highly effective policy. The study's findings demonstrated that financial incentives, such as e-bike travel allowances, significantly influence commuting behaviours. When allowances of 5 to 10 cents per kilometre were introduced, the modal split for e-bike commuting increased dramatically from 25% to 55%. Given the clear potential of e-bikes for longer commutes—often exceeding 30 kilometres—offering a financial incentive can make this option even more attractive for employees.

Significantly, 74% of the academic medical centre's population live within 30 kilometres of the hospital, making e-bikes a highly viable and sustainable option for most employees. Providing a travel allowance of 18 cents per kilometre, as already offered for standard cycling, would mean that individuals who cycle 20 km every day would receive approximately €72 per month. Depending on the lease costs, this could allow employees to effectively "make money" by cycling more frequently, making it an even more appealing option.

Moreover, promoting e-bike leasing not only benefits employees by reducing commuting costs, but it also offers employers potential savings on insurance and healthcare costs due to the health benefits of regular cycling. This policy would complement existing measures and provide a robust financial incentive, helping to create a more sustainable and health-conscious commuting culture across the hospital.

3. Implementing Parking Authorisation for Shift Workers
Given the unique challenges employees face with irregular hours, especially those working night shifts, it is essential to implement a parking authorisation system tailored to their needs. While promoting a shift away from car commuting is important, it is also crucial to consider the safety and convenience of these employees. Public transport may not always be available during off-peak hours, and employees may feel unsafe commuting by bike or walking late at night.

To balance the need for safety with the hospital's sustainability goals, it is recommended that parking authorisation be granted only on days when employees are working irregular hours or shifts. Additionally, providing all employees with two free parking passes per month for exceptional circumstances would give them the flexibility to drive when necessary without undermining the overall goal of reducing car use. By limiting parking authorisation to specific situations, the hospital can ensure that employees feel supported in their commuting choices while encouraging the use of more sustainable alternatives whenever possible.

4. Providing Tailor-made Commuting Advice
One of the key barriers to adopting alternative transport modes is the time and effort required to research and plan new routes, particularly in the event of public transport disruptions. Employees are often too busy or lack the motivation to look up alternative options, which can discourage them from switching to more sustainable commuting modes. To address this, the hospital should offer tailor-made commuting advice that provides employees with clear, personalised information on their travel options. This advice

should include standard and alternative routes, and differences in costs, ensuring that employees are well informed about their commuting choices without the need to search for information themselves.

Moreover, promoting e-bike leasing not only benefits employees by reducing commuting costs, but it also offers employers potential savings on insurance and healthcare costs due to the health benefits of regular cycling. Employees who cycle regularly are likely to experience improved physical health and lower absenteeism, creating a compelling business case for further supporting this mode of commuting. By encouraging e-bike use, employers can reduce long-term health-related expenses while fostering a healthier, more active workforce. This policy would complement existing measures and provide a robust financial incentive, helping to create a more sustainable, health-conscious commuting culture across the hospital.

9.4 Limitations & future research

This study offers valuable insights into the commuting behaviours of hospital employees, but several limitations must be acknowledged.

Voluntary participation and unique group
The voluntary nature of participation in the Living Lab may have introduced bias, as those more enthusiastic and motivated to explore sustainable commuting options were likely overrepresented in the study. This eager population may not reflect the attitudes and behaviours of the less enthusiastic or less willing segments of the broader employee base, potentially skewing the results toward a more optimistic outlook on adopting sustainable commuting practices. This resulted in a homogeneous group performing non-trading and/or strategic behaviour, resulting in the inability to estimate the LCCM and retrieve more than one class. Therefore, the findings might overstate the feasibility and appeal of alternative commuting modes for the general hospital workforce. The full reimbursement for public transport was such a strong incentive that it's unclear to what extent this alone may have driven the observed modal shift.

Participant representativeness
One major limitation is the lack of representativeness in the Living Lab's participant population. The commuting distances of participants differed significantly from those of the broader employee base: 7% lived within 10 km, 45% lived between 11 and 30 km, and 48% lived more than 30 km from the hospital. By contrast, the actual commuting distances for the 13,000 hospital employees were 33%, 40%, and 26%, respectively. This discrepancy raises questions about the generalisability of the findings, as the voluntary nature of participation may have introduced bias, with more enthusiastic individuals likely to have taken part.

Complexity of the Choice Experiment
The detailed nature of the Discrete Choice Experiment (DCE) presented challenges, particularly with the smaller sample size. Originally designed for broader use within the whole academic medical centre's population of 13,000, the experiment's complexity made it difficult to achieve statistical significance in this smaller group. Additionally, this smaller group resulted in being more homogeneous in their preferences than expected, which prevented the estimation of a Latent Class Choice Model (LCCM) due to a lack of sufficient heterogeneity. In a larger population, this issue would likely not have been as pronounced, as more diverse preferences and behaviours would provide the necessary variation for LCCM estimation. As a result, the findings may not fully represent the broader employee population's commuting preferences.

Lack of context for non-standard employment
Another limitation is the absence of specific context related to shift work and on-call shifts when participants made their commuting choices. Shift workers face distinct challenges, such as non-standard hours and public transport unavailability during off-peak times. Some respondents acknowledge that they filled in the survey, as if it was a normal day.

To address the limitations outlined above and build on the current study's findings, several future research directions are recommended.

Explore perceived comfort
Building on the findings of this study and the updated conceptual model in Figure 9.1, future research should delve deeper into how perceived comfort influences the adoption of sustainable commuting alter-

natives, particularly for employees with non-standard schedules. Due to the high preference for public transport and (e-)bikes within the Living Lab population, this group provides an ideal opportunity to examine the perceived comfort levels of these two modalities in more detail. Future studies should focus on key factors such as safety concerns, ease of use, and flexibility, especially for different commuting distances and work schedules. Understanding these factors in relation to cycling and public transport will offer valuable insights into how these sustainable modes can be better designed and promoted. Additionally, research into how perceptions of comfort shift when financial incentives or policy measures, such as e-bike allowances or parking restrictions, are introduced could provide practical guidance for further enhancing the adoption of sustainable commuting options.

Expand participant base

Future research should extend the DCE to include the full population of hospital employees. This would provide a more representative sample and allow researchers to test for heterogeneity among employees with varying levels of enthusiasm and readiness to adopt sustainable commuting practices. Switching to unlabelled alternatives could also help reduce non-trading or strategic behaviour, and removing the 0.23 cents per kilometre car cost from the experiment may provide a more accurate reflection of actual commuting expenses.

Account for commuting reachability

The current study's DCE was based on commuting distance, which may not fully capture employees' actual commuting experiences, particularly in terms of public transport travel times. Future research could focus on commute reachability within specific time frames, rather than just distance, to provide a more accurate understanding of how employees choose their commuting options.

10

Reflective gaze

Governance refers to the framework of rules and processes through which decisions are made and implemented in an organisation. In this research project involving multiple stakeholders, governance played a key role in shaping the research scope and outcomes. The differing objectives of the academic medical centre, Pon, and my own introduced complexities that sometimes constrained the study's focus.

A major challenge was aligning the interests of all parties. The academic medical centre focused on ensuring employee satisfaction and minimising disruption to operations, while Pon aimed to promote sustainable mobility, particularly e-bikes. As the researcher, my goal was to objectively explore commuting behaviours. These competing priorities sometimes narrowed the research scope.

The academic medical centre, concerned about how the choice experiment would be perceived, influenced the framing of the survey to avoid making car commuting seem like a dominant option. This led to excessive explanation in the experiment, potentially biasing participants towards sustainable options. Moreover, the reimbursement rate of €0.23 per kilometre for car commuting may have made the car seem less attractive, introducing further bias.

Initially, the plan was to roll out the survey to all 13,000 employees, but due to logistical and privacy concerns, it was limited to the smaller Living Lab group. This choice experiment, designed for a larger population, may have overwhelmed participants, influencing their responses to align with familiar commuting habits rather than exploring new options.

Data collection was also delayed due to privacy issues and lengthy approval processes, limiting the study's depth. Socio-demographic data were not fully collected, and the second round of the experiment was conducted too late for inclusion in the analysis, reducing the overall insights.

Stakeholder interests heavily influenced the research. The academic medical centre's focus on public perception, combined with its decision to retract parking authorisation for employees, may have created a negative bias against car commuting despite employees' actual preferences. Additionally, participants knew their responses would be reviewed by the academic medical centre, which may have led to strategic answers that aligned with the hospital's sustainability goals, potentially distorting the data.

The multi-value environment, with each stakeholder having different tolerance levels for outcomes, also shaped the research. Pon and my own interests in e-bikes led to a deeper exploration of this option, while alternatives like public transport or carpooling were less thoroughly examined.

This governance dynamic highlights the complexities of managing socio-technical systems, a key focus of the CoSEM programme. The varying priorities of stakeholders had a direct impact on the research results, emphasising the need for clear governance mechanisms that balance stakeholder interests without compromising the research's integrity.

In conclusion, while governance ensured alignment with stakeholder goals, it also introduced biases that affected the research outcomes. Future studies should aim for more neutral frameworks that allow for broader exploration and minimise the influence of competing stakeholder interests.

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A

Appendix A. Celebratory event

Figure A.1: Keynote speakers

Figure A.2: Pop-up exhibition

Figure A.3: Celebratory event

B

Appendix B. Methodological approach

B.1 Development procedure DCE

The development of the DCE followed a structured strategy consisting of several key steps:

- *In-depth Interviews:* Initial interviews conducted by Zadeits (2024) with employees of the academic hospital provided valuable insights for shaping the DCE, despite these participants not being part of the Living Lab.
- *Literature Review:* A thorough review of existing literature was conducted to identify relevant attributes, levels, and methodological approaches. This step aligned with previous research practices and informed the design's theoretical foundation.
- *Stakeholder Consultation:* Collaboration with Pon and the Living Lab project team was critical in refining the selected attributes, their levels, and the phrasing of questions. This step ensured that the design was both practical and relevant to the study's objectives.
- *Piloting:* The DCE was piloted with the entire Living Lab project team. Feedback from this pilot was used to make final adjustments to the design before distribution.

