# Cycling to the hospital

## A research on what affects hospital employees' willingness to cycle for commuting

TIL5060: TIL Thesis

Date: July 2025

S. A. M. Jacobs

Delft University of Technology

pon

TU Delft

# Cycling to the hospital

## A research on what affects hospital employees' willingness to cycle for commuting

by

Sara Augusta Maria Jacobs

This report is submitted to obtain the degrees of Master of Science in Transport Infrastructure and Logistics at Delft University of Technology

To be defended publicly on July 21, 2025.

**Thesis committee:**

| | |
|---|---|
| Chair: | Dr. E. J. E. Molin |
| Second supervisor: | Dr. Ir. N. van Oort |
| Supervisor Pon: | Mr. R. Gense |
| Supervisor Pon: | Ms. K. R. M. Maas |

| | |
|---|---|
| Project Duration: | February, 2025 - July, 2025 |
| Faculty: | Civil Engineering and Geosciences |
| Student number: | 4837193 |

| | |
|---|---|
| Cover: | Generated using OpenAI through ChatGPT, based on a design request tailored to the research theme |
| Style: | TU Delft Report Style, with modifications by Sara Jacobs |

An electronic version of this thesis is available at http://repository.tudelft.nl/

TU Delft

# Preface

This thesis marks the end of my time in Delft and the completion of my academic journey, during which I pursued a Bachelor's at the faculty Technology Policy And Management, followed by a Master's in Transport, Infrastructure and Logistics. Overall, it has been an intense but rewarding period, one I look back on with great joy. I have learned an incredible amount, and many of the insights I gained were applied during the writing of this thesis.

I would like to thank all those who supported me throughout this journey. First, my supervisor Mr. Molin, thank you very much for your technical insights and the clear guidance throughout the entire project. I always knew what was expected of me and felt comfortable reaching out to you with questions at any stage.

I also want to express my gratitude to my second supervisor, Mr. van Oort. I am very thankful for your support and detailed feedback throughout the whole process. In addition, I greatly enjoyed being part of the Smart Public Transport Student Lab, where I had the opportunity to learn from and collaborate with fellow students.

Beyond my TU Delft supervisors, I would like to thank my supervisors at Pon for giving me the opportunity to carry out this research. I experienced this period as both enjoyable and highly educational. First, thank you Raymond for your advice and expertise, especially in helping me see the bigger picture when needed. And Kim, thank you so much for your time and support. It was a pleasure working with you. I really appreciated your hands-on involvement and genuine interest in the research. Besides the content itself, I also enjoyed working with you on a personal level.

I would also like to thank the academic hospital staff for providing the necessary information and for allowing me to carry out research among their employees. Without their cooperation, this study would not have been possible in its current form.

Lastly, I want to thank my family and friends. Without their ongoing support, I would not have been able to complete this thesis in the way I did. During the intense and stressful periods, they provided moments of calm, encouragement, and companionship.

I look forward to the next steps, wherever they may lead, and I will take all the experiences and lessons I've learned with me into the future.

*S. A. M. Jacobs*
*Delft, July 2025*

# Summary


## Introduction

The climate crisis demands urgent action and significant reductions in greenhouse gas emissions. Transportation is a major contributor to global emissions, with commuting making up a substantial portion (CBS 2025). Given this large share, both governments and businesses are increasingly focused on minimizing emissions. As a result, a new regulation has been introduce where companies with more than 100 employees are required to report the CO2 emissions generated by employee commuting (RVO 2023). Promoting a shift toward more sustainable modes of transport is therefore essential, as these alternatives have a significantly lower environmental impact. An example of organizations who experience a high volume of daily movement are hospitals. Therefore is this study specifically focused on an academic hospital with 12.000 employees. The hospital is situated in a densely populated area, at the surrounding terrain are various organizations located including universities, high schools, other medical institutions, several private companies, and this continues to expand. Furthermore, hospital employees often commute at various times throughout the day, which sets them apart from typical commuters who usually travel during peak hours only. This highlights the unique dynamics of a hospital setting, making it a special and interesting group for research. Furthermore is this research is a collaboration between that academic hospital, Pon Holdings and the TU Delft.

A significant challenge for the hospital is the severe congestion in this area, particularly during peak hours (Zadeits 2024). With additional organizations soon joining the complex, this problem is anticipated to worsen. Recognizing these issues, the hospital launched a Living Lab project in 2024. For seven months, this initiative saw 300 employees voluntarily commit to commuting to the hospital using only sustainable methods. The Living Lab was designed not only to solve current congestion problem but also to reduce the high proportion of car commuters and subsequently lower CO2 emissions (Academic hospital 2025).

The Living Lab served as the foundation for this research. The goal of this study was to gain deeper insight into the factors that could encourage a modal shift among hospital employees, specifically focusing on increasing the use of bicycles for commuting. This research aimed to fill a gap, as no previous studies have explored the specific shift to cycling only, within this particular target group of hospital staff. The Living Lab involved only employees who voluntarily signed up for the project and therefore could be perceived as sustainability-focused. In contrast, this study aims to engage a broader and more representative group of employees. By doing so, it aimed to better reflect the general hospital population. Based on these considerations, the following main research question was developed:

*To what extent do transportation mode attributes influence the choice of (electric) bicycle commuting over alternative modes among employees in the healthcare sector?*

To answer the main research question, several sub-questions were developed. These focus on the lasting impact of the Living Lab, the contextual factors surrounding the hospital, the different attitudes among employees, and the possibility of different segments within the employee group. This makes it possible to explore whether their opinions are generally aligned or show clear differences.

## Methodology and operationalization

To gain a better understanding of international literature and how this specific study relates to existing findings, a literature review was conducted. This review revealed many insightful points, emphasizing that numerous factors influence mode choice. These factors range from the attributes of different travel modes to personal and psychosocial characteristics, as well as the role employers play in shaping commuting decisions. It became clear that choosing a mode of transport is not solely based on travel time, many other influences play a role. For example, the adoption of cycling showed interesting patterns, as this process is highly dependent on individual preferences and the way in which cycling is introduced or promoted (van der Steen et al. 2025).

After completing the literature review, the next step was to collect new data on the commuting preferences of hospital employees. This data was gathered through a survey. The survey consisted of several components, including questions about the Living Lab, a Discrete Choice Experiment (DCE), assessments of employee attitudes, and their personal characteristics. To gain insights into the choices of employees was a Discrete Choice Model (DCM) used. This method helps to understand how individuals choose between travel modes by presenting them with hypothetical scenarios in which mode attributes are varied (Friedel et al. 2022). Respondents then select their preferred option from each set, revealing their underlying preferences. This process is carried out through a Discrete Choice Experiment. In this experiment, respondents were shown different commuting alternatives: city bike, e-bike, and their current mode of transport (either car or public transport). The original target group included only employees who commuted by car or public transport, but this was later expanded to include those who already commuted by bike. This group was added because some may be cycling due to a lack of other options, and their behavior might change if their circumstances change. Also incorporating employees who currently commute by bike, ensured that a broad range of opinions was captured. Each choice set presented three alternatives, with the third always being either car or public transport. These alternatives are based on different attributes which are varied per choice set.

The attributes varied in the experiment were selected in close collaboration with the hospital and Pon. These included: bicycle facilities available to employees, the cost of purchasing an e-bike, parking costs at the hospital garage, the time it takes to find a parking spot, and travel delay (both on the road and in public transport). Additionally, a weather variable was included as a context variable, applying equally to all alternatives in a given choice set. In total, respondents were presented with 9 different choice sets, each showing a unique combination of these attributes to assess their impact on mode preference. The target group for the Discrete Choice Experiment were people who traveled less than 30 kilometers because using a bike for trips commuting trips longer than 30 kilometers is not very attractive anymore. Because of this is decided to show the experiment only to people who travel less than 30 kilometer during a single trip. However the rest of the survey is still shown to the people who do travel more than 30 kilometers per single trip.

Aside from the Discrete Choice Experiment, the survey also tested the attitudes of respondents. To do this, they were presented with various statements covering different themes and were asked to rate their level of agreement using a Likert scale, ranging from "strongly agree" to "strongly disagree." The themes of these statements were related to safety, health, sustainability, and delay. The results of these statements were analyzed to identify potential relationships between attitudes and sociodemographic characteristics.

In addition, specific questions were included for participants of the Living Lab. These questions aimed to assess whether participants still commute in a sustainable way and how their cycling experience has improved or worsened. Apart from the Living Lab questions, the survey also included a question for all respondents about what could potentially improve their cycling experience, even if they do not currently commute by bike. This was an open-ended question, allowing for a qualitative approach to gather insights from both cyclists and those who use other modes of transport. To analyze the responses, thematic coding was applied by grouping the answers into relevant themes based on their content. The last part of the survey was used to ask the employees about their personal characteristic. Here variables like gender, current mode of transport, function and vehicle possession where asked among other things. These characteristics were added to understand the population of the respondents and be able to search for specific pattern in choice behavior.

The results of the Discrete Choice Experiment were analyzed using different models. The first model estimated was the Multinomial Logit (MNL) model. This model follows the principles of the Random Utility Maximization (RUM), which assumes that individuals choose the alternative that maximizes their utility. As a result, the probability of an alternative being chosen depends on its utility. Additionally, a Nested Logit (NL) model was estimated. The MNL model assumes that all alternatives are unrelated, but in this case, two alternatives, the city bike and the e-bike, are both bicycles and therefore share similarities. For this reason, it was necessary to explore whether a nest could be formed between these two options to better reflect the decision-making process.

In addition to the MNL and NL models, two additional models were estimated: an interaction model and a Latent Class Choice Model (LCCM). The interaction model, based on the MNL framework, includes interaction terms to capture how the effect of one variable depends on another. This allows the model to account for heterogeneity in preferences across individuals, for example, whether delays are perceived differently by men and women. The LCCM identifies unobserved subgroups within the population, each with its own choice behavior. It estimates both class-specific choice models and the probability of class membership based on individual characteristics.

# Results

In total 275 employees of the hospital filled in the survey, from that group 161 were part of the Discrete Choice Experiment. The amount of female respondents was higher then the amount of male respondent. The same can be said for the amount of people who currently travel by public transport compared to the other modes of transport, this was significantly higher. Also it became clear that there was a relatively small share of employees who travel less then 7,5 kilometer for a single trip.