Choice of Efficient Design

The decision to use an efficient design was driven by the impracticality of employing a full factorial design, which would have resulted in approximately 1000 choice sets. An efficient design allows for a more manageable number of choice sets while maintaining attribute balance and avoiding dominant alternatives. Dominant alternatives, perceived as superior in at least one aspect while comparable in others, limit the ability to gather meaningful trade-off information. This approach effectively minimises standard errors and ensures robust parameter estimates.

Use of Priors

Priors — predetermined estimates of parameter values — are a crucial component of efficient designs. As Arentze and Molin (2013) and Molin and Kroesen (2023) conducted similar research about travel behaviour in the Netherlands, the estimated parameters outcomes are suitable to use as priors in this research. By incorporating these priors, the design was able to balance the utilities of the choice alternatives, reducing the potential for bias and improving the overall accuracy of the estimates.

Degrees of Freedom & Testing for Linearity

Ngene requires selecting the number of choice sets before generating an efficient design. This number depends on the model's parameters and the information each choice provides. Each choice set adds a degree of freedom, which must exceed the number of parameters estimated. In this study, certain parameters were tested for linearity. For instance, the perceived difference between parking costs of €1 to €2 and €5 to €6 may not be linear. Similarly, the delay attribute was also tested for linearity, necessitating two extra parameters for each. This requires the minimum number of choice sets at six for experiment 2 and five for experiments 1 and 3. To ensure sufficient information and maintain attribute balance, the number of choice sets was doubled to twelve, which aligns with the recommended number of around ten choice sets (Molin, 2024).

Attribute Level Balance and Choice Sets

Efficient designs strive to achieve attribute balance, ensuring that each attribute level is represented an equal number of times across the choice sets. This balance is crucial for minimising the standard errors of parameter estimates, thereby maximising the information obtained about trade-offs and enhancing the model's reliability. To maintain this balance, the number of choice sets must be divisible by the number of levels for each attribute. In this study, with all attributes having three levels, attribute balance is preserved using twelve choice sets. Ideally, all attribute levels should be either even or odd, a criterion met here as all attributes share the same number of levels.

Use of Ngene and Design Validation

Ngene software was employed to generate an efficient design. The resulting designs were subsequently checked for dominant alternatives using Multinomial Logit (MNL) utilities and probabilities. For each of the three experiments, a separate design is generated since different alternatives and attributes are used.

C

Appendix C. Literature review

C.1 Literature review: Commuting modalities

Given the rapidly evolving nature of transportation research, a thorough and up-to-date review of relevant literature was crucial. The study by Arentze and Molin (2013), was included due to its relevance and similar focus. However, due to the quickly evolving field of transportation, it was decided to only include articles published after Arentze and Molin (2013), thus after 2013. Additionally, the search was limited to the keyword commuting since that is the only type of work-related travel this research focuses on. Between the results, the documents were assessed based on the following inclusion and exclusion criteria, stated in Table C.1. After these limitations, a total of 65 documents were found.

Table C.1: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Articles published after 2012	Unrelated to travel behaviour
Possible modalities in the Netherlands	Life event effects
Taste heterogeneity	Focus on single modality
Shared mobility	Focus only on income
Attitudes or perceptions	Based on residential-self selected
	Autonomous vehicles
	After intervention behaviour

The resulting articles were analysed for the included modality alternatives, mode-related attributes, socio-demographics, and attitudes/perceptions. Table C.2 summarizes the findings. Note that while some researchers described concepts like safety or environmental factors, these were categorized differently based on their context. When mentioned as mode-related attributes, they referred to the safety or environmental friendliness of a specific modality. However, when discussed as attitudes and perceptions, they referred to the general aspects of safety and environmental concerns.

Table C.2: Literature review overview

ID	Author	Alternatives	Mode-related attributes	Socio-demographics	Attitudes and perceptions
1	Lee, Circella, Mokhtarian & Guhathakurta (2020)	Car as a driver, car as a passenger, public transit, walking, biking, skateboarding	time/mode constrained, activity intensity, land use diversity, transit service quality	gender, race and ethnicity, educational attainment, household composition, income, transit pass, residential neighbourhood type, having drivers license, cars per household	Pro environmental policies, pro exercise, car as a tool
2	Brand, Dons & Anaya-Boig, et al. (2021)	Car, public transport, bike, walking, cycling	CO2 emissions, distance travelled, travel time	City, cycling occasion, sex, age, BMI, income, employement status, education level, household composition, car accessibility	Self-related health
3	Kamruzzaman, Mostafiz Shatu, Hine & Turrell (2015)	Bus, train, ferry, car, walk, motorcycle, bicycle, taxi, and other	Peak hour frequency, travel time, dwelling density, land use diversity	Gender, car availability, employment status (part-time/full-time), level of education, income, living arrangement, country of birth, age, household size, health status	Closenees to public transport, ease of walking to places, wanted to live close to shops, closeness to open space, near to bushland, closeness to schools/childcare/city/work/ freeways/main roads. Reliability, pleasantness, global warming, environment, reduce traffic congestion, safety, PT difficulty
4	Parmar, Saiyed & Dave (2023)	Car, motorized transport, Bus, metro, non-motorized transport	On/Off-street parking, access/egress distance, employer-paid parking, parking duration, parking search time, parking egress time, in-vehicle time, trip cost	Sex, Age, Income, Education Level, Employment Status, Household Characteristics, Members in HH, Number of Cars/ MTW/Bicycles in HH	Individuality, environment, economy, comfort, flexibility, convenience, safety, health
5	Van, Choocharukul & Fujii (2014)	Car, public transit	Travel costs, environmental friendly, safety, loudness, dirtiness	Gender, License, Car Ownership	Convenience, usefulness, constructiveness, symbolic affective, instrumental, social orderliness, level of control
6	Luo, Chahine, Gkritza & Cai (2023)	Private car, bus, walking, bike-sharing, shared e-scooter, ride-hailing[1], multimodal	Cost, In-vehicle time, Out-vehicle time (connection time, waiting time, walking time)	Gender, Age, Household income, Employment, Education level, Car ownership, Driver's license, Household children count	General travel experience, shared mobility opinion, reliability, convenience, comfort, safety, social image, environmental concern, health, travel companion, congestion avoidance, parking avoidance, bus connection, bike lanes
7	Eagling & Ryley (2015)	Car, bus, coach, cycle, walk, taxi, rail	Slowliness rail, crowdedness rail, travel cost, travel time, parking space, parking costs, information provision, road congestion	Age, route type, length of journey	Distance home/work train station, journey suitability, company car preference, private car preference, reliability, irregularity, frequency, seat availability
8	Esztergár-Kiss, Shulha, Aba & Tettamanti (2021)	Cycling, walking, tram, car, P+R, bike-sharing	Travel time, emission, travel cost, health effect, environmental effect	Gender, year of birth, education, home address, frequency modality	Environmental awareness, health awareness
9	Gao, Shao & Sun (2019)	Car, metro, bus, taxi	Time, cost, comfort, delay, congestion, waiting time, average trip miles, ratio supply to demand, in-vehicle crowding	Age, gender, income, education level, commuting distance, commuting time, marital status, occupation, license type, flexible work time	Economy, society, environment
10	Guo, Feng & Timmermans (2020)	Car, metro, bus, bike, walk	Travel cost, travel time, congestion time, out-of-vehicle time, have seats or not	Gender, age, marital status, number of workers, annual income, tenure, living area, type of employee, job location, commute mode	Flexibility, easy to find a similar or not
-[2]	Arentze & Molin (2013)	Private car, bike, public transport (bus, tram, train, PT bike), multi-modal with P+R	Travel time, travel costs, possible delay, egress walk time, park search time, parking costs, transfer time, seat availability, station facilities, wait time	Gender, Age, Education level, Work status (part-time/ full-time), partner, age youngest child in household	Type of journey/ circumstances
-[2]	Molin & Kroesen (2023)	Bus, bike, car, carpool, P+R + (e-)bike, P+R + shuttle, Train + (e-)bike, car + shuttle	Travel time, transfer/ pick-up time, delay due to congestion, parking time, booking parking spot, daily reward, travel allowance	-	Policy measures
-[2]	Molin, Mokhtarian & Kroesen (2016)	Car, bicycle, train, shuttle bus	Waiting time, timeliness (no worries being on time), planning is easy, costs	Gender, age, education level, income, household composition, employment status, fixed work location, city size, car availability	status giving, environmentally friendly, relaxing, comfortable, time-saving, flexible, convenient and pleasant

[1] Ride-hailing is an on-demand service where customers order customized rides through a smartphone app, similar to a taxi service.
[2] Included articles apart from the search string.

C.2 Translations into Dutch

Alternatives, attributes and attribute levels translated to Dutch

Table C.3: Alternatives and attributes in Dutch

Alternatives (ENG)	Alternatieven (NL)	Attributes (ENG)	Attributen (NL)
(E-)bike	(Elektrische) fiets	Travel time [minutes]	Reistijd [minuten]
Lease e-bike	Elektrische lease fiets	Parking time [minutes]	Parkeertijd [minuten]
Car	Auto	Egress walking time [minutes]	Looptijd [minuten]
Bus/light rail	Bus/sneltram	Delay time [minutes]	Vertraging [minuten]
Train	Trein	Transfer time [minutes]	Overstaptijd [minuten]
Shared (e-)bike	(Elektrische) deelfiets	Parking costs [euros]	Parkeerkosten [euros]
		Travel allowance [cents/kilometre]	Reisvergoeding [cent/kilometer]
		E-bike lease costs [euro/month]	E-bike lease kosten [euro\maand]

Socio-demographics and attitudes in Dutch

Table C.4: Socio-demographics translated

Socio-demographics (ENG)	Socio-demografische gegevens (NL)
Age	Leeftijd
Gender	Geslacht
Education level	Hoogstgenoten opleiding
Income	Inkomen
Household composition	Samenstelling huishouden
Personnel number	Personeelsnummer
Function family	Functiefamilie
Possibility to work from home	Thuiswerk mogelijkheid
Type of working shift	Soort werkdienst

Table C.5: Function family translated

Function family (ENG)	Functiefamilie (NL)
Analytical personnel	Analytisch personeel
Physician assistants and basic physician	Arts-ass. en basisartsen
Facility	Facilitair
In training	In opleiding
Clinical (co-)treatment	Klinisch (mede-)behandelen
Clinical support	Klinisch ondersteunen
Management	Management
Medical specialist	Medisch specialisten
Staff, administration and secretariat	Staf, administratie en secretariaat
Nursing and care	Verpleging en verzorging
Scientific research and education	Wetenschappelijk onderzoek en onderwijs

Table C.6: Likert scale translated

5-point Likert scale (ENG)	5-punts Likert schaal (NL)
1. Strongly disagree	1. Helemaal mee oneens
2. Disagree	2. Mee oneens
3. Neutral	3. Neutraal
4. Agree	4. Mee eens
5. Strongly Agree	5. Helemaal mee eens

Gewoonten & normen

- Een manier van reizen kiezen voor woon-werkverkeer, is iets wat ik doe zonder na te denken. (+)
- Ik sta open voor een duurzame manier van reizen voor woon-werkverkeer, ook als dit anders is dan hoe ik meestal reis. (+)

Betrouwbaarheid

- Als ik met de fiets/e-bike reis, maak ik mij zorgen of ik wel op tijd in het academisch ziekenhuis ben. (-)
- Als ik met de auto reis, maak ik mij zorgen of ik wel op tijd in het academisch ziekenhuis ben. (-)
- Als ik met het OV reis, maak ik mij zorgen of ik wel op tijd in het academisch ziekenhuis ben. (-)

Comfort

- Na een werkdag vind ik reizen met de fiets/e-bike comfortabel. (+)
- Na een werkdag vind ik reizen met de auto comfortabel. (+)
- Na een werkdag vind ik reizen met het OV comfortabel. (+)

Ernissen vertraging

- Ik vind het vervelend om tijdens mijn woon-werk reis, te wachten op vertraagd openbaar vervoer. (-)
- Ik erger mij aan verkeersopstoppingen tijdens mijn woon-werk reis. (-)

Milieu belang

- Ik denk dat de ’klimaat/ecologische crisis’ sterk overdreven is. (-)
- Ik geloof dat de mens het milieu ernstige schade toebrengt. (-)

Gezondheidsbelang

- Lichaamsbeweging is belangrijk voor mij. (+)
- Buiten zijn helpt mij om mijn hoofd leeg te maken. (+)
- Ik hou in mijn leven veel rekening met mijn gezondheid. (+)

D

Appendix D. Operationalisation

D.1 Coding for model estimation

Table D.1: Coding alternatives

Experiment 1		Experiment 2		Experiment 3	
Alternative	*Coding*	*Alternative*	*Coding*	*Alternative*	*Coding*
Car	0	Car	0	Car	0
Bike	1	Lease e-bike	1	Train + bus/light rail	1
Lease e-bike	2	Train + bus/light rail	2	Train + shared e-bike	2
Bus/light rail	3	Train + shared e-bike	3	Car + shared e-bike	3
		Car + shared e-bike	4		

Table D.2: Attribute level coding experiment 1

Experiment 1			
Alternative	*Attribute*	*Attribute level*	*Coding*
Bike	Allowance	20 ct/km	0
		25 ct/km	1
		30 ct/km	2
E-bike lease	Allowance	0 ct/km	0
		5 ct/km	1
		10 ct/km	2
	Lease costs	38 €/month	0
		48 €/month	1
		58 €/month	2
Car	Parking time	2 min	0
		4 min	1
		6 min	2
	Egress time	5 min	0
		10 min	1
		15 min	2
	Delay time	0 min	0
		10 min	1
		20 min	2
	Parking costs	2 €/day	0
		4 €/day	1
		7 €/day	2
	Allowance	10 ct/km	0
		15 ct/km	1
		20 ct/km	2
Bus/ light rail	Delay time	0 min	0
		4 min	1
		8 min	2

Table D.3: Attribute level coding experiment 2 and 3

Experiment 2

Alternative	*Attribute*	*Attribute level*	*Coding*
E-bike lease	Allowance	0 ct/km	0
		5 ct/km	1
		10 ct/km	2
	Lease costs	38 €/month	0
		48 €/month	1
		58 €/month	2
Car	Parking time	2 min	0
		4 min	1
		6 min	2
	Egress time	5 min	0
		10 min	1
		15 min	2
	Delay time	0 min	0
		10 min	1
		20 min	2
	Parking costs	2 €/day	0
		4 €/day	1
		7 €/day	2
	Allowance	10 ct/km	0
		15 ct/km	1
		20 ct/km	2
Train + Bus/ light rail	Delay time	0 min	0
		4 min	1
		8 min	2
	Transfer time	5 min	0
		8 min	1
		11 min	2
Train + shared e-bike	Delay time	0 min	0
		4 min	1
		8 min	2
	Allowance	0 ct/km	0
		10 ct/km	1
		20 ct/km	2
	Unavailability	0 x/month	0
		1 x/month	1
		2 x/month	2
Car + shared e-bike	PR costs	0 €/day	0
		1 €/day	1
		2 €/day	2
	Allowance	10 ct/km	0
		15 ct/km	1
		20 ct/km	2
	Unavailability	0 x/month	0
		1 x/month	1
		2 x/month	2

Experiment 3

Alternative	*Attribute*	*Attribute level*	*Coding*
Car	Parking time	2 min	0
		4 min	1
		6 min	2
	Egress time	5 min	0
		10 min	1
		15 min	2
	Delay time	0 min	0
		10 min	1
		20 min	2
	Parking costs	2 €/day	0
		4 €/day	1
		7 €/day	2
	Allowance	10 ct/km	0
		15 ct/km	1
		20 ct/km	2
Train + Bus/ light rail	Delay time	0 min	0
		4 min	1
		8 min	2
	Transfer time	5 min	0
		8 min	1
		11 min	2
Train + shared e-bike	Delay time	0 min	0
		4 min	1
		8 min	2
	Allowance	0 ct/km	0
		10 ct/km	1
		20 ct/km	2
	Unavailability	0 x/month	0
		1 x/month	1
		2 x/month	2
Car + shared e-bike	Allowance	10 ct/km	0
		15 ct/km	1
		20 ct/km	2
	Unavailability	0 x/month	0
		1 x/month	1
		2 x/month	2

Table D.4: Coding socio-demographics and attitudes

Variable	Description	Coding	
RID	Respondent identified, unique to this suvery		
GENDER	Gender	0	Male
		1	Female
AGE	Age	0	<25 years old
		1	25 - 35 years old
		2	36 - 45 years old
		3	46 - 55 years old
		4	>55 years old
FFAMILY	Function family	0	Analytical personnel
		1	Physician assistants and basic physician
		2	Facility
		3	In training
		4	Clinical (co-)treatment
		5	Clinical support
		6	Management
		7	Medical specialist
		8	Staff, administration and secretariat
		9	Nursing and care
		10	Scientific research and education
SHIFT	Type of working shift	0	Day, no shift
		1	Evening, night, weekend shift
		2	On-call shift
		3	On-call + day shift
		4	On-call + evening, night, weekend shift
IRREGULAR	Irregular schedules	0	No
		1	Yes
COM_DIST	Commuting distance category	0	<10 km
		1	11 - 30 km
		2	>30 km
EDU	Educuation	0	MAVO/HAVO/VWO
		1	MBO
		2	HBO
		3	WO
		4	PHD
HH	Household composition	0	Single household
		1	Single parent with child(ren)
		2	Living with partner (no children)
		3	Living with partner and child(ren)
CHILD	Youngest child within the household	0	<= 6 years
		1	7 - 18 years
		2	>18 years or none
INC	Income yearly (bruto)	0	<€25.000
		1	€25.000 - €49.999
		2	€50.000 - €74.999
		3	€75.000 - €99.999
		4	€100.000 - €150.000
		5	>150.000
		6	I would rather not say
	Positive statements +	1	Strongly disagree
		2	Disagree
		3	Neutral
		4	Agree
		5	Strongly agree
	Negative statements -	1	Strongly agree
		2	Agree
		3	Neutral
		4	Disagree
		5	Strongly disagree

D.2 Ngene abbreviations, priors and syntax

Since respondents were divided into three groups based on their commuting distance, three separate experiments were conducted to generate three distinct experimental designs. This section includes the full Ngene syntaxes for each experiment, and the detailed procedure for checking dominance is included for transparency and reproducibility. Table D.5 presents the abbreviations and priors used for the alternatives, while Table D.6 shows the attributes and their corresponding levels. The Ngene syntaxes for each experiment, visualizing these designs, are provided after the tables.