The results from the statements presented to employees show that overall attitudes toward safety are very positive. Most respondents perceive their commuting route as safe. Similarly, many people feel physically fit enough to cycle to work. However, they generally disagreed with the statement that they would like to be more physically active. In addition, a large share of respondents agreed that the academic hospital should encourage its employees to commute sustainably. A similar, though slightly lower, level of support was expressed when asked if they would be willing to travel a bit longer for a more sustainable option. Lastly, responses to the statement about experiencing delays in recent months were highly divided. This largely depended on the current mode of transport used. Car users rated this statement more highly than public transport users and significantly higher than cyclists. There was also a clear relationship between a respondent's current travel mode and their agreement with the sustainability-related statements: those who commute by car tended to agree less with these statements overall.

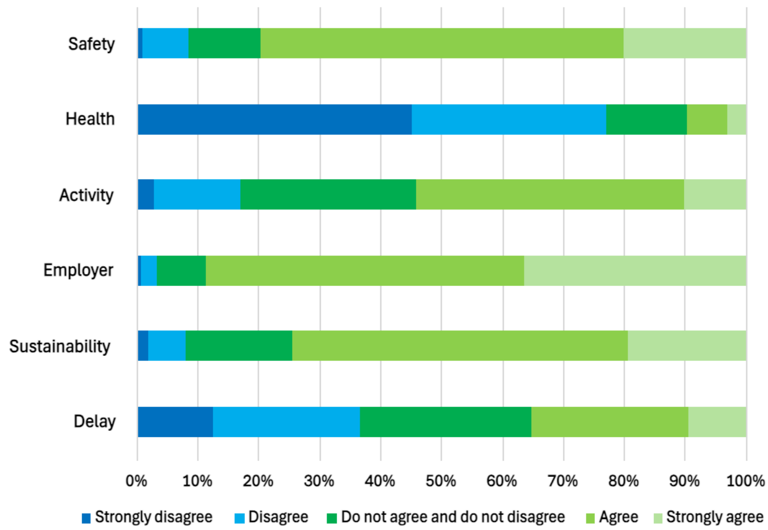



**Figure 1:** Answers distribution to statements

The results from the questions about the Living Lab show a clear trend: more than 80% of participants still commute in a sustainable way. However, this also means that some participants have reverted to previous habits and no longer travel sustainably. This marks a 10% increase in non-sustainable commuting compared to the end of the Living Lab. Almost everyone who adopted more sustainable travel methods, specifically cycling, reported a better experience than they initially expected. This feedback is even more positive than what was gathered at the conclusion of the Living Lab. Health benefits and the feeling of contributing to sustainability were among the most important factors that improved their perception. These results suggest that continued use of a sustainable travel mode tends to increase overall satisfaction.

The multiple-response and open-ended question about factors that could improve the bicycle commuting experience revealed several common requests. A major one was reimbursement for rain clothing, ideally combined with facilities to hang wet clothes to dry. Additionally, many respondents asked for more charging points for e-bike batteries. Beyond these predefined topics, frequent suggestions included the introduction of shared e-bikes at public transport stations and an increase in the reimbursement offered through the current bike plan. The hospital offers a bike plan where employees receive partial reimbursement and can pay off the rest through a tax-advantaged loan. These options show a qualitative way of gaining insight in what could lead people toward a commuting trip by bike.

Across all models, it became clear that weather had the greatest impact on mode choice. Delay was the second most influential factor. Overall, the e-bike showed the highest utility in good weather, while public transport had the highest utility in bad weather. The other attributes also showed signs of influence; however, they were often not statistically significant. Therefore, the strength of these attributes cannot be determined with certainty. The interaction effects show that travel preferences are strongly shaped by individual attitudes and experiences. Sustainability-minded individuals and those recently affected by delays are more sensitive to delays and parking costs. City and e-bike users are also more delay-averse than motorized transport users. Those with health concerns are more sensitive to walking and parking time, reflecting reliance on the car. Respondents who expect employer support for sustainable commuting are more sensitive to e-bike costs, especially women. Including these interactions improved model performance, highlighting the relevance of attitudinal factors, though not all effects were statistically significant. From Figure 2, it can be seen that the e-bike was chosen most frequently, followed by the city bike, while public transport was chosen the least. This is likely because the shares for the city bike and car remained relatively stable compared to the current mode distribution. Public transport, on the other hand, saw a significant decrease in probability. This suggests that many individuals who currently travel by public transport often chose the e-bike in the experiment.

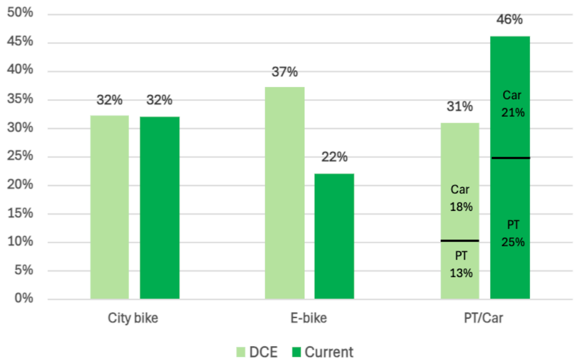



**Figure 2:** Modal split experiment versus current behavior

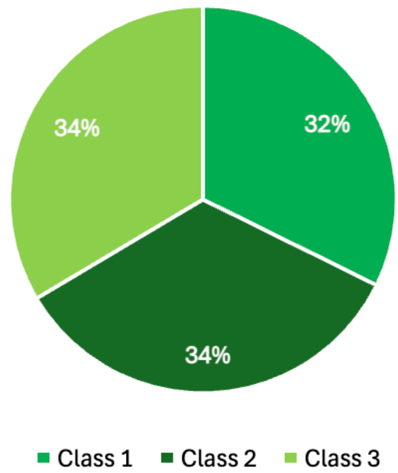



**Figure 3:** Distribution between classes

The Latent Class Choice Model identifies three distinct commuter profiles with differing preferences and sensitivities. The classes can be labeled as follows:

- Class 1: Sensitive mixture
- Class 2: Rigid motorized patterns
- Class 3: Influenceable e-bikers

Class 1 prefers the city but is highly responsive to travel conditions such as cost, time, and weather, suggesting flexible behavior shaped by context. Class 2 favors motorized transport, is relatively insensitive to travel attributes, and shows limited openness to cycling alternatives despite being aware of existing programs. Class 3 shows a baseline preference for the e-bike and moderate sensitivity to attributes, particularly cycling facilities. This group appears open to change but is often unaware of available support. The classes are very evenly distributed as can be seen in Figure 3.

# Conclusion

This research combines quantitative insights from the Discrete Choice Experiment with qualitative input from open-ended responses to understand commuting preferences. The findings show that employee preferences are diverse, with no single commuter profile. Delay was the most influential attribute overall, particularly for current cyclists, while weather had a strong, mode-dependent impact. Car and public transport users were less affected by delay, likely due to habituation. Facilities mainly influenced current e-bike users, suggesting that the provided interventions were not broadly appealing. However, the results indicate clear potential for behavioral change, with a probability of 42% for car users and 50% for public transport users to choose a cycling alternative. In total, when also taken current e-bike and city bike users into account, 70% of respondents are likely to choose a bike alternative, highlighting opportunities for targeted, positive incentives beyond those tested in the experiment.

All of this indicates that there is room for improvement, but the effectiveness of potential interventions strongly depends on the target group and the current mode of transport they are using. Everyone has different preferences, and different factors influence their behavior. For example, individuals who frequently experience delays need tailored solutions that directly address that issue.

When it comes to weather, no direct solution can be offered, as it cannot be influenced. However, findings from the Living Lab suggest that well-timed interventions can have a long-term effect on travel behavior. This implies that interventions should ideally be introduced during the summer, when the weather is good and cycling is more appealing. By the time weather conditions worsen, individuals may have already formed new commuting habits, making them less sensitive to less favorable weather.

Based on all the findings, a wide range of actions can be considered. These include adjusting existing regulations, such as modifying the current bike plan or reorganizing the travel allowance system to also reward multimodal travel. Encouraging multimodal travel could help address the issue of delays, which mostly occur during the final part of the journey. Currently, there are no incentives in place to support such travel behavior. In addition, successful measures from the Living Lab, such as shared e-bikes, could be reintroduced. These contribute to solving the "last-mile" challenge by reducing car use around the hospital and helping to avoid delays. New policies could also be introduced, such as awareness campaigns aimed at informing hospital employees about alternative commuting options that may be more attractive to them. These campaigns could help shift perceptions and encourage more sustainable travel behavior.

However, this research also has some limitations. One notable issue was the high number of non-traders among the respondents. This may have been caused by the visual design of the choice sets or by the limited differences between them, which could have led to a loss of concentration. Additionally, a large portion of the responses came from participants of the Living Lab. These individuals are more sustainability-minded and already engaged with similar research, which could introduce bias into the results. Furthermore, car and public transport were often treated as the same alternative, referred to as the current mode, when compared to bicycle alternatives. However, because these two modes differ significantly, this may have introduced estimation errors.

Based on the limitations and findings of this study, there is considerable room for further research. Future studies could focus specifically on car and public transport users or explore a new target group, such as newly hired employees. These groups may offer fresh perspectives and allow for testing new interventions. Another area for further investigation is travel behavior in relation to the reimbursement of travel allowances. By analyzing this data, commonly used public transport stations or busy travel routes can be identified. This information could then be used to assess optimal locations for implementing shared e-bikes or other mobility solutions.

# Contents

# List of Figures

# List of Tables

# Nomenclature

## Abbreviations

| Abbreviation | Definition |
|---|---|
| PT | Public Transport |
| DCM | Discrete Choice Modelling |
| DCE | Discrete Choice Experiment |
| SP | Stated Preference |
| RP | Revealed Preference |
| RUT | Random Utility Theory |
| RUM | Random Utility Maximization |
| LCCM | Latent Class Choice Modeling |
| EFA | Exploratory Factor Analysis |
| PAF | Principal Axis Factoring |
| MNL | Multinominal Logit |
| NL | Nested Logit |
| MLE | Maximum Likelihood Estimation |
| LL | Log Likelihood |
| AIC | Akaike Information Criterion |
| BIC | Bayesian Information Criterion |
| ASC | Alternative Specific Constant |

# 1

# Introduction

## 1.1. Problem statement

The climate crisis is one of the most urgent challenges of this time, with its severe consequences already affecting the planet. Rising temperatures and sea levels are among the many impacts of this crisis (Mikhaylov et al. 2020). Since 1980, global temperatures have risen by 1,1°C, intensifying heatwaves that threaten human health and ecosystems (Lindsey & Dahlman 2024). Additionally, melting glaciers and ice caps are causing sea levels to rise, increasing flood risks for coastal communities (Mikhaylov et al. 2020). These are just a few examples of the many negative effects of climate change.