Table D.5: Alternatives' abbreviations and priors

Alternative	ASC abbreviation	ASC priors	Source
Bike	C_BIKE	0.75	(Arentze & Molin, 2013)
E-bike lease	C_EBIKE_LEASE	1.3	(Molin & Kroesen, 2023)
Car	-	-	(Molin & Kroesen, 2023)
Bus/tram	C_BUSTRAM	-0.76	(Molin & Kroesen, 2023)
Train + bus/tram	C_TRAIN_BUSTRAM	-0.33	(Molin & Kroesen, 2023)
Train + shared e-bike	C_TRAIN_SBIKE	-0.74	(Molin & Kroesen, 2023)
Car (P+R) + shared e-bike	C_CAR_SBIKE	-2.1	(Molin & Kroesen, 2023)

Table D.6: Attributes' abbreviations and priors

Attributes	Description	Attribute abbreviation	Attribute levels	Attribute weights	Priors	Source
Travel time	In vehicle time	Fixed	Fixed	Fixed	Fixed	-
Parking time	Time it takes to find a parking place and park your car	CAR_PARK_TIME	2, 4, 6 min	t_park_car	-0.079	(Arentze & Molin, 2013)
Egress time	Time it takes to walk from end station or parking place to the entrance	EGRESS_TIME	5, 10, 15 min	t_egress	-0.101	(Arentze & Molin, 2013)
Delay	Extra time added to the travel time due to delays or congestion	CAR_DELAY PT_DELAY	20, 10, 0 min 8, 4, 0 min	t_delay_car t_delay_bustram t_delay_train_bustram t_delay_train_sbike	-0.110 | -0.020 -0.025 | -0.017 -0.064 | -0.042 -0.025 | -0.017	(Molin & Kroesen, 2023)
Transfer time	Time to transfer from one modality to another	TRANSFER	5, 8, 11 min	t_transfer	-0.054	(Molin & Kroesen, 2023)
Parking costs	Car parking costs per day	CAR_PARK_COST PR_PARK_COST	7, 4, 2 €/day 2, 1, 0 €/day	c_park_car c_park_pr_car	-0.350 | -0.178 -0.209 | -0.100	(Molin & Kroesen, 2023) (Arentze & Molin, 2013)
Travel allowance	Travel allowance that is accredited per kilometre	BIKE_ALLOW EBIKE_ALLOW SBIKE_ALLOW CAR_SBIKE_ALLOW CAR_ALLOW	20, 25, 30 ct/km 0, 5, 10 ct/km 0, 10, 20 ct/km 10, 15, 20 ct/km 10, 15, 20 ct/km	a_bike a_ebike a_train_sbike a_car_sbike a_car	0.040 0.031 0.015 0.015 0.007	(Molin & Kroesen, 2023)
E-bike lease costs	Monthly costs for private lease of an e-bike	EBIKE_LEASE_COST	38, 48, 58 €/month	c_ebike_lease	-0.098	(Arentze & Molin, 2013)
#Shared bike unavailable	Amount of times per month that a shared e-bike is unavailable	SBIKE_UNAV	0, 1, 2 x/month	u_sbike_train u_sbike_car	-0.337 -0.337	(Arentze & Molin, 2013)

Experiment 1: Commuting distance <10 km

```
design
;alts
= BIKE, EBIKE_LEASE, CAR, BUSTRAM
;rows = 12
;eff = (mnl,d)

;model:
U(BIKE) = a_bike[0.01]*BIKE_ALLOW[20,25,30]
  + C_BIKE[0.75]
/
U(EBIKE_LEASE) =  a_ebike[0.025] * EBIKE_ALLOW[0,5,10]
     + c_ebike_lease[-0.098] * EBIKE_LEASE_COST[0,1,2]
     + C_EBIKE[1.3]
/
U(CAR) = t_park_car[-0.079] * CAR_PARK_TIME[2,4,6]
 + t_egress[-0.101] * EGRESS_TIME[5,10,15]
 + t_delay_car.effects[-0.11|-0.02] * CAR_DELAY[10,5,0]
 + c_park_car.effects[-0.35|-0.178] * CAR_PARK_COST[7,4,2]
 + a_car[0.01] * CAR_ALLOW[10,15,20]
/
U(BUSTRAM) = t_delay_bustram.effects[-0.025|-0.017] * PTDELAY[8,4,0]
 + C_BUSTRAM[-0.76]
$
```

Experiment 2: Commuting distance 11 - 30 km

```
design
;alts = EBIKE_LEASE, CAR, TR_BUSTRAM, TR_SBIKE, CAR_SBIKE
;rows = 12
;eff = (mnl,d)

;model:
U(EBIKE_LEASE) =  a_ebike[0.025] * EBIKE_ALLOW[0,5,10]
     + c_ebike_lease[-0.098] * EBIKE_LEASE_COST[0,1,2]
     + C_EBIKELEASE[1.3]
/
U(CAR) = t_park_car[-0.079] * CAR_PARK_TIME[2,4,6]
 + t_egress[-0.101] * EGRESS_TIME[5,10,15]
 + t_delay_car.effects[-0.11|-0.02] * CAR_DELAY[20,10,0]
 + c_park_car.effects[-0.35|-0.178] * CAR_PARK_COST[7,4,2]
 + a_car[0.01] * CAR_ALLOW[10,15,20]
/
U(TR_BUSTRAM) = t_delay_train_bustram.effects[-0.064|-0.042] * PTDELAY[8,4,0]
    + t_transfer[-0.054] * TRANSFER[5,8,11]
    + C_TRAIN_BUSTRAM[-0.33]
/
U(TR_SBIKE) = t_delay_train_sbike.effects[-0.025|-0.017] * PTDELAY[8,4,0]
  + a_train_sbike[0.015] * SBIKE_ALLOW[0,10,20]
  + u_sbike_train[-0.337] * SBIKE_UNAV[0,1,2]
  + C_TRAIN_SBIKE[-0.74]
/
U(CAR_SBIKE) = c_park_car_pr.effects[-0.209|-0.10] * PR_PARKCOST[2,1,0]
   + a_sbike_car[0.015] * CAR_SBIKE_ALLOW[10,15,20]
   + u_sbike_car[-0.337] * SBIKE_UNAV[0,1,2]
   + C_CAR_SBIKE [-2.1]
$
```

Experiment 3: Commuting distance >30 km

```
design
;alts = CAR, TR_BUSTRAM, TR_SBIKE, CAR_SBIKE
;rows = 12
;eff = (mnl,d)

;model:
U(CAR) = t_park_car[-0.079] * CAR_PARK_TIME[2,4,6]
 + t_egress[-0.101] * EGRESS_TIME[5,10,15]
 + t_delay_car.effects[-0.11|-0.02] * CAR_DELAY[20,10,0]
 + c_park_car.effects[-0.35|-0.178] * CAR_PARK_COST[7,4,2]
```

```
 + a_car[0.01] * CAR_ALLOW[10,15,20]
/
U(TR_BUSTRAM) = t_delay_train_bustram.effects[-0.064|-0.042] * PTDELAY[8,4,0]
    + t_transfer[-0.054] * TRANSFER[5,8,11]
    + C_TRAIN_BUSTRAM[-0.33]
/
U(TR_SBIKE) = t_delay_train_sbike.effects[-0.025|-0.017] * PTDELAY[8,4,0]
  + a_train_sbike[0.015] * SBIKE_ALLOW[0,10,20]
  + u_sbike_train[-0.337] * SBIKE_UNAV[0,1,2]
  + C_TRAIN_SBIKE[-0.74]
/
U(CAR_SBIKE) = c_park_car_pr.effects[-0.209|-0.10] * PR_PARKCOST[2,1,0]
   + a_sbike_car[0.015] * CAR_SBIKE_ALLOW[10,15,20]
   + u_sbike_car[-0.337] * SBIKE_UNAV[0,1,2]
   + C_CAR_SBIKE [-2.1]
$
```

D.3 Generated design

For each experiment, three different designs are created through Ngene. As stated in Section 3, the risk of obtaining dominant alternatives is reduced through an efficient design. Yet, before creating the questionnaire with the generated designs, the probabilities and utilities were first checked to see whether dominance occurred. The general guideline for determining dominance is as follows: the knowledge concerning trade-offs is more limited the closer an alternative's predicted probability nears one. Therefore, the rule of thumb that applies is that expected choice probabilities, calculated through the utilities, must be <0.90.

D.3.1 Experiment 1: design and properties

Level coding has been applied for the E-bike lease alternative since the order of magnitude of lease cost per month is out of line with the other levels. Especially with the travel allowance per kilometer, which is given in cents. Before applying level coding, the utilities of the e-bike lease alternative were greatly negative (≈-3.279) compared to other alternatives, resulting in unrealistic low choice probabilities (≈0.014). The design that was created, thus using level coding, is discussed hereafter. Based on the utilities presented in Table D.1, the expected probabilities were retrieved and stated in Table D.2. The highest expected probability for this experiment is 0.580, belonging to the E-bike lease alternative, which is below 0.90 and therefore no dominance occurs here. The final design of these values is used to create the questionnaire, presented in D.7.

Figure D.1: Experiment 1: MNL utilities

#	Bike	E-bike lease	Car	Bus/tram
1	0.950	1.354	-2.051	-0.777
2	1.000	1.327	-0.055	-0.785
3	1.050	1.202	-0.815	-0.785
4	1.000	1.327	-0.121	-0.718
5	1.050	1.104	-0.923	-0.777
6	0.950	1.229	-0.966	-0.785
7	1.000	1.229	-0.611	-0.718
8	0.950	1.300	-1.482	-0.718
9	1.050	1.550	-1.969	-0.777
10	0.950	1.300	-1.604	-0.777
11	1.000	1.550	-1.464	-0.785
12	1.050	1.452	-2.051	-0.718

Figure D.2: Experiment 1: MNL probabilities

#	Bike	E-bike lease	Car	Bus/tram
1	0.367	0.550	0.018	0.065
2	0.344	0.478	0.120	0.058
3	0.403	0.470	0.062	0.064
4	0.346	0.480	0.113	0.062
5	0.425	0.448	0.059	0.068
6	0.378	0.500	0.056	0.067
7	0.379	0.477	0.076	0.068
8	0.371	0.526	0.033	0.070
9	0.350	0.577	0.017	0.056
10	0.374	0.531	0.029	0.066
11	0.335	0.580	0.028	0.056
12	0.369	0.551	0.017	0.063

Table D.7: Experiment 1: Generated Choice set

#	BIKE ALLOW	EBIKE ALLOW	EBIKE LEASE COST	CAR PARK TIME	EGRESS TIME	CAR DELAY	CAR PARK COST	CAR ALLOW	PT DELAY
1	20	10	2	4	15	5	7	15	4
2	25	5	1	2	5	5	2	10	8
3	30	0	1	2	15	0	2	20	8
4	25	5	1	6	5	0	2	20	0
5	30	0	2	2	5	10	7	20	4
6	20	5	2	6	10	10	2	10	8
7	25	5	2	2	5	0	4	10	0
8	20	0	0	6	10	5	4	20	0
9	30	10	0	4	15	10	4	15	4
10	20	0	0	6	10	0	7	10	4
11	25	10	0	4	10	10	4	15	8
12	30	10	1	4	15	5	7	15	0

D.3.2 Experiment 2: design and properties

For the same reason as in the first experiment, level coding is applied for the E-bike lease alternative. The expected probabilities for the second experiment were obtained and listed in Table D.9 based on the utilities shown in Table D.8. The E-bike lease alternative has the highest anticipated probability for this experiment (0.806), yet it is not a dominant alternative since it is less than 0.90. The questionnaire is created using the final design that aligns with these values and is shown in D.10.

Table D.8: Experiment 2: MNL utilities

#	E-bike lease	Car	Train + bus/tram	Train + shared bike	Car + shared bike
1	1.202	-2.141	-0.664	-0.398	-2.009
2	1.425	-0.801	-0.804	-1.222	-1.491
3	1.354	-1.779	-0.642	-0.794	-2.758
4	1.202	-0.221	-0.804	-1.102	-2.050
5	1.550	-1.686	-0.664	-1.094	-2.312
6	1.202	-0.977	-0.494	-1.131	-2.496
7	1.425	-0.815	-0.966	-1.222	-2.315
8	1.229	-0.560	-0.988	-0.952	-2.237
9	1.229	-0.683	-0.988	-1.289	-1.641
10	1.202	-1.879	-0.818	-0.757	-2.165
11	1.550	-1.704	-0.656	-0.465	-2.421
12	1.354	-0.866	-0.656	-0.698	-2.649

Table D.9: Experiment 2: MNL probabilities

#	E-bike lease	Car	Train + bus/tram	Train + shared bike	Car + shared bike
1	0.698	0.025	0.108	0.141	0.028
2	0.746	0.081	0.080	0.053	0.040
3	0.762	0.033	0.104	0.089	0.012
4	0.660	0.159	0.089	0.066	0.026
5	0.806	0.032	0.088	0.057	0.017
6	0.705	0.080	0.129	0.068	0.017
7	0.774	0.082	0.071	0.055	0.018
8	0.704	0.118	0.077	0.080	0.022
9	0.717	0.106	0.078	0.058	0.041
10	0.739	0.034	0.098	0.104	0.025
11	0.769	0.030	0.085	0.102	0.014
12	0.720	0.078	0.096	0.092	0.013

Table D.10: Experiment 2: Generated Choice Set

#	EBIKE ALLOW	EBIKE LEASE COST	CAR PARK TIME	EGRESS TIME	CAR DELAY	CAR PARK COST	CAR ALLOW	TRAIN + BUS/TRAM PT DELAY	TRAIN + BUS/TRAM TRANSFER TIME	TRAIN + SHARED BIKE PT DELAY	TRAIN + SHARED BIKE ALLOW	TRAIN + SHARED BIKE UNAVAI	CAR + SHARED BIKE PARK COST	CAR + SHARED BIKE ALLOW	CAR + SHARED BIKE UNAVAI
1	0	1	4	15	20	7	15	8	5	0	20	0	2	20	0
2	5	0	2	5	20	4	15	4	8	0	10	2	0	20	0
3	10	2	4	15	0	4	10	4	5	4	20	1	2	15	2
4	0	1	6	5	0	2	10	4	8	8	0	1	1	10	0
5	10	0	4	10	20	7	10	8	5	4	0	1	1	15	1
6	0	1	6	5	10	4	20	0	5	4	20	2	2	10	1
7	5	0	2	15	0	2	20	4	11	0	10	2	0	10	2
8	5	2	2	10	10	2	10	8	11	8	10	1	1	20	1
9	5	2	2	5	0	7	20	8	11	8	10	2	0	10	0
10	0	1	4	15	10	4	15	0	11	4	0	0	0	20	2
11	10	0	6	10	10	7	15	0	8	8	20	0	2	15	1
12	10	2	6	10	20	2	20	0	8	0	0	0	1	15	2

D.3.3 Experiment 3: design and properties

Based on the utilities displayed in Table D.3, the expected probabilities for the second experiment were calculated and listed in Table D.4. For the third experiment, all the alternatives have a negative probability and thus are below an expected probability of 0.90, excluding any dominance. The final design of the questionnaire aligns with these principles and is shown in D.11.

Table D.11: Experiment 3: Generated Choice Set

#	CAR PARK TIME	EGRESS TIME	CAR DELAY	CAR PARK COST	CAR ALLOW	TRAIN + BUS/TRAM PT DELAY	TRAIN + BUS/TRAM TRANSFER TIME	TRAIN + SHARED BIKE PT DELAY	TRAIN + SHARED BIKE ALLOW	TRAIN + SHARED BIKE UNAVAI	CAR + SHARED BIKE PARK COST	CAR + SHARED BIKE ALLOW	CAR + SHARED BIKE UNAVAI
1	4	5	0	4	15	4	8	0	10	2	1	15	1
2	6	15	10	2	10	8	8	4	0	2	1	10	1
3	2	10	20	4	10	0	11	8	10	2	2	10	2
4	4	10	20	7	15	4	11	0	20	2	2	20	0
5	6	5	20	2	20	0	5	0	0	0	0	10	0
6	4	15	20	4	15	4	8	8	0	0	0	20	2
7	6	5	0	7	10	0	5	8	10	1	1	20	0
8	6	10	10	4	20	0	11	4	20	1	0	10	0
9	2	5	10	7	20	8	8	4	0	1	0	20	2
10	4	15	0	7	15	8	11	0	10	0	1	15	2
11	2	15	0	2	20	8	5	8	20	1	2	15	1
12	2	10	10	2	10	4	5	4	20	0	2	15	1

Figure D.3: Experiment 3: MNL utilities

#	Car	Train + bus/tram	Train + shared bike	Car + shared bike
1	-0.719	-0.804	-1.222	-2.312
2	-1.381	-0.826	-1.431	-2.387
3	-1.356	-0.818	-1.289	-2.833
4	-1.636	-0.966	-1.072	-2.009
5	-0.361	-0.494	-0.698	-1.641
6	-1.969	-0.804	-0.765	-2.165
7	-1.099	-0.494	-0.952	-1.900
8	-1.482	-0.818	-0.794	-1.641
9	-0.833	-0.826	-1.094	-2.165
10	-1.901	-0.988	-0.548	-2.649
11	-0.815	-0.664	-0.802	-2.421
12	-0.560	-0.642	-0.457	-2.421

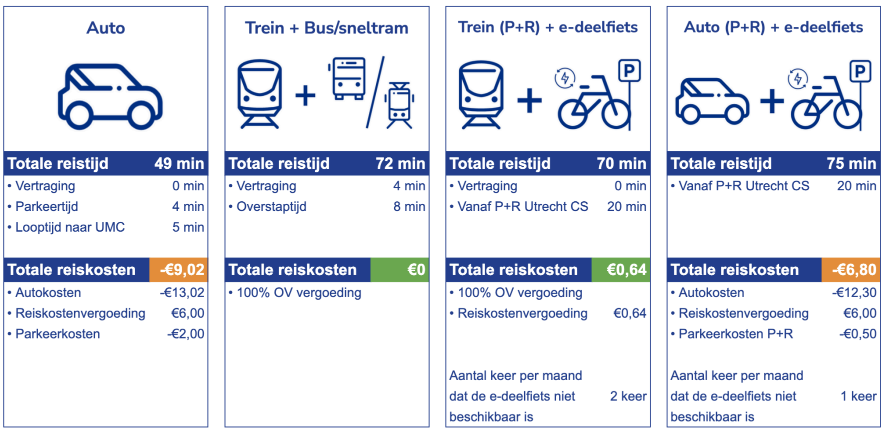
Figure D.4: Experiment 3: MNL probabilities

#	Car	Train + bus/tram	Train + shared bike	Car + shared bike
1	0.367	0.337	0.222	0.075
2	0.246	0.429	0.234	0.090
3	0.249	0.427	0.267	0.057
4	0.185	0.362	0.325	0.128
5	0.349	0.305	0.249	0.097
6	0.120	0.383	0.399	0.098
7	0.225	0.413	0.261	0.101
8	0.173	0.336	0.344	0.147
9	0.329	0.331	0.253	0.087
10	0.128	0.318	0.494	0.060
11	0.296	0.344	0.300	0.059
12	0.314	0.289	0.348	0.049

D.4 Invitation Questionnaire

The full invitation text through which participants were invited for the questionnaire can be found here in Dutch and English.

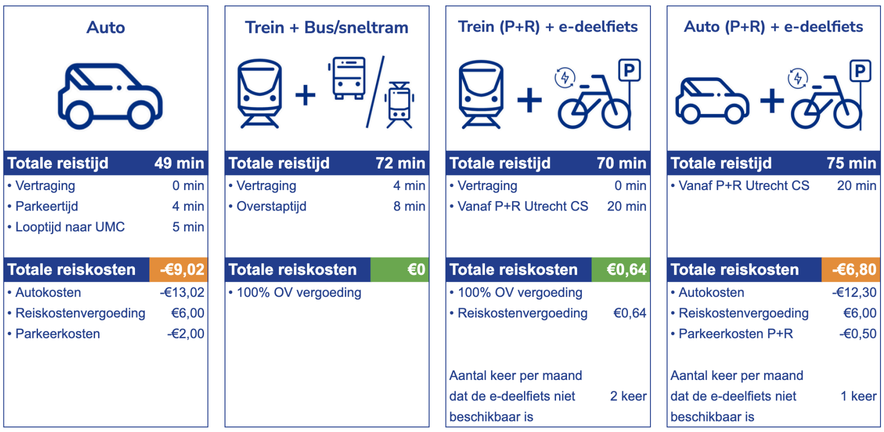
Beste Proeftuin deelnemer, Als één van de onderdelen van de Proeftuin, word je uitgenodigd om deel te nemen aan een onderzoek wat uitgevoerd wordt door Noortje van der Meulen student van de TU Delft, in samenwerking met Pon Mobility Nederland en een academisch ziekenhuis. Dit onderzoek bestaat uit een keuze experiment waarbij de voorkeuren verschillende woon-werk reizen worden getoetst. De uitkomsten van dit onderzoek worden voor zowel de Proeftuin, Pon Mobility Nederland als het afstudeeronderzoek gebruikt. Het invullen van de enquête duurt ongeveer 6 minuten. We vragen je naar waarheid te antwoorden op vragen over reisvoorkeuren, gewoonten en persoonlijke kenmerken. Alleen geaggregeerde en statistische gegevens worden gebruikt in het eindrapport, zodat individuele antwoorden niet herleidbaar zijn. Als je vragen hebt over het onderzoek of de enquête, of als je contact met mij wilt opnemen, kun je mij bereiken via e-mail: [EMAIL ADRES]
Een voorbeeld scenario als onderdeel van het keuze experiment is hieronder weergegeven. Afhankelijk van jouw woon-werk afstand krijg je een bepaald keuze experiment te zien met verschillende vervoerwijzen. De vraag welke telkens gesteld wordt is als volgt: "Welk vervoermiddel zou jij in deze situatie kiezen voor jouw woon-werk reis?".