Efforts to mitigate climate change have led to the establishment of significant international treaties and regulations aimed at reducing greenhouse gas emissions. The European Green Deal is focused on achieving climate neutrality by 2050. A central component of this deal is the "Fit for 55" package, which aims to cut net greenhouse gas emissions by at least 55% by 2030 compared to 1990 levels (European Council 2025). The 2015 Paris Agreement is another example of a treaty involving 195 parties committed to limiting the global warming to 1,5°C (United Nations 2025).

Transportation is the second-largest contributor to global emissions (Statista 2025). In 2023, $CO_2$ emissions from passenger cars in the Netherlands totaled 14.4 megatons (CBS 2025). While transportation serves various purposes, commuting represents a significant portion, accounting for 25,8% of the total distance traveled. It is estimated that approximately 3,7 megatons of $CO_2$ emissions are attributable to commuting by car (CBS 2025). Public transport is already significantly more sustainable than car travel; however, it still emits an average of 33 grams of $CO_2$ per kilometer, compared to an average of 148 grams per kilometer for cars (Milieu Centraal 2025).

Given the substantial emission shares, reducing commuting-related emissions has become a key priority for both the government and businesses. As a result, a new regulation has been introduced: starting July 1, 2024: companies with more than 100 employees will be required to report the $CO_2$ emissions generated by employee commuting (RVO 2023).

In the Netherlands in 2022, were 30% of all trips to and from work made by car, compared to 27% by bike and 5% by public transport (KiM 2023). This high share of car commuting contributes to congestion, particularly during peak hours. According to Rijkswaterstaat (2024), the total travel time lost due to congestion amounted to 61.8 million hours in 2023. This means that high car use for commuting not only increases emissions but also reduces accessibility. Accessibility can also reduces due to delays in pubic transport. Nichols et al. (2024) stated that jobs become 4-9% less accessible due to delays in public transport.

The combination of commuting's significant impact on emissions and accessibility, along with new CO reporting regulations, makes it essential for organizations to address their transportation footprint and set their sights on a potential model shift. This is also relevant for healthcare institutions, where a large workforce contributes to daily travel-related emissions. A reason for this is that many employees in hospitals work irregular shifts and that is why they often have to rely on private transportation (Lim et al. 2024). Therefore, the target group of this research is the healthcare sector, specifically the employees of an academic hospital.

The specific academic hospital will remain private due to privacy reasons, therefore the hospital will be referred to as "An academic hospital".

In July 2023, a new collective bargaining agreement was introduced for hospitals, increasing the travel allowance for all modes of transportation from €0,05 to €0,18 per kilometer (Dutch Association of Hospitals 2023). However, this policy does not offer additional incentives for private sustainable transportation. At the academic hospital, public transportation is fully reimbursed for employees, yet there is still no motivation to choose cycling over driving. This regulation involves multiple stakeholders, creating a complex framework of government and municipal regulations that the hospital must comply with. Additionally, the hospital's management team plays a crucial role in ensuring employee well-being.

If the hospital wants to focus on creating a modal shift then the key trade-off lies between the incentives the hospital implements and the commuting convenience for employees. While the hospital can introduce measures to promote cycling, such as improved facilities or financial incentives, these must be balanced against employee preferences for comfort, travel time, and reliability. The challenge is determining how much impact hospital-led initiatives can have versus employees' willingness to adapt their commuting habits, making it crucial to balance policy intervention with personal choice.

## 1.2. Living Lab Sustainable Travel

In 2024, a seven-month Living Lab was launched at the academic hospital in collaboration with Pon. During this period, 300 employees voluntarily commuted to the hospital using only sustainable modes of transport, car use was discouraged (Academic hospital 2025). To support this, participants received high travel allowance for cycling, normally this was €0,05 per kilometer and in the Living Lab this increased to €0,16. Public transport costs were fully reimbursed, and Hely (e-)bike hubs were made available at two nearby train station and at the hospital. Hely e-bikes are shared bicycles placed at train stations and can be used for the last part of the journey, between the station and the hospital (Hely 2025).

Additionally, to encourage remote work and reduce travel, participants could use a Shuttel app to register their work-from-home days and receive a reimbursement (Shuttel 2025). To access these benefits, participants gave up their parking privileges between 6:00 and 12:00. If they wanted to park during these hours then they had to pay the normal parking fees, which is €3 per day (Academic hospital 2025). Because of these hours, employees working irregular shifts were still allowed to park for free.

During the Living Lab, all participants' travel activities were tracked and analyzed. Furthermore, several surveys, focus groups, and interventions were conducted to gain insight into participants' experiences and gather their opinions.

As mentioned in the Problem statement 1.1, regulations recently changed following the new collective bargaining agreement. These changes include a higher travel allowance of €0.18 per kilometer and full reimbursement for public transport (Dutch Association of Hospitals 2023). This means that the benefits introduced during the Living Lab are now available to the entire company. However, after the Living Lab ended, the Hely bikes at the stations were removed, and the Shuttel app was no longer in use.

The Living Lab was developed to address three specific goals: achieving a 55% reduction in CO emissions by 2030, reducing the number of parking actions, and promoting a healthy and positive employer-employee relationship. Currently, the area faces heavy congestion and crowdedness in the parking garages. These problems, along with the high emissions caused by car use, prompted the organization to take action. The goal was to show car commuters that there are attractive and sustainable alternatives available.

Two different studies were conducted in relation to Living Lab. These two previous studies and the results of the Living Lab form the cause of this research. An overview of the main research conclusions for each study and how these studies relate to one another is represented in Figure 1.1. The first study by Zadeits (2024) was a qualitative investigation that explored hospital staff perceptions of sustainable transportation alternatives through in-depth interviews. In total 14 interview where performed. These interviews gave the opportunity to gain insights into the attitudes, beliefs, and perceived equity of the employees concerning sustainable modes of transport (Zadeits 2024). The results of these interviews showed that the e-bike is favored for its speed, cost savings, and health benefits, especially by those within cycling range. Furthermore it highlighted two distinct groups: employees with irregular working hours and those with regular hours. Those with irregular hours were not in favor of using shared e-bikes at the central station due to poor public transport connections at night or in the evening. For them, park-and-ride (P+R) options with shared e-bike were more convenient. In contrast, employees with regular hours were more positive about the shared bikes at Utrecht Central Station. The study by Zadeits (2024) was conducted to advise the academic medical center on which mobility alternatives to consider for the Living Lab and to assess how people would respond to these options, based on key factors influencing their mode choice.

The study of van der Meulen 2024 was carried out during the Living Lab. This study had a quantitative approach. Using a Discrete Choice Experiment (DCE), this research examined under which circumstances hospital employees would consider adopting sustainable commuting modes and which factors were most influential. This experiment was conducted with only the participants from the Living Lab.

The study found that financial incentives and congestion had a major impact on commuting choices. The full public transport reimbursement and a higher cycling allowance significantly reduced car use. However older employees still preferred cars, while younger ones favored cycling, often due to health and environmental concerns. Surprisingly, shift workers were more open to public transport and cycling than expected, despite safety concerns at night. Lease e-bikes proved especially popular, even for long commutes, showing that with the right support, sustainable commuting is feasible, even for those with irregular schedules.

All studies provided valuable insights and highlighted different strengths. The interviews enabled in-depth exploration of why people prefer certain travel alternatives, revealing underlying motivations. In contrast, the DCE allowed for broader input and helped determine whether the interview findings held true across a larger employee group.

This research will focus more specifically on the bicycle and explore what factors could encourage employees to switch from their current commuting mode to cycling. This focus was chosen because the bicycle alternatives were consistently well-received in previous studies. Additionally, this research aims to reach a larger group of employees to better assess overall support within the hospital population.

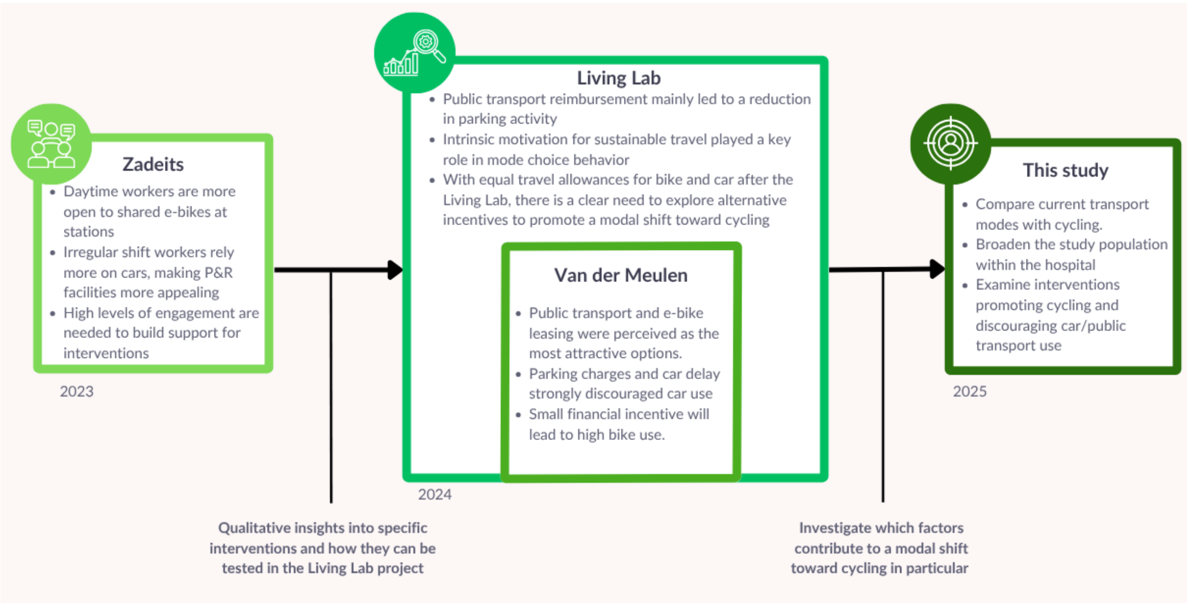



**Figure 1.1:** Overview research chain, (Zadeits 2024; van der Meulen 2024; Academic hospital 2025)

## 1.3. Knowledge gap

In addition to the Living Lab and the associated studies, many other research projects focus on employees' commuting behavior and how this can be adjusted and made more sustainable. Many companies are now trying to encourage cycling and promote a modal shift toward more sustainable modes of transportation. A study by Molin and Kroesen (2023) focusing on ASML employees examined the impact of combining disincentives and incentives to reduce car commuting. The findings revealed that time and cost factors had the most significant influence on mode choice. Another study conducted in Vancouver assessed the impact of road pricing and parking charges. The findings indicated that while financial disincentives were highly effective in reducing car use, they did not significantly encourage a shift to alternative travel modes. Instead, the primary impact was seen in increased carpooling rather than a switch to other transportation options (Washbrook et al. 2006).

However, the DCE in Copenhagen (Vedel et al. 2017) primarily focused on how route characteristics and crowding influence commuter preferences. The results showed that cyclists are willing to travel longer for better infrastructure, such as dedicated cycle tracks and green surroundings. Lower crowding and a reduced number of stops made routes significantly more attractive, emphasizing the importance of infrastructure improvements in promoting bike commuting (Vedel et al. 2017).

These studies demonstrate that many different factors influence mode choice decisions, with each study providing unique results and findings depending on the target groups and countries involved. This indicates that there is still considerable room for exploration, particularly as no research has specifically examined what motivates people in the medical sector to switch from their current mode of transport to cycling. Hospital employees are a specific group of commuters, as they often have irregular schedules due to night shifts or weekend work, which can make cycling to the hospital more challenging for them. The opportunities for investigating this topic will be explored further below, highlighting the existing knowledge gap.

Over the years, certain developments have significantly influenced people's mode choice for transportation. One major factor is the rise of the e-bike, now available in various models and sizes, with sales steadily increasing (Rérat 2021; Jones et al. 2024). As a result, the number of cycling trips per year and the total kilometers traveled by bike have risen rapidly. E-bikes are currently popular, and trends, as well as social influences such as observing colleagues or friends, play a significant role in shaping an individual's mode choice (Biernat et al. 2020). These factors highlight the importance of understanding how the e-bike trend could contribute to a shift towards more sustainable commuting behavior. Moreover, A research done in Basel highlighted the substitution of transport modes due to the rise of the e-bike (Kipfer 2024). Here is was revealed that traditional bicycles and public transportation were most often replaced by e-bikes.

Another significant change is the new collective labor agreement for hospitals, introduced in 2023 (Dutch Association of Hospitals 2023). This agreement impacts the incentives for employees in the medical sector, as there is no specific incentive to choose cycling over driving. The travel allowance remains the same for both modes of transport. In the previous Living Lab, the increased incentive for cycling was considered, but the higher allowance for car use was not (Academic hospital 2025). Therefore, this study aims to analyze how the increased allowance for both commuting methods affects employees' transportation choices.

Furthermore, this research will have a broader sample population compared to previous studies. The study by Zadeits (2024) involved 14 participants, while the study by van der Meulen (2024) included 180 participants. This research aims to involve 300 participants, providing a larger sample size to draw more representative conclusions about the entire hospital workforce. In the earlier studies, participants were predominantly individuals with a strong interest in sustainability who voluntarily applied to participate in the Living Lab. In this study, the participant pool will be expanded to include not only those highly motivated by sustainability but also a new group of people who are not necessarily very focused on sustainability. To achieve this, physical recruitment will be carried out at the hospital to ensure that a random selection of employees is approached for participation. This approach aligns with the adoption curve theory, where research first engages the 'Innovators', the ones who joined in the interviews of Zadeits (2024), followed by the 'Early Adopters', the participants of van der Meulen (2024) study and then progressively includes broader groups to gain more comprehensive insights (Rogers 2003).

This study focuses on a specific group of people in a particular environment, namely a hospital, making it important to include contextual variables, as these can significantly influence decision-making (Boncinelli et al. 2020). Previous research has not fully explored how travel scenarios, such as weather and road congestion, affect mode choice (Tomlinson & Benson 2021; Sabir et al. 2007). While policymakers cannot control these factors, understanding their impact helps assess the robustness of policy changes. Additionally, considering these factors offers a long-term perspective, helping to design policies that remain effective under different conditions. For example, if congestion currently has a significant impact, this influence could grow over the years as traffic volumes increase.

It also remains unclear how psychological characteristics influence their choices and what the motivations of hospital employees are. To better understand people's attitudes and perceptions regarding bicycle use, these factors must also be considered. If psychological factors influence a certain attitude and the reasons behind this attitude are understood, policymakers can better address this gap by implementing tailored policies.

The combination of this big but specific group of respondents, along with the addition of new factors such as context and psychological influences, and the constantly evolving landscape surrounding the problem, creates a broad and valuable knowledge gap.

## 1.4. Research goal

The primary objective of this research is to identify how various attributes influence the choice of (electric) bicycle commuting over alternative transportation modes among employees in the healthcare sector, and to assess the trade-offs they make between these attributes. By understanding these attributes, this study aims to provide well-founded advice to the hospital on potential interventions that would suit employees and encourage a shift toward bike commuting.

This research builds upon the valuable insights gained from the previous Living Lab conducted within the hospital setting. While this Living Lab provided a strong foundation of information regarding employee commuting behavior, this new study seeks to expand on those findings by reaching a broader and more diverse group of participants. The aim is to gain a more comprehensive understanding of commuting preferences and identify opportunities to influence a larger portion of the hospital workforce.

However, the more diverse target group is not the only difference compared to previous studies. While Zadeits (2024) primarily focused on qualitative data and van der Meulen (2024) on quantitative data, this project seeks to bridge the gap between both approaches. It aims to connect insights from past projects with new findings from a broader group of participants.

In contrast to previous studies, which considered various possible transportation methods, this research focuses solely on comparing an employee's current mode of transportation with a potential cycling alternative. This approach takes into account that all attributes related to the cycling journey may vary. However, the primary objective remains to keep the bicycle at the center of the analysis.

By examining all relevant aspects: context, psychological influences, current behavior, and previous responses, this research aims to provide a comprehensive understanding of the entire commuting landscape. Understanding the broader context of people's choices and preferences will contribute to more effective strategies to promote sustainable commuting alternatives.

This project is being conducted as the final component of the Master's program in Transport, Infrastructure, and Logistics. Therefore, the project is guided by the TU Delft, providing academic support and ensuring a methodologically sound approach. Additionally, Pon Holdings is a key stakeholder, contributing their expertise and maintaining a project relationship with the academic hospital through the broader Living Lab initiative. This research is just one component of the larger Living Lab project, focusing specifically on understanding commuting behavior and promoting cycling as a viable transportation option.

This study aims to provide a comprehensive understanding of the factors influencing commuting behavior, capturing both general trends and individual preferences. By identifying which attributes are most important to employees when considering a switch to cycling, the research could help hospital policymakers make informed decisions to promote sustainable transportation choices. This aligns with the broader goal of reducing pollution from commuting and enhancing employee well-being.

## 1.5. Research question

This chapter presents the research questions that guide this study, formulated based on the research objective and the identified knowledge gap and the research goal. The questions are designed to address the specific areas where existing literature is limited or inconclusive, ensuring that the study contributes meaningful insights.

A main research question has been formulated, supported by four sub-questions to help provide a comprehensive answer. Each question will be explained, along with its significance to the overall research.

**Main research question:**

*"To what extent do transportation mode attributes influence the choice of (electric) bicycle commuting over alternative modes among employees in the healthcare sector?"*

**Sub-questions:**

1. *To what extent does earlier participation in the Living Lab affect participants' sustainable commuting behavior after its conclusion?*

   This sub-question aims to bridge the findings from the Living Lab with the current experiences of participants, assessing whether those results still hold true. By comparing the outcomes observed during the Living Lab with participants' current opinions and travel behavior, it can be evaluated whether the initiative had a lasting impact or if the effects were only temporary.

2. *How does the context of the academic hospital and the commuting trip, affect employees' transport mode preferences?*

   To gain a clear understanding of which contextual variables influence mode choice, it is first necessary to identify the available contextual factors and how they relate to the travel behavior of hospital employees. Later on, by incorporating context into a Discrete Choice Experiment (DCE), the relative importance of contextual factors on mode choice behavior can be assessed, as well as their potential impact on the choice of cycling. This method allows one to quantify the relative importance of different contextual attributes by presenting participants with hypothetical commuting scenarios and observing their choices.

3. *What psychosocial factors influence employees' attitude towards (electric) bicycle commuting in the healthcare sector?*

   Psychosocial factors such as delay sensitivity and the perception of safety can play a significant role in mode choice. Therefore, it is important to understand how hospital employees view these psychosocial factors and whether they influence their mode choices.

4. *What distinct latent segments exist within the hospital population based on their travel mode preferences and socio-demographic characteristics?*

   Understanding the heterogeneity within the hospital population is crucial for tailoring effective mobility policies. By identifying distinct groups based on how employees weigh transportation trade-offs and their attitude influence on commuting options, it is possible to develop targeted interventions.

The structure of the research questions is based on the aim to first assess the current situation and evaluate the impact of the Living Lab. This is addressed through sub-question 1. Next, new research is conducted to explore the broader level of support among employees. Sub-questions 2, 3, and 4 introduce a new experiment designed to collect fresh data within a wider group of employees. The combined analysis of the new experimental results and the existing Living Lab data will provide a comprehensive understanding of the behavior and needs of the academic hospital's employees, allowing for a well-informed answer to the main research question.

## 1.6. Thesis outline

This thesis is structured into nine chapters, each building upon the previous to address the central research question. Chapter 1 serves as an introduction, providing the background to the research problem and establishing the relevance and objectives of the study. It outlines what needs to be solved and why this issue is significant. Chapter 2 discusses the methodology, explaining the research design and the specific methods used to gather data and answer the research question. In Chapter 3, a comprehensive literature review is presented. This chapter explores relevant studies and comparable projects from around the world, offering valuable insights and forming a foundation for answering several sub-questions. Chapter 4 focuses on the operationalization of key concepts and the development of the survey. It explains how the survey was constructed, how it functions, and the approach taken for its distribution. Chapter Chapter 5 focuses on the descriptive statistics of the respondents' sociodemographic characteristics, their attitudes, and the possible relationships between them. Next 6 presents the results of the Living Lab questions, along with insights into the current situation and areas for improvement as identified by employees. Following this, Chapter 7 discusses the results of the Discrete Choice Experiment. Based on all the results, Chapter 8 provides an overview of their meanings and how they relate to one another. Finally, Chapter 9 offers the conclusion and discussion, summarizing the key insights, reflecting on the implications of the findings, and considering the limitations of the research. This chapter also suggests directions for future research. The thesis ends with a list of references and includes relevant supplementary materials in the appendices.