LET OP! Dit onderzoek is onderdeel van een master thesis project. De hypothetische scenario's zijn deels gebaseerd zijn op de situatie rondom het academisch ziekenhuis, maar bevatten ook waarden die niet van toepassing zijn of zullen zijn voor de medewerkers van het academisch ziekenhuis. Om de enquête te starten klik hier.

Dear Proeftuin participant,
As one of the components of the Proeftuin, you are invited to take part in a study conducted by Noortje van der Meulen student from TU Delft, in collaboration with Pon Mobility Netherlands and the academic hospital. This research consists of a choice experiment testing preferences for different commuting trips. The results of this survey will be used for both the Living Lab, Pon Mobility Netherlands and the thesis research. Completing the survey will take about 6 minutes. We ask you to truthfully answer questions about travel preferences, habits and personal characteristics. Only aggregated and statistical data will be used in the final report, so individual answers are not traceable. If you have any questions about the study or survey, or if you would like to contact me, you can reach me via email at: [EMAIL ADDRESS]

A sample scenario as part of the choice experiment is shown below. Depending on your commuting distance, you will be shown a certain choice experiment with different modes of transport. The question asked each time is as follows: 'Which mode of transport would you choose for your commute in this situation?'.



PLEASE NOTE: This research is part of a master thesis project. The hypothetical scenarios are partly based on the situation around the academic hospital but also contain values that do not or will not apply to the academic hospital employees.To start the survey click here.

E

Appendix E. Descriptive statistics

E.1 Exploratory Factor Analysis

The questionnaire distributed among the Living Lab participants included fifteen questions measuring their attitudes. These attitudes, also known as latent variables, cannot be observed directly but through a set of indicator variables. A factor analysis is performed to determine the set of indicator variables. The factor resulting from the analysis explains the correlations between similarities within the indicators, thus the common variance. For this case, a Principal Axis Factoring method with oblique rotation is performed since orthogonal rotation assumes no correlations between the underlying factors.

The principal axis factoring (PAF) method is properly conducted through an exploratory factor analysis in the software SPSS, which iteratively derives a simple structure and an interpretable solution. The solution consists of appropriate and suitable factors which can be used as covariates within the LCCM. The Exploratory Factor Analysis consists of five steps:

1. Check the communalities
2. Check the number of factors
3. Achieve a simple structure
4. Compare with the orthogonal solution
5. Check the interpretability of the solution

To determine whether each indicator correlates sufficiently with other indicators, the communalities are considered. The rule of thumb used is that indicators may be removed when the communality is below 0.25. Figure E.1 shows the low communalities of the indicators *habit1* and *habit2*. Since no pattern matrix was achieved while keeping these two indicators it was chosen to remove them.

Communalities

	Initial
habit1	,100
habit2	,139
reliab1	,358
reliab2	,310
reliab3	,283
comf1	,415
comf2	,228
comf3	,251
annoy1	,239
annoy2	,271
env1	,308
env2	,343
health1	,587
health2	,518
health3	,462

Extraction Method: Principal Axis Factoring.

Figure E.1: Communalities indicators

After removing the indicators *habit1* and *habit2*, the next step is to check the number of factors. Ideally, each factor has three high-loading indicators, yet as the feasibility of this is limited, two a minimum of two is adopted. The pattern matrix extracted at the first iteration, through oblique rotation and without the habit indicators, is visible in Figure E.2. The matrix shows that a fine number of factors is achieved since all five factors have 2 or more high-loading indicators.

Pattern Matrix[a]

	Factor				
	1	2	3	4	5
health1	,923				
health2	,764				
health3	,672				
reliab2		,718			
annoy2		,503			
comf2		-,441			
reliab3			,593		
annoy1			,550		
comf3			-,452		
env2				-,678	
env1				,658	
comf1					,744
reliab1					-,646

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 9 iterations.

Figure E.2: Exploratory Factor Analysis (oblique)

Next, the goal is to obtain a simple structure. Whether a simple structure is obtained depends on the loadings, i.e. the numerical values within the matrix indicating the strength and direction of the relationship between variables and factors. Loadings are ideally considered high when above 0.60, yet minimally above 0.50. Low loadings are below 0.30 and therefore negligible. Loadings in between are within a grey area. A simple structure is derived when each indicator loads high on one factor and low on all the other factors. From this pattern matrix, it can be concluded that the simple structure is almost achieved at the first iteration. Only the indicators *comf2* and *comf3* have no high loadings. Yet, whenever an indicator

Rotated Factor Matrix[a]

	Factor 1	2	3	4	5
health1	,884				
health2	,748				
health3	,663				
comf1		-,727			
reliab1		,665			
reliab2			,708		
annoy2			,501		
comf2			-,453	,314	
reliab3				,590	
annoy1				,547	
comf3				-,472	
env2					,672
env1					-,663

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Figure E.4: Rotated Factor Matrix (orthogonal)

has a loading within the grey, it may be considered to keep them whenever the content fits the factor well. For both indicators, this holds true because factor 2 represents attitudes towards car commuting, while factor 3 represents attitudes towards public transport commuting.

After obtaining a simple structure, it must be determined whether the orthogonal rotation also derives a simple structure. As orthogonal solutions are typically easier to interpret, this rotation is preferred. To determine whether the orthogonal rotation is better, the factor correlation matrix of the oblique rotation is checked. When this matrix contains correlations above 0.50, it implies dependency among the factors and thus no orthogonal factors. Figure E.3 presents the matrix and shows all negligible correlations <0.30, except for grey area factors 1 and 5, thus pointing towards orthogonal factors. On top of that, the rotated factor matrix of the orthogonal solution in Figure E.4, is compared to the pattern matrix of the oblique solution in Figure E.2. As the pattern matrix is not much better than the rotated factor matrix, the preference goes to the orthogonal solution.

Factor Correlation Matrix

Factor	1	2	3	4	5
1	1,000	,221	,109	-,164	,350
2	,221	1,000	-,160	-,106	-,089
3	,109	-,160	1,000	-,057	,021
4	-,164	-,106	-,057	1,000	-,113
5	,350	-,089	,021	-,113	1,000

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

Figure E.3: Factor Correlation Matrix (oblique)

Finally, it is determined whether the solution is interpretable. For a solution to be considered interpretable, it is necessary to be able to bring indications that load heavily on a factor under a common denominator. As this is the case, the factors can be labelled according to this common denominator, of which an overview is presented in Table E.1. The factor scores belonging to each of them, are calculated by the average responses of the indicators belonging to the different factors.

Table E.1: Factors obtained through PAF

Factor 1: Health consciousness		
health1	Physical activity is important to me.	+
health2	Being outside helps me clear my mind.	+
health3	I seriously take my health into account in my life.	+
Factor 2: (E-)bike commuting attitude		
comf1	After a work day, I find travelling by (e-)bike comfortable.	+
reliab1	Travelling by (e-)bike makes me worry about whether I will be at the academic hospital on time.	-
Factor 3: Car commuting attitude		
reliab2	Travelling by car makes me worry about whether I will be at the academic hospital on time.	-
annoy2	I am annoyed by traffic jams during my commute.	-
comf2	After a work day, I find travelling by car comfortable.	+
Factor 4: PT commuting attitude		
reliab3	Travelling by PT makes me worry about whether I will be at the academic hospital on time.	-
annoy1	I am annoyed by waiting for delayed PT during my commute.	-
comf3	After a work day, I find travelling by PT comfortable.	+
Factor 5: Environmental consciousness		
env1	The "environmental/ecological crisis" facing humankind has been greatly exaggerated.	-
env2	I think that humans are seriously abusing the environment.	-

The only two factors excluded from the PAF analysis are *habit1* and *habit2*. However, since habitual car commuting was highlighted by one of the interviewees as significant, it was decided to retain this theme in the experiment. Consequently, the statement *habit1*, which directly addresses this point, is included as an individual measurement scale.