# 2
# Methodology

This study uses a combination of quantitative and qualitative methods, which together help analyze data, identify patterns, and generate insights relevant to the research objectives. By combining these approaches, the study provides a well-rounded analysis, ensuring both theoretical depth and practical relevance. The following sections describe the key methods used and their role in the overall research process.

## 2.1. Data collection

Data is collected in different ways and at various stages of the research. Some data already exists and needs to be further examined, while other data must still be gathered.

### Existing data

The first sub-question relates to the results and data collected during the 2024 Living Lab. These results require further analysis to understand how they relate to the current situation. Since the available data stems from 2024, additional data is needed to gain a clear picture of the present-day context.

Data collection during the Living Lab took place in multiple forms and through various methods. One example is the detailed tracking of travel data, which recorded how frequently and at what times participants used specific modes of transportation. In addition to travel data, surveys were conducted to gather participants' opinions and experiences. These surveys were completed by all 300 participants of the Living Lab.

The initial survey served as a baseline measurement to assess participants' travel behavior and goals before the pilot began. It included closed-ended questions about how people currently commute and what their goals were regarding the frequency of sustainable commuting during the Living Lab period. A second, mid-term survey was carried out to evaluate participants' experiences during the Living Lab and their intentions going forward. These experiences focused on traveling by bicycle and public transport, highlighting what participants liked or disliked. Participants were also asked how their behavior had changed since the start of the program and how often they currently commute in a sustainable way. These were also close-end questions with several options presented.

### New data

To collect new insights, a survey was distributed with the primary aim of gathering new data. This survey will serve multiple purposes. The exact content of the questionnaire is outlined in section 2.3. It is important that the questions correspond to, and build upon, those used in the Living Lab, to ensure comparability between datasets.

## 2.2. Literature review

A literature review is essential to identify what information and conclusions can be drawn from international research. The previous studies by Zadeits (2024) and van der Meulen (2024) have already shown many relevant findings that need to be considered for further research. Therefore, it is important to thoroughly analyze these studies, among others. However, it is also important to review international literature not directly related to the academic hospital, as it may offer valuable new insights.

To answer sub-question 2, it was first necessary to determine which contextual variables typically influence people's choice of transportation mode. Once a broad understanding of these variables is established, it can then be assessed which are relevant for the employees of the academic hospital, and these can then be tested. The same approach applies to sub-question 3 as to sub-question 4. It was essential to gather background information on the psychological factors that influence people's attitudes in a broader context. Therefore, a preliminary literature review was necessary to determine which factors should be included in the survey for the employees of the academic hospital.

In addition to gathering information to answer the research questions, a literature review was conducted on the various methods used in this project. This ensures that all methodologies are correctly applied and effectively aligned with one another.

Several tools were used in the literature study to gather accurate and insightful information. Scopus and Google Scholar are the primary databases consulted. In addition, the snowballing method was applied to ensure that trusted sources are further explored and potentially overlooked studies are identified. Snowballing is a literature search method used to find additional relevant articles by looking at both the references listed in a relevant article and the newer articles that have cited it. Within Scopus, a combination of different search terms was applied in order to find the most relevant and high-quality selection of academic papers. Furthermore are the criteria for inclusion and exclusion provided in Appendix A.

TITLE(”nurse” OR ”healthcare” OR ”hospital”) AND TITLE(shift) OR TITLE-ABS-KEY(”accessibility”) AND TITLE-ABS-KEY(”commut*”)

TITLE((”attitude” OR ”preference” OR ((”social” AND ”norm”)) AND TITLE((”mode” and ”choice”)) OR TITLE-ABS-KEY((”travel” and ”behavio*”)) AND TITLE-ABS-KEY(”commut*”)

TITLE-ABS-KEY((”trip” OR ”mode” AND (”characteristic” ) AND TITLE-ABS-KEY((”mode” and ”choice”)) OR TITLE-ABS-KEY((”travel” and ”behavio*”)) AND TITLE-ABS-KEY(”commut*”)

TITLE-ABS-KEY((”cycling” OR ”cycle” OR ”bike” OR ”biking”)) AND TITLE-ABS-KEY((”modal” AND ”shift”)) AND TITLE-ABS-KEY(”commut*”)

## 2.3. Survey design

A survey was distributed among hospital employees to collect data relevant to understanding their commuting behavior and preferences. The overall structure of the survey is outlined below, with further details on each section provided in the following text.

1. Current travel method
2. Discrete Choice Experiment
3. Living Lab questions
4. Statements
5. Sociodemographic characteristics

First, the survey began with a clear explanation to ensure respondents understand the process and know what to expect. The discrete choice sets will be presented at the start of the survey when respondents' attention is highest. Since the choice sets require more cognitive effort and consideration, showing them first is likely to yield better-quality responses.

After the DCE, are the Living Lab question added. These questions are only shown to participants of the Living Lab. In case the respondent did no participate in the Living Lab, then they directly be sent to the statements. Following this, respondents will be asked about their sociodemographic characteristics and personal characteristics. People can sometimes think of these questions as personal and sensitive, therefore it is better to place them towards the end of the survey (Nardi 2018).

Finally, the survey will include an optional comment section. This allows respondents to share their thoughts and provide feedback, giving them a sense of being heard and potentially offering valuable insights for the research.

The survey was done in Microsoft Forms and was distributed to hospital employees via email and SharePoint. Microsoft Forms is used because Microsoft is the standard platform within both the academic hospital and TU Delft, allowing employees to complete the survey within their familiar work environment. This approach ensures that no personal information of the employees needs to be shared with external parties.

The survey was tested before distribution to ensure clarity and accessibility for all hospital employees. This testing was conducted with a diverse group of friends and family, varying in age, gender, and education level. Based on their feedback, several adjustments were made to the visuals, structure, and content. For example, some questions and examples were placed on separate pages to prevent respondents from comparing them, which could influence their answers. Additionally, the survey was reviewed by a communication specialist at the hospital to ensure that all language used was at a B1 reading level. Based on this expert review, several jargon terms were removed to improve overall comprehension.

Lastly, branching logic was incorporated into the survey to tailor the experience based on respondents' answers. Branching is a method where the respondent is guided through different question paths depending on their earlier responses. This was applied to several key factors, including the distance they travel to the hospital, their current mode of transport, and whether they participated in the Living Lab. For example, participants of the Living Lab were directed to a dedicated set of questions related to their experience during the project. Additionally, respondents' current mode of transport and travel time determined which version of the experiment they were shown. These specific pathways were designed to ensure that each respondent only received questions relevant to their personal situation, improving clarity and avoiding unnecessary or confusing content.

## 2.4. Cross-sectional analysis

A cross-sectional analysis can help to answer sub-question 1. During the Living Lab, valuable data has been collected, trough survey's. These surveys contained questions about the travel behavioral changes of participants and their experiences during the Living Lab. Before any comparisons can be made, it is essential to understand how this data is distributed. Therefore, the descriptive statistics of the responses must first be examined. These statistics can serve as a baseline for comparing the new results. If the data is well-organized and all descriptive values are clearly presented, the same process should also be applied to the results of the new survey. Descriptive statistics are used to summarize and describe key aspects of a dataset, allowing for easier interpretation and comparison (Sheard 2018). They help identify patterns, trends, and relationships between variables.

Once this step is completed, the focus can shift to the comparison through a cross-sectional analysis, which enables a proper comparison of data collected at two different points in time. In addition to the closed-ended questions with limited answer options, both the previous and current surveys include open-ended questions. These open responses must also be analyzed, which can be done using thematic coding to identify recurring themes and insights. Thematic coding is a method used in qualitative research to analyze textual or other qualitative data by identifying patterns or themes within the data (Gibbs 2012). Thematic analysis can be either data-driven or concept-driven. In a data-driven approach, themes are developed without a predefined framework, emerging naturally based on what is observed in the data. In contrast, a concept-driven analysis uses predefined codes or themes derived from existing theories or prior research, guiding the analysis with a structured framework (Gibbs 2012).

For this research, a data-driven approach was used to analyze the answers given on the open question of the Living Lab survey and the new survey. This approach is chosen because there is no specific target or hypothesis, allowing all information related to potential trends and themes about bike commuting to be considered. This meant that each response from a hospital employee was translated into a specific statement, topic, or intervention. If an employee mentioned multiple topics, each was recorded separately. For every response, it was checked whether the same topic had also been mentioned by another employee, and if so, they were grouped together. In the end, all responses were analyzed and compiled into a list of interventions, topics, and ideas, highlighting which ones were mentioned most frequently.

The only requirement was that the data must relate to bike commuting or explain why an alternative mode of transport is more attractive than cycling. Answers solely based on public transport and car use are not included in this analysis. A direct cross-sectional comparison based on thematic coding is unfortunately not possible. However, it is possible to compare these responses in a general sense to identify whether any trends or patterns can be observed.

## 2.5. Discrete Choice Model

To answer sub-question 2, 3 and 4 Discrete Choice Modeling (DCM) was used. DCM is a widely used research method to retrieve data on how how individuals make choices between discrete alternatives. DCMs are particularly effective in studying the effects of categorical variables on choice behavior within a population. The methodology involves presenting respondents with a series of hypothetical scenarios, each containing multiple choice options with systematically varied attributes. Respondents are asked to select their preferred option from each set, revealing their underlying preferences (Friedel et al. 2022). Presenting the respondents the different alternatives is done with a Discrete Choice Experiment (DCE).

Within DCM can data be collected by Stated Preference (SP) or trough Revealed Preference (RP). With SP methods, are preferences are elicited through hypothetical scenarios rather than observed behavior in real markets, this is RP. SP methods allows to explore potential behaviors in situations where market data is unavailable or impractical. However, SP data may contain biases and random errors because the decision-making process may differ from actual behavior. Conversely, RP data, based on observed real-world choices, provides a more accurate reflection of actual behavior but may not capture preferences for new or hypothetical scenarios (Ben-Akiva & Lerman 1985). Additionally, testing with RP methods generally requires more respondents and more complex data collection compared to SP methods. RP data typically yield only one observation per respondent based on actual behavior, whereas SP methods can generate multiple observations per respondent through hypothetical scenarios, providing more flexibility and efficiency in data collection (Abdullah et al. 2011). In this research, SP was used because the number of respondents could not be precisely estimated in advance. Therefore, it was important to extract as much information as possible from each individual respondent. Additionally, the goal was to present people with options they do not currently have or that are not yet available to them. This made the use of a stated preference approach the most suitable method for data collection.