E.2 Traveller-related attitudes

Table E.2: Results sample's traveller-related attitudes

		Total		Experiment 1		Experiment 2		Experiment 3	
	Coding	*Frequency*	*Percentage*	*Frequency*	*Percentage*	*Frequency*	*Percentage*	*Frequency*	*Percentage*
1: Health conscious	1.00 - 1.99	1	0,5%	1	7,7%	0	0,0%	0	0,0%
	2.00 - 2.99	3	1,6%	1	7,7%	1	1,2%	1	1,1%
	3.00	3	1,6%	0	0,0%	1	1,2%	2	2,3%
	3.01 - 3.99	37	20,2%	3	23,1%	18	21,7%	16	18,4%
	4.00 - 5.00	139	76,0%	8	61,5%	63	75,9%	68	78,2%
2: Pro (e-)bike commuting experience	1.00 - 1.99	3	1,6%	0	0,0%	1	1,2%	2	2,3%
	2.00 - 2.99	13	7,1%	1	7,7%	5	6,0%	7	8,0%
	3.00	18	9,8%	1	7,7%	4	4,8%	13	14,9%
	3.01 - 3.99	28	15,3%	1	7,7%	11	13,3%	16	18,4%
	4.00 - 5.00	121	66,1%	10	76,9%	62	74,7%	49	56,3%
3: Pro car commuting experience	1.00 - 1.99	31	16,9%	0	0,0%	14	16,9%	17	19,5%
	2.00 - 2.99	83	45,4%	9	69,2%	33	39,8%	41	47,1%
	3.00	26	14,2%	2	15,4%	13	15,7%	11	12,6%
	3.01 - 3.99	36	19,7%	2	15,4%	19	22,9%	15	17,2%
	4.00 - 5.00	7	3,8%	0	0,0%	4	4,8%	3	3,4%
4: Pro PT commuting experience	1.00 - 1.99	30	16,4%	4	30,8%	20	24,1%	6	6,9%
	2.00 - 2.99	98	53,6%	8	61,5%	47	56,6%	43	49,4%
	3.00	21	11,5%	1	7,7%	5	6,0%	15	17,2%
	3.01 - 3.99	29	15,8%	0	0,0%	8	9,6%	21	24,1%
	4.00 - 5.00	5	2,7%	0	0,0%	3	3,6%	2	2,3%
5: Environmentally conscious	1.00 - 1.99	2	1,1%	0	0,0%	0	0,0%	2	2,3%
	2.00 - 2.99	28	15,3%	0	0,0%	16	19,3%	12	13,8%
	3.00	128	69,9%	13	100,0%	51	61,4%	64	73,6%
	3.01 - 3.99	15	8,2%	0	0,0%	9	10,8%	6	6,9%
	4.00 - 5.00	10	5,5%	0	0,0%	7	8,4%	3	3,4%
6: Commuting as usual	1.00 - 1.99	21	11,5%	0	0,0%	3	3,6%	2	2,3%
	2.00 - 2.99	93	50,8%	0	0,0%	8	9,6%	8	9,2%
	3.00	16	8,7%	4	30,8%	32	38,6%	40	46,0%
	3.01 - 3.99	38	20,8%	2	15,4%	12	14,5%	13	14,9%
	4.00 - 5.00	15	8,2%	7	53,8%	28	33,7%	24	27,6%

Table E.3: Modality-related attitudes in case of irregular schedules and shift work

		Irregular = YES n = 44		**Irregular = NO** n = 139		**Shift = YES** n = 30		**Shift = NO** n = 153	
	Coding	*Frequency*	*Percentage*	*Frequency*	*Percentage*	*Frequency*	*Percentage*	*Frequency*	*Percentage*
1: Health conscious	1.00 - 1.99	1	2,3%	0	0,0%	0	0,0%	1	0,7%
	2.00 - 2.99	0	0,0%	5	3,6%	1	3,3%	4	2,6%
	3.00	2	4,5%	11	7,9%	1	3,3%	12	7,8%
	3.01 - 3.99	0	0,0%	0	0,0%	0	0,0%	0	0,0%
	4.00 - 5.00	41	93,2%	123	88,5%	28	93,3%	136	88,9%
2: Pro (e-)bike commuting experience	1.00 - 1.99	12	27,3%	18	12,9%	8	26,7%	22	14,4%
	2.00 - 2.99	24	54,5%	74	53,2%	15	50,0%	83	54,2%
	3.00	2	4,5%	19	13,7%	1	3,3%	20	13,1%
	3.01 - 3.99	6	13,6%	23	16,5%	6	20,0%	23	15,0%
	4.00 - 5.00	0	0,0%	5	3,6%	0	0,0%	5	3,3%
3: Pro car commuting experience	1.00 - 1.99	1	2,3%	1	0,7%	1	3,3%	1	0,7%
	2.00 - 2.99	2	4,5%	26	18,7%	3	10,0%	25	16,3%
	3.00	36	81,8%	92	66,2%	21	70,0%	107	69,9%
	3.01 - 3.99	3	6,8%	12	8,6%	4	13,3%	11	7,2%
	4.00 - 5.00	2	4,5%	8	5,8%	1	3,3%	9	5,9%
4: Pro PT commuting experience	1.00 - 1.99	1	2,3%	0	0,0%	0	0,0%	1	0,7%
	2.00 - 2.99	1	2,3%	2	1,4%	1	3,3%	2	1,3%
	3.00	0	0,0%	3	2,2%	0	0,0%	3	2,0%
	3.01 - 3.99	9	20,5%	28	20,1%	5	16,7%	32	20,9%
	4.00 - 5.00	33	75,0%	106	76,3%	24	80,0%	115	75,2%
5: Environmentally conscious	1.00 - 1.99	0	0,0%	0	0,0%	0	0,0%	0	0,0%
	2.00 - 2.99	1	2,3%	3	2,2%	0	0,0%	4	2,6%
	3.00	9	20,5%	30	21,6%	6	20,0%	33	21,6%
	3.01 - 3.99	0	0,0%	0	0,0%	0	0,0%	0	0,0%
	4.00 - 5.00	34	77,3%	106	76,3%	24	80,0%	116	75,8%
6: Commuting as usual	1.00 - 1.99	5	11,4%	26	18,7%	3	10,0%	28	18,3%
	2.00 - 2.99	25	56,8%	58	41,7%	14	46,7%	69	45,1%
	3.00	6	13,6%	20	14,4%	5	16,7%	21	13,7%
	3.01 - 3.99	8	18,2%	28	20,1%	7	23,3%	29	19,0%
	4.00 - 5.00	0	0,0%	7	5,0%	1	3,3%	6	3,9%

F

Appendix F. Apollo syntax

F.1 Apollo syntaxes

Experiment 1: Main effect MNL

```
######################################
#### Step 1: Load modules and data ####
######################################

# Clear memory
rm(list = ls())

# Load Apollo library
library(apollo)

# Initialise code
apollo_initialise()

# Set core controls
apollo_control = list(
  modelName       = "MNL_ex1",
  modelDescr      = "MNL model for experiment 1 (1 class)",
  indivID         = "RID",
  outputDirectory = "output",
  panelData = TRUE
)

# Load data
database = read.csv('data_010.csv', sep = ";", header = TRUE)

# Sort ID column
database = database[order(database[["RID"]]), ]

######################################
###### Step 2: Define parameters ######
######################################

# Define parameters
apollo_beta = c(
  C_BIKE           = 0,
  C_EBIKE          = 0,
  C_BUSTRAM        = 0,
  a_bike           = 0,
  a_ebike          = 0,
  c_ebike_lease    = 0,
  t_delay_bustram  = 0
)

# Set fixed parameters. If no parameter is fixed, do not fill it
apollo_fixed = c("C_BIKE")

# Validate inputs
```

```
apollo_inputs = apollo_validateInputs()

######################################
##### Step 3: Define the MNL model ####
######################################

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V=list()
  V[["BIKE"]]  = C_BIKE + a_bike * BIKE_ALLOW
  V[["EBIKE_LEASE"]]  = C_EBIKE + a_ebike * EBIKE_ALLOW + c_ebike_lease * EBIKE_LEASE_COST
  V[["BUSTRAM"]]  = C_BUSTRAM + t_delay_bustram * PT_DELAY

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(BIKE=1, EBIKE_LEASE=2, BUSTRAM=3),
    avail         = list(BIKE=1, EBIKE_LEASE=1, BUSTRAM=1),
    choiceVar     = CHOICE,
    utilities     = V
  )

  ### Compute probabilities using MNL model
  P[["model"]] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return (P)
}

######################################
## Step 4: Estimate and print output ##
######################################

# Estimate
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

# Print output
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE))

# Save output
apollo_saveOutput(model)
```

Experiment 1: MNL with interaction effects

```
# Define parameters
apollo_beta = c(
  C_BIKE                = 0,
  C_EBIKE               = 0,
  C_BUSTRAM             = 0,
  a_bike                = 0,
  a_ebike               = 0,
  c_ebike_lease         = 0,
  t_delay_bustram       = 0,

  #Socio-demographics
  C_EBIKE_I_gender      = 0,
  C_BUSTRAM_I_gender    = 0,

  C_EBIKE_I_age         = 0,
  C_BUSTRAM_I_age       = 0,
```

```

  C_EBIKE_I_shift       = 0,
  C_BUSTRAM_I_shift     = 0,

  C_EBIKE_I_irregular   = 0,
  C_BUSTRAM_I_irregular = 0
)

# Set fixed parameters
apollo_fixed = c("C_BIKE")


  ### Create alternative specific constants and coefficients using interactions with socio-
      demographics
  C_EBIKE_value   = C_EBIKE  + C_EBIKE_I_gender * gender + C_EBIKE_I_age * age + C_EBIKE_I_shift *
      shift + C_EBIKE_I_irregular * irregular
  C_BUSTRAM_value  = C_BUSTRAM + C_TR_BUSTRAM_I_gender * gender + C_TR_BUSTRAM_I_age * age +
      C_TR_BUSTRAM_I_shift * shift + C_TR_BUSTRAM_I_irregular * irregular

  ### List of utilities
  V=list()
  V[["BIKE"]]  = C_BIKE + a_bike * BIKE_ALLOW
  V[["EBIKE_LEASE"]]  = C_EBIKE_value + a_ebike * EBIKE_ALLOW + c_ebike_lease * EBIKE_LEASE_COST
  V[["BUSTRAM"]]  = C_BUSTRAM_value + t_delay_bustram * PT_DELAY

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(BIKE=1, EBIKE_LEASE=2, BUSTRAM=3),
    avail         = list(BIKE=1, EBIKE_LEASE=1, BUSTRAM=1),
    choiceVar     = CHOICE,
    utilities     = V)
}
```