The DCM approach is conceptually rooted in the work of Thurstone (1927), who introduced the Law of Comparative Judgment, a probabilistic model for analyzing how individuals compare pairs of stimuli. The DCM framework was significantly advanced by McFadden (1974), who formalized the methodology based on the Random Utility Maximization theory (RUM). RUM suggests that the likelihood of an individual choosing a particular alternative depends solely on the differences in the utility of each option. According to this model, individuals are expected to choose the option that offers the highest perceived utility (Feng et al. 2022).

### 2.5.1. Discrete Choice Experiment

As mentioned before is DCE a way to collects data on preferences by presenting choice scenarios with varying attributes. DCM analyzes this data to quantify how attributes influence decisions, turning choices into predictive models. This research requires presenting a choice set of commuting mode alternatives. However, the primary focus lies in understanding what factors motivate people to switch from their current mode of transportation to an (electric) bike.

Respondents are presented with choice sets containing alternatives, each described by attributes with varying levels. These alternatives represent different transportation modes, and each attribute is systematically varied across the alternatives (Webb et al. 2021). For this research, respondents will choose between three alternatives:

1. City bike
2. E-bike
3. (a) Car
   (b) Public transport

The number of choice sets in a DCE must balance statistical efficiency with respondent burden. While more choice sets improve data quality, too many can lead to respondent fatigue and lower response quality. Akinc et al. (2024) used 18 choice sets in their study, finding that while 58% of respondents felt this was an appropriate amount, 40% felt it was too many. This emphasizes the need to keep respondents engaged without overwhelming them. The number of choice sets depends on the number of attributes and their levels. In the study by van der Meulen (2024), eight attributes led to 12 choice sets, whereas a full factorial design could result in thousands. A fractional factorial design helps reduce the number of profiles and choice sets while still capturing the main effects of attributes, keeping the experiment practical (Tazliqoh et al. 2019).

Since this study includes fewer alternatives and attributes, the required number of choice sets is also lower. However, a full factorial design would still result in too many choice sets. Therefore, it is necessary to determine which type of fractional design to use: random, orthogonal, or efficient. In a random fractional design is a random sample drawn from the full factorial design, however his can lead to high correlation between the attributes in the choice sets, limiting the possibility to separately estimate the effects for the attributes. This cannot happen in a orthogonal design, because the correlation between the attributes are all zero. Meaning that all attributes can be estimated without being confounded by another attribute. This method however can still cause a lot of choice sets to make sure that there is no correlation. A solution for this is an efficient design, because with this method is is focused on minimizing the standard error and maximizing the information from the trade-offs. . This design helps reduce the number of choice sets while maintaining the ability to analyze key effects accurately (Alamri et al. 2023).

As questioned in sub-question 2, understanding how the context influences respondents' choices is crucial. A well-defined context can create a more realistic choice situation for respondents (Boncinelli et al. 2020). The context attributes will remain the same across all alternatives but are used to present scenarios that could influence decision-making.

In the study by Molin and Kroesen (2023), was found that for a distance of 20 kilometers, still 1 in 5 people commute by bike. Therefore, it is beneficial to consider different experiments based on commuting distances and create distinct scenarios for varying travel ranges. According to Rybels et al. (2024) are the number of bicycle commuting trips highest between 0 and 5,8 kilometers. While there is still a notable proportion of trips made up to approximately 13 kilometers, a significant drop in cycling usage is evident between 13 and 20 kilometers. This distribution suggests that creating separate experiments for different distance segments could provide valuable insights. Because the choice sets needed to reflect realistic commuting scenarios, different versions of the experiment were created based on the single travel distance of employees. While the attribute levels remained the same, total travel time and other trip characteristics were adjusted according to each distance category. The following versions are proposed:

- **Version 1:** 0 - 7,5 kilometers
- **Version 2:** 7,6 - 15 kilometers
- **Version 3:** 15,1 - 30 kilometers

## 2.6. Estimating models

### 2.6.1. Random Utility Maximization

As mentioned earlier is RUM a method which is often used for DCEs. RUM posits that the utility an individual derives from a particular option consists of a systematic (observable) component and a random (unobservable) component (Gundlach et al. 2018). The probability of an option being chosen depends on the relative utility it provides compared to the other available options (Louviere et al. 2010). The method assumes that individuals make rational choices by selecting the option that maximizes their utility. By analyzing the choices made across different scenarios, researchers can estimate the relative importance of the attributes, quantify trade-offs between them, and predict choice behavior under different conditions.

In Equation 2.1 is the formula given of the total utility as it would be experiences by a decision maker for a specific alternative. The observed utility captures all factors related to observable characteristics, such as gender and age. In contrast, the unobserved utility accounts for elements that cannot be attributed to observable factors, including heterogeneity in preferences and randomness in choices (Cranenburgh 2023).

$$U_{in} = V_{in} + \varepsilon_{in} \tag{2.1}$$

$U_{in}$ Utility of alternative $i$ for decision maker $n$
$V_{in}$ Observed utility of alternative $i$ for decision maker $n$
$\varepsilon_{in}$ Unobserved utility of alternative $i$ for decision maker $n$

In the next Equation 2.2 is the formula given on how to calculate the observed utility of an alternative. Here is the marginal utility $\beta$. These values can be found per attribute by performing a Maximum Likelihood Estimation (MLE).

$$V_{in} = \sum_{m} \beta_m \cdot x_{im} \tag{2.2}$$

$V_i$ Observed utility of alternative $i$
$\beta_m$ Marginal utility for attribute $m$
$x_{im}$ Level of attribute $m$ in alternative $i$

### 2.6.2. Multinominal Logit Model

In the following Equation 2.3 of the RUM theory is the probability that alterative *i* will be chosen in a chosen set. This is based on the Multinational Logit model (MNL). The MNL model is a method used to analyze the data obtained from the DCE. It estimates the probabilities of the alternatives in a choice set being chosen.

$$P_i = \frac{e^{V_i}}{\sum_J e^{V_j}} \tag{2.3}$$

$P_i$ Probability that alternative $i$ will be chosen

### 2.6.3. Nested Logit Model

The MNL model assumes the Independence of Irrelevant Alternatives (IIA), meaning that the relative odds of choosing between any two alternatives are unaffected by the presence of other alternatives. However, in this case, two of the alternatives involve biking, which may not be fully independent of each other. Therefore, the IIA assumption may not hold. To address this, the model can also be tested using a Nested Logit (NL) model. The NL model relaxes the IIA assumption by allowing for correlation in unobserved utility components within groups, or nests, of similar alternatives (Hensher & Greene 2002).

The alternatives in a choice set are divided into sub-sets where each alternative belongs to one sub-set (nest) (Heiss 2002). In this context, the two biking options can be grouped into a single nest, acknowledging their similarity and potential dependence. The second nest consists of only one alternative, the respondent's current mode of transport (car or public transport). This results in a two-nest structure. The model is estimated based on the RUM framework, just like the standard MNL model. Ultimately, the model fit will show whether the added nesting structure provides a significantly better explanation of choice behavior. If the model fit does not improve, it suggests that the alternatives in the bicycle nest do not exhibit meaningful correlation, and the added complexity is not justified. Equation 2.4 shows the probability function for a specific alternative to be chosen given it is in a specific nest.

$$P_{ni} = P_{ni|k} \cdot P_{nk} \tag{2.4}$$

$P_{ni|k}$ Conditional probability that alternative $i$ given nest $k$ will be chosen
$P_{ni|k}$ Marginal probability of choosing nest $k$

### 2.6.4. Latent Class Choice Modeling

In a MNL model, preferences are estimated for the entire sample as if all individuals share the same decision-making process. This implies homogeneity in preferences across the population, effectively treating it as a single class. However, this assumption often overlooks unobserved heterogeneity in behavior.

Latent Class Choice Models (LCCMs) extend traditional discrete choice models by capturing this unobserved heterogeneity. This is done by segmenting individuals into discrete classes or groups based on similar choice patterns (Lahoz et al. 2023). Within each class, preferences are assumed to be homogeneous, but between classes, preferences can differ significantly. This approach allows for the identification of distinct subgroups with varying tastes or decision rules (Ben-Akiva et al. 1999), thereby introducing heterogeneity between classes while maintaining homogeneity within each class.

Equation 2.5 presents the Latent Class Choice Model (LCCM) formulation. This model consists of two sub-models: the *class membership model* and the *class-specific choice model*. The class membership model estimates the probability that a particular decision-maker belongs to a specific class, while the class-specific choice model determines the likelihood of that individual choosing a particular alternative within that class (Lahoz et al. 2023).

$$P_n(i \mid \beta) = \sum_{s=1}^{S} \pi_{ns} P_n(i \mid \beta_s) \tag{2.5}$$

$P_n(i \mid \beta)$: Probability that decision maker $n$ chooses alternative $i$ with the set of parameters $\beta$
$\pi_{ns}$: Class membership probability of decision maker $n$ belonging to class $S$
$P_n(i \mid \beta_s)$: Probability that decision maker $n$ chooses alternative $i$ in case he belongs to class $S$
$\sum_{s=1}^{S}$: Summation over all $S$ classes

Equation 2.5 shows that the probability depends on other probabilities, indicating that the LCCM is composed of multiple sub-models, one for each latent class. Each class is characterized by its own set of parameters and class-specific probabilities. These class-specific models are estimated using a MNL framework. In essence, if the LCCM is estimated with just one class, the result is equivalent to a standard MNL model.

The class membership model indicates the probability that a decision-maker belongs to a specific class. This model can be specified as a function of sociodemographic characteristics. In this model restricts the logit function the probabilities to sum up to one. The model is formulated in in Equations 2.6 and 2.7.

$$\pi_{ns} = \frac{e^{r_{ns}}}{\sum_{l \in S} e^{r_{nl}}} \tag{2.6}$$

$$r_{ns} = \delta_s + \sum_{q \in Q} \gamma_{sq} z_{nq} \tag{2.7}$$

$\pi_{ns}$: Probability of decision maker $n$ belongs to class $s$
$r_n$: Class membership score that individual $n$ associates with class $s$
$\delta$: Class membership parameter
$\gamma$: Class membership parameter
$z$: Sociodemographic

Equation 2.8 represents the likelihood of observing the sequence of choices made by all individuals in the sample, considering that each individual could belong to any of the latent classes. Then MLE is necessary in LCCM to estimate model parameters that maximize this likelihood, capturing both the latent segmentation of the population and the behavior within each segment (Sfeir et al. 2022).

$$LL(\beta) = \sum_{n=1}^{N} \ln \left( \sum_{s=1}^{S} \pi_{ns} \left( P_n(i_t \mid \beta_s) \right) \right) \tag{2.8}$$

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

The number of classes to be used is determined based on the model fit of the estimated models. If the model with two classes shows a better fit than the model with three classes, then the two-class model should be selected. Once the optimal number of classes has been identified, the classes can be interpreted. This is done by examining the parameters of each class model and analyzing what they reveal about the characteristics of individuals in each class. Each class is then assigned a label based on its key features. These interpretations are informed by the variables included in the models, which in this study may include sociodemographic characteristics, mode attributes, and attitudes.

### 2.6.5. Model fit

To evaluate how well the models explain respondents' choice behavior, model fit statistics can be assessed. For each model, key indicators such as the Log-Likelihood (LL), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and McFadden R-squared were examined. The LL evaluates how likely it is to observe the choices actually made, given the estimated parameters. Its goal is to assess the absolute fit of the model to the data. A higher (less negative) LL indicates a better fit. Furthermore, the McFadden R-squared compares the log-likelihood of the estimated model with that of a null model, allowing an assessment of whether the new model provides a better explanation of the results. Values closer to 1 indicate a better fit (McFadden 1974).

Lastly AIC and BIC, these are information criteria used to evaluate the trade-off between model fit and complexity. Both metrics penalize the number of parameters to avoid overfitting. Lower values of AIC and BIC indicate a better model, with BIC applying a stricter penalty on complexity than AIC.

## 2.7. Attitude analysis

To answer sub-question 4, it is necessary to examine the attitudes of hospital employees. To address this, a series of statements covering various themes will be presented to the respondents and they responded using a Likert scale, ranging from "strongly disagree" to "strongly agree." The goal is to identify patterns and relationships both among the statements themselves and between the statements and the respondents' personal characteristics.

To explore these relationships of both the attitudes toward the statements and the personal characteristics of the respondents must first be the descriptive statistics examined. The descriptive statistics for personal characteristics provide insight into the distribution within the respondent group. The descriptive statistics for the statements offer information on the average responses and the variation in answers, helping us assess the diversity of opinions. This data was collected and analyzed using SPSS.

### 2.7.1. Principal Factor Analysis

Once this is done, Exploratory Factor Analysis (EFA) can be predicted for the results of the statement. This is a statistical method to find hidden patterns in survey answers (Columbia University Mailman School of Public Health 2025). It helps group similar responses together to show what might be influencing people's answers. Factor analysis was developed by psychologist and statistician Charles Spearman 1904 and further refined over the years.

EFA can be performed using different statements presented to respondents. These statements are associated with specific factors and are designed to measure underlying attitudes (Rungie et al. 2012). Once the survey data is collected, Principal Axis Factoring (PAF) can be applied to analyze the shared variance between variables and identify underlying factors (Osborne 2014). PAF is one of the extraction methods which can be used within EFA. This method helps reveal hidden constructs and patterns within the responses, providing insights into the attitudes being measured.

PAF is also done in SPSS. PAF is a form of dimensions reduction. Before extraction, the suitability of the data for factor analysis was assessed using two standard tests: Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test a KMO value above 0,60 and a statistically significant Bartlett's test ($p < 0{,}05$) were considered indicators that the correlation matrix was appropriate for factor analysis. To facilitate interpretability of the factor structure, both Direct Oblimin (oblique method) and Varimax rotation (orthogonal method) were applied. Based on the results of the factor loading matrix and the factor correlation matrix, is the most appropriate rotation method was selected.

First, the Direct Oblimin rotation is applied, and the results are interpreted based on the communalities. Any statement with a communality below 0.25 is removed from the analysis. This process is repeated until no communalities fall below the minimum threshold. The factor loading matrix is then used to evaluate which statements load onto which factors. Loadings slightly above 0.5, and preferably 0.6 or higher, suggest that a statement likely belongs to a specific factor. Statements that load below 0.3 on all factors are automatically removed. It is also important to check for cross-loadings—cases where an item loads significantly on more than one factor. If an item does not load clearly on any factor or cross-loads in a problematic way, it may be removed as well.

Next, it is checked whether the model meets the criterion of simple structure. This refers to a factor solution where each item loads strongly on only one factor and has minimal loadings on others, making the interpretation of factors more straightforward. Finally, after completing the Direct Oblimin rotation, a Varimax rotation is also assessed for comparison. This allows evaluation of whether an orthogonal (uncorrelated) solution offers a clearer or more interpretable structure than the oblique (correlated) one.

### 2.7.2. Statistical tests

#### Independent Sample T-test and One-way ANOVA

The Independent Samples T-Test and One-Way ANOVA are similar statistical tests; however, the key difference is that the T-Test compares the means of two groups, while ANOVA can compare the means across more than two groups. These tests provide insight into the relationship between employees' attitudes and their sociodemographic characteristics. This can potentially offer deeper understanding of the reasoning behind certain attitudes and how these are distributed across the total respondent group.

An independent samples t-test is often used to determine if there's a significant difference between their average values. This test helps decide whether any observed difference is statistically meaningful or simply due to random variation, assuming the two groups are unrelated. A crucial assumption for the independent samples t-test is the equality of variances. This assumption is formally tested using Levene's Test. If Levene's test is not significant (meaning its p-value is greater than 0,05), one can proceed assuming equal variances. However, if Levene's test is significant, then the assumption of equal variances is violated (Ross & Willson 2017). After determining whether equal variances can be assumed, the next step is to check whether the t-test for equality of means is significant. If this is the case, the null hypothesis of equal means can be rejected, meaning that there is a significant difference between the two estimated groups. Conversely, if the result is not significant, the null hypothesis cannot be rejected, and it is assumed that there is no difference in the mean values between the two groups.

A one-way ANOVA was used to test whether the mean scores differed significantly across three or more independent groups. If the ANOVA result indicates a significant difference, post hoc tests are then conducted to pinpoint the exact locations of these differences. The choice of post hoc test depends on the variance assumption: if equal variances are assumed, Tukey's HSD is a common and appropriate choice. Conversely, if equal variances cannot be assumed, the Games-Howell post hoc test is more suitable, as it does not rely on the homogeneity of variance assumption and is robust even with unequal sample sizes (Ross & Willson 2017).

# 3 Literature review

A literature review was conducted to assess existing international research on commuting, with a specific focus on hospital-related travel and the factors that influence mode choice in this context. This review serves as the foundation for designing the survey. It helps assess whether insights from previous studies are also relevant for this research and whether these can be tested within the specific context of the current study.

Sub-questions 2, 3 and 4 focus on various attributes that may influence mode choice. To answer these questions, it is essential to first identify which factors have been recognized in the literature and how they might apply to hospital employees. Gaining a clear overview of these factors enables the development of targeted survey questions and helps determine which attributes are most relevant for this study.

The scope of the literature review extends beyond cycling, encompassing other modes of transport as well. This broader approach was chosen because understanding the motivations behind the use of all transport modes is essential. While promoting a shift towards cycling is a central focus, it is equally important to understand why individuals choose, or avoid, other options.

Overall, is the main purpose of this literature review is to gather relevant information and evaluate whether the factors identified in existing studies have a similar impact in the context of this research. This will allow for meaningful comparisons between findings from the literature and those later on observed in this study. The practical execution of the literature review, including the inclusion and exclusion criteria, is described in detail in Appendix A.

## 3.1. Commuting options

In the Netherlands, there are many different ways in which people commute to and from work. Each mode of transport comes with its own set of advantages and disadvantages, often depending on where someone lives and what resources are available to them. As a result, not everyone has access to the same commuting options.

In 2023, nearly half (49%) of all commuting trips in the Netherlands were made by car, while only 5% were made by train (CBS 2024). Active modes of transport have a significant share as well: 25,5% of commuting trips were made by bicycle, and 4% by walking. These figures suggest that the car remains the most commonly used mode for commuting. However, the average commuting distance is 11,2 kilometers (CBS 2023), which is well within cycling range. At an average cycling speed of 18 kilometers per hour, this distance can be covered in just over 30 minutes (SWOV 2025). In fact, the average commuting time in the Netherlands is around 32 minutes for a single trip (**reistijdCBS**).

In recent years, working from home has become increasingly common, significantly reducing the number of commuting trips. Interestingly, there is a clear relationship between commuting distance and the frequency of working from home. People who live farther from their workplace tend to work from home more often. As a result, the average one-way commute for those who regularly work from home is around 45 minutes, approximately 15 minutes longer than the national average (**reistijdCBS**).

Perceived acceptable travel time also varies depending on the mode of transport. On average, people consider 35 minutes to be an acceptable travel time for commuting by car, 25 minutes for cycling, and as much as 47 minutes for public transport. Walking has the lowest acceptable travel time, at just 20 minutes. The relatively high tolerance for public transport travel time can be explained by the fact that passengers can often use this time productively, for example by reading, working, or relaxing during the trip (Hamersma & Roeleven 2024).

### 3.1.1. Hospital commuting

This study specifically focuses on commuting to and from hospitals, which differs in several ways from commuting to other types of workplaces. Therefore it is important to gain understanding of what makes commuting to a hospital different compared to regular commuting.

Firstly, hospital staff often perform physically and emotionally demanding work (Alghamdi & Bahari 2025). After a long shift, employees may be completely exhausted or emotionally drained. Choosing a suitable mode of transport in such situations may help alleviate stress and improve overall well-being (Booker et al. 2024).

In addition, many hospital employees are required to be on call, resulting in irregular and unpredictable working hours. This often increases their reliance on private vehicles, as public transport may not be available during off-peak hours (van der Meulen 2024). Active transport modes, such as walking or cycling, may also feel less safe or practical in certain situations, particularly for women traveling during late or early hours. However, it is noticeable that after a shift, nurses may be tired and therefore have less control over their car, which could potentially lead to accidents. Drowsy driving is a persistent issue among night-shift nurses and is associated with elevated rates of vehicle crashes (Smith et al. 2020).