Experiment 2: Main effect MNL

```
    # Define parameters
apollo_beta = c(
  C_EBIKE               = 0,
  C_CAR                 = 0,
  C_TRAIN_BUSTRAM       = 0,
  C_TRAIN_SBIKE         = 0,
  C_CAR_SBIKE           = 0,
  a_ebike               = 0,
  c_ebike_lease         = 0,
  t_park_car            = 0,
  t_egress              = 0,
  t_delay_car           = 0,
  c_park_car            = 0,
  a_car                 = 0,
  t_delay_train_bustram = 0,
  t_transfer            = 0,
  t_delay_train_sbike   = 0,
  a_train_sbike         = 0,
  u_sbike_train         = 0,
  c_park_car_pr         = 0,
  a_sbike_car           = 0,
  u_sbike_car           = 0
  )

# Set fixed parameters
apollo_fixed = c("C_CAR")

  ### List of utilities
  V=list()
  V[["EBIKE_LEASE"]]  = C_EBIKE + a_ebike * EBIKE_ALLOW + c_ebike_lease * EBIKE_LEASE_COST
  V[["CAR"]]  = C_CAR + t_park_car * CAR_PARK_TIME + t_egress * EGRESS_TIME + t_delay_car *
      CAR_DELAY + c_park_car * CAR_PARK_COST + a_car * CAR_ALLOW
  V[["TR_BUSTRAM"]]  = C_TRAIN_BUSTRAM + t_delay_train_bustram * TR_BUSTRAM_PT_DELAY + t_transfer *
       TRANSFER
  V[["TR_SBIKE"]]  = C_TRAIN_SBIKE + t_delay_train_sbike * TR_SBIKE_DELAY + a_train_sbike *
      SBIKE_ALLOW + u_sbike_train * TR_SBIKE_UNAV
```

```
  V[["CAR_SBIKE"]]  = C_CAR_SBIKE + c_park_car_pr * PR_PARKCOST + a_sbike_car * CAR_SBIKE_ALLOW +
      u_sbike_car * CAR_SBIKE_UNAV

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(EBIKE_LEASE=1, CAR=2, TR_BUSTRAM=3, TR_SBIKE=4, CAR_SBIKE=5),
    avail         = list(EBIKE_LEASE=1, CAR=1, TR_BUSTRAM=1, TR_SBIKE=1, CAR_SBIKE=1),
    choiceVar     = CHOICE,
    utilities     = V
  )
```

Experiment 2: MNL with interaction effects

```
    # Define parameters
apollo_beta = c(
  C_EBIKE               = 0,
  C_CAR                 = 0,
  C_TRAIN_BUSTRAM       = 0,
  C_TRAIN_SBIKE         = 0,
  C_CAR_SBIKE           = 0,
  a_ebike               = 0,
  c_ebike_lease         = 0,
  t_park_car            = 0,
  t_egress              = 0,
  t_delay_car           = 0,
  c_park_car            = 0,
  a_car                 = 0,
  t_delay_train_bustram = 0,
  t_transfer            = 0,
  t_delay_train_sbike   = 0,
  a_train_sbike         = 0,
  u_sbike_train         = 0,
  c_park_car_pr         = 0,
  a_sbike_car           = 0,
  u_sbike_car           = 0,

  #Socio-demographics
  C_EBIKE_I_gender      = 0,
  C_TR_BUSTRAM_I_gender = 0,
  C_TR_SBIKE_I_gender   = 0,
  C_CAR_SBIKE_I_gender  = 0,

  C_EBIKE_I_age         = 0,
  C_TR_BUSTRAM_I_age    = 0,
  C_TR_SBIKE_I_age      = 0,
  C_CAR_SBIKE_I_age     = 0,

  C_EBIKE_I_shift       = 0,
  C_TR_BUSTRAM_I_shift  = 0,
  C_TR_SBIKE_I_shift    = 0,
  C_CAR_SBIKE_I_shift   = 0,

  C_EBIKE_I_irregular      = 0,
  C_TR_BUSTRAM_I_irregular = 0,
  C_TR_SBIKE_I_irregular   = 0,
  C_CAR_SBIKE_I_irregular  = 0

  )

# Set fixed parameters
apollo_fixed = c("C_CAR")

  ### Create alternative specific constants and coefficients using interactions with socio-
      demographics
  C_EBIKE_value   = C_EBIKE  + C_EBIKE_I_gender * gender + C_EBIKE_I_age * age + C_EBIKE_I_shift *
      shift + C_EBIKE_I_irregular * irregular
  C_TR_BUSTRAM_value  = C_TRAIN_BUSTRAM + C_TR_BUSTRAM_I_gender * gender + C_TR_BUSTRAM_I_age * age
       + C_TR_BUSTRAM_I_shift * shift + C_TR_BUSTRAM_I_irregular * irregular
  C_TR_SBIKE_value  = C_TRAIN_SBIKE + C_TR_SBIKE_I_gender * gender + C_TR_SBIKE_I_age * age +
      C_TR_SBIKE_I_shift * shift + C_TR_SBIKE_I_irregular * irregular
```

```
  C_CAR_SBIKE_value  = C_CAR_SBIKE + C_CAR_SBIKE_I_gender * gender + C_CAR_SBIKE_I_age * age +
      C_CAR_SBIKE_I_shift * shift + C_CAR_SBIKE_I_irregular * irregular

  ### List of utilities
  V=list()
  V[["EBIKE_LEASE"]]  = C_EBIKE_value + a_ebike * EBIKE_ALLOW + c_ebike_lease * EBIKE_LEASE_COST
  V[["CAR"]]  = C_CAR + t_park_car * CAR_PARK_TIME + t_egress * EGRESS_TIME + t_delay_car *
      CAR_DELAY + c_park_car * CAR_PARK_COST + a_car * CAR_ALLOW
  V[["TR_BUSTRAM"]]  = C_TR_BUSTRAM_value + t_delay_train_bustram * TR_BUSTRAM_PT_DELAY +
      t_transfer * TRANSFER
  V[["TR_SBIKE"]]  = C_TR_SBIKE_value + t_delay_train_sbike * TR_SBIKE_DELAY + a_train_sbike *
      SBIKE_ALLOW + u_sbike_train * TR_SBIKE_UNAV
  V[["CAR_SBIKE"]]  = C_CAR_SBIKE_value + c_park_car_pr * PR_PARKCOST + a_sbike_car *
      CAR_SBIKE_ALLOW + u_sbike_car * CAR_SBIKE_UNAV

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(EBIKE_LEASE=1, CAR=2, TR_BUSTRAM=3, TR_SBIKE=4, CAR_SBIKE=5),
    avail         = list(EBIKE_LEASE=1, CAR=1, TR_BUSTRAM=1, TR_SBIKE=1, CAR_SBIKE=1),
    choiceVar     = CHOICE,
    utilities     = V
  )
```

Experiment 3: Main effect MNL

```
    # Define parameters
apollo_beta = c(
  C_CAR                  = 0,
  C_TRAIN_BUSTRAM        = 0,
  C_TRAIN_SBIKE          = 0,
  t_park_car             = 0,
  t_egress               = 0,
  t_delay_car            = 0,
  c_park_car             = 0,
  a_car                  = 0,
  t_delay_train_bustram  = 0,
  t_transfer             = 0,
  t_delay_train_sbike    = 0,
  a_train_sbike          = 0,
  u_sbike_train          = 0
)

# Set fixed parameters
apollo_fixed = c("C_CAR")

  ### List of utilities
  V=list()
  V[["CAR"]]  = C_CAR + t_park_car * CAR_PARK_TIME + t_egress * EGRESS_TIME + t_delay_car *
      CAR_DELAY + c_park_car * CAR_PARK_COST + a_car * CAR_ALLOW
  V[["TR_BUSTRAM"]]  = C_TRAIN_BUSTRAM + t_delay_train_bustram * TR_BUSTRAM_PT_DELAY + t_transfer *
       TRANSFER
  V[["TR_SBIKE"]]  = C_TRAIN_SBIKE + t_delay_train_sbike * TR_SBIKE_DELAY + a_train_sbike *
      SBIKE_ALLOW + u_sbike_train * TR_SBIKE_UNAV

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(CAR=1, TR_BUSTRAM=2, TR_SBIKE=3),
    avail         = list(CAR=1, TR_BUSTRAM=1, TR_SBIKE=1),
    choiceVar     = CHOICE,
    utilities     = V
  )
```

Experiment 3: MNL with interaction effects

```
    # Define parameters
apollo_beta = c(
  C_CAR                  = 0,
  C_TRAIN_BUSTRAM        = 0,
  C_TRAIN_SBIKE          = 0,
  t_park_car             = 0,
  t_egress               = 0,
```

```
  t_delay_car            = 0,
  c_park_car             = 0,
  a_car                  = 0,
  t_delay_train_bustram  = 0,
  t_transfer             = 0,
  t_delay_train_sbike    = 0,
  a_train_sbike          = 0,
  u_sbike_train          = 0,

  #Socio-demographics
  C_TR_BUSTRAM_I_gender = 0,
  C_TR_SBIKE_I_gender   = 0,

  C_TR_BUSTRAM_I_age    = 0,
  C_TR_SBIKE_I_age      = 0,

  C_TR_BUSTRAM_I_shift  = 0,
  C_TR_SBIKE_I_shift    = 0,

  C_TR_BUSTRAM_I_irregular = 0,
  C_TR_SBIKE_I_irregular   = 0

)

# Set fixed parameters
apollo_fixed = c("C_CAR")

  ### Create alternative specific constants and coefficients using interactions with socio-
      demographics
  C_TR_BUSTRAM_value  = C_TRAIN_BUSTRAM + C_TR_BUSTRAM_I_gender * gender + C_TR_BUSTRAM_I_age * age
       + C_TR_BUSTRAM_I_shift * shift + C_TR_BUSTRAM_I_irregular * irregular
  C_TR_SBIKE_value  = C_TRAIN_SBIKE + C_TR_SBIKE_I_gender * gender + C_TR_SBIKE_I_age * age +
      C_TR_SBIKE_I_shift * shift + C_TR_SBIKE_I_irregular * irregular

  ### List of utilities
  V=list()
  V[["CAR"]]  = C_CAR + t_park_car * CAR_PARK_TIME + t_egress * EGRESS_TIME + t_delay_car *
      CAR_DELAY + c_park_car * CAR_PARK_COST + a_car * CAR_ALLOW
  V[["TR_BUSTRAM"]]  =  C_TR_BUSTRAM_value + t_delay_train_bustram * TR_BUSTRAM_PT_DELAY +
      t_transfer * TRANSFER
  V[["TR_SBIKE"]]  = C_TR_SBIKE_value + t_delay_train_sbike * TR_SBIKE_DELAY + a_train_sbike *
      SBIKE_ALLOW + u_sbike_train * TR_SBIKE_UNAV

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(CAR=1, TR_BUSTRAM=2, TR_SBIKE=3),
    avail         = list(CAR=1, TR_BUSTRAM=1, TR_SBIKE=1),
    choiceVar     = CHOICE,
    utilities     = V
  )
```