Another important aspect is the accessibility of hospital locations. As hospitals are public institutions, they often generate high traffic volumes in their surrounding areas, which can negatively impact accessibility (Du et al. 2024). On the other hand, their public nature can also lead to better integration within urban infrastructure compared to private companies, potentially making them more accessible by various transport modes.

## 3.2. Mode choice

Numerous factors can influence mode choice. These factors vary among individuals, dependent on their sociodemographic variables, and are also influenced by the context of the choices themselves. Not only do these factors influence choices, but also the process by which people make decisions and their overall choice behavior. All of these possible influences will be discussed in this section.

### 3.2.1. Mode and trip characteristics

Adamidis et al. (2025) stated that travel time remains a strong predictors of mode choice. Travelers generally prefer faster and more reliable transport modes, particularly for work-related trips. Ha et al. (2020) even state that a 10-minute longer travel time by transit, compared to driving, increases the probability of driving by 30.5%.

The trip duration is closely related to transport mode. Short trips (under 16,5 minutes) tend to encourage the use of active modes such as walking and cycling. Medium-length trips (16,5–29 minutes) are most commonly served by public transit, while trips over 30 minutes are more likely to involve car use or, depending on the context, public transport (Le & Teng 2023). For trips longer than 42 minutes, public transport tends to become more attractive again due to comfort and the opportunity to be productive during travel (Ko et al. 2019). The distance to destinations plays a major role as well. Longer travel distances reduce the appeal of walking and cycling, while frequent trips increase the likelihood of choosing more convenient and comfortable modes (Ababio-Donkor et al. 2020). Additionally, shorter commute distances tend to promote the use of both active transport and public transit (Zhou 2012).

Furthermore, complexity of the trip influences mode choice. When individuals have multiple destinations they are more likely to prefer the flexibility of car travel (Le & Teng 2023). For example when combining errands with childcare. This applies not only to potential stops after work but also to situations where someone needs to visit multiple destinations during their workday (Chen et al. 2008). Transfers and associated out-of-vehicle times, such as waiting and walking between modes, also significantly affect the attractiveness of public transport. These aspects can create friction in the journey, pushing individuals toward more direct options like private vehicles (Iseki et al. 2006).

Cost is another key factor in choosing a mode of transport. When travelers are faced with multiple options, fare price and parking cost often becomes the decisive factor, with the cheapest alternative being preferred (Adamidis et al. 2025). However, when cost is not a limiting factor, taxi's frequently emerge as the favored mode due to their convenience and direct service (Ulahannan & Birrell 2022).

Reliability further shapes mode choice, particularly in the context of public transport. Recurring delays can reduce accessibility and prompt changes in behavior. For example, in Scania, Sweden, delays in public transit services resulted in a 4–9% decline in job accessibility, demonstrating how service disruptions can influence commuting decisions (Nichols et al. 2024). Closely linked to reliability is the frequency of service. High-frequency public transport systems reduce waiting times and increase convenience, making them significantly more attractive to users. However, for longer trips, frequency becomes less critical compared to other factors such as comfort or directness (Göransson & Andersson 2023).

Finally, the time of day also affects travel mode decisions. During the evening and night, there is a marked decline in the use of walking, cycling, and public transit, largely due to reduced service availability, perceived safety, and visibility (Molin & Timmermans 2010).

### 3.2.2. Context variables

There are different types of context variables. Variables that determine the physical context of a trip exist, variables that describe a specific situation during the day, or context concerning the current rules and regulations.

An example of such a day-specific context variable is the weather. Several studies state that rain has a significant effect on people's mode choice due to the fact that people are less likely to cycle or walk somewhere (Böcker & Thorsson 2013; Klöckner & Friedrichsmeier 2011). In addition, rain can even increase the likelihood of not making a trip at all. (Molin & Timmermans 2010).

Another day-specific context variable is the luggage people bring on their trip. Often, heavy luggage leads to a higher likelihood of choosing motorized modes or not traveling by train (Molin & Timmermans 2010). Furthermore are people more likely to use a car instead of public transport in case of time-sensitive situation (Klöckner & Friedrichsmeier 2011).

However, the physical context also plays a significant role in shaping travel behavior. Enhancing public transport accessibility is crucial to encouraging a shift away from car use (Schwanen et al. 2006). Dense, mixed-use urban areas promote walking, cycling, and transit use, while greater access to transit stops and highly connected street networks further support active and sustainable travel. In contrast, a lot of parking availability tends to reinforce car use (Le & Teng 2023). This is confirmed by McCarthy et al. (2017), who also sheds light on the access to the road that makes driving more convenient.

### 3.2.3. Sociodemographic characteristics

Previously the effect of contextual variables on mode choice is discussed. While these elements are critical in shaping the environment in which decisions are made, they do not act alone. People's responses to contextual conditions are deeply influenced by their sociodemographic characteristics.

Socio-demographic factors such as income, age, education, gender, and household structure play a significant role in shaping individuals' travel behavior and mode choice. Higher income is consistently associated with increased car ownership and use, while lower- and middle-income individuals are more likely to rely on public transport or active modes like walking and cycling (Schwanen et al. 2006; Ababio-Donkor et al. 2020; Ko et al. 2019). Car availability is one of the strongest predictors of car use, with studies showing that variables like income, trip purpose, and auto ownership explain up to 90% of the variation in mode choice (Hartgen 1974; McCarthy et al. 2017).

Age also influences travel preferences: older adults tend to avoid active modes, often favoring cars or public transport (Ko et al. 2019; Lu & Gan 2024), while younger individuals, especially those living with friends, are more likely to use public transit, due to social influence and shared routines (Zhou 2012). Education level also shows a difference, with more educated individuals generally preferring environmentally friendly or active transport modes (Ababio-Donkor et al. 2020).

Gender and household structure also matter. Men are more likely to drive, whereas women show a greater tendency to use public transport or walk (Ko et al. 2019). Households with children or dual earners tend to prioritize flexibility and time efficiency, often resulting in higher car use (McCarthy et al. 2017). Conversely, individuals living alone or without children show a stronger preference for public or active transport options (Ko et al. 2019).

Employment status and work patterns further shape travel routines. Part-time workers or those with flexible schedules tend to exhibit more varied mode use (Ton et al. 2020), while parenting and employment responsibilities influence the need for reliable and flexible travel (Scheiner & Holz-Rau 2007). Finally, the length of residence plays a subtle but important role: individuals who have recently relocated are more likely to use public transport, possibly due to limited familiarity with local driving conditions, whereas long-term residents are more inclined to rely on cars (Ko et al. 2019).

### 3.2.4. Psychosocial characteristics

While structural factors play a dominant role in determining travel behavior, attitudinal and psychological variables also contribute significantly to an individual's commuting decisions. Among these, environmental norms are a substantial contributor to cycle use, with individuals who are more environmentally focused often choosing cycling for their commute (O'Reilly et al. 2024).

Beyond individual environmental values, social and cultural norms further shape mobility behavior, particularly within families. Car ownership and use are frequently perceived as essential for effective parenting, and concerns regarding safety when walking or using public transport can reinforce car dependence (McCarthy et al. 2017). This is compounded by cultural perceptions, where many parents view alternative modes as impractical or less respectable. Furthermore, an individual's opinions are often shaped by the views of their peers and community. Social norms, especially among younger individuals and those coming from larger households, can significantly influence the perception and acceptance of various transport modes (van Lierop & Bahamonde-Birke 2021).

Commuting itself can be a source of stress, particularly due to delays in public transport or car congestion (Zhang et al. 2021). Conversely, studies have found that commuting by bicycle can reduce stress and be perceived as mentally and physically relaxing (Fraboni et al. 2022). The desire for comfort is another key psychological factor, generally valued highly by car commuters. This strong preference for private vehicles often leads individuals who prioritize comfort to view walking and cycling negatively (Molin et al. 2016; Parmar et al. 2023). Moreover, safety is a paramount concern, especially for cyclists, given their vulnerability on the road. The provision of separate car and bike lanes is crucial for enhancing perceived and actual safety (Fraboni et al. 2022), benefiting both cyclists and motorized vehicle occupants (Felix et al. 2019).

This all means that a multitude of psychosocial factors, including environmental concerns, social and cultural influences, perceived stress, comfort preferences, and safety perceptions, collectively shape an individual's attitude toward their commuting trip and ultimate mode choice. Understanding these underlying psychological drivers is crucial for developing effective interventions to promote sustainable travel.

### 3.2.5. Choice behavior

People make choices, and there are many different theories that attempt to explain how these decisions are made. Numerous factors and influences can play a role in shaping this process. Therefore, it is important to assess different theories to better understand why people make certain decisions.

One example of a choice behavior theory is Prospect Theory by Kahneman and Tversky (1979). This theory suggests that people do not make decisions purely based on final outcomes, but rather on perceived gains and losses relative to a reference point. It also introduces the concept of loss aversion, stating that losses are felt more strongly than equivalent gains. Furthermore, people tend to overweight low probabilities and underweight moderate to high probabilities.

In the context of mode choice, this may be reflected in individuals avoiding public transport due to the possibility of significant delays, even if infrequent, while continuing to drive despite consistently experiencing minor delays. Overall, this theory illustrates that decision-making is often irrational and strongly influenced by the way choices are framed Kahneman and Tversky (1979).

This view is contradicted by the Rational Choice Theory (RCT) of Posner (1997). This theory assumes that individuals act to maximize their utility by choosing the most efficient means to achieve their goals, based on available information and personal preferences. People weigh different options and select the one that provides the greatest benefit. However, these decisions are made within certain constraints, such as budget, time, or availability of alternatives.

A theory closely related to RCT is the Random Utility Theory (RUT) (Ben-Akiva et al. 1999). While RCT serves more as a philosophical framework, RUT offers a practical extension that can be applied to empirically test utility maximization. Moreover, RUT is more specifically focused on the field of transportation. Despite their differences, both theories are based on the assumption that individuals make decisions aimed at maximizing utility, choosing the alternative with the highest perceived benefit.

Also, there is the Theory of Planned Behavior (TPB) by Ajzen (1991), which explains how intentions lead to behavior. The theory suggests that three key psychological factors influence an individual's behavior: attitude, subjective norm, and perceived behavioral control (Forward 2004). Attitude refers to whether a person views the behavior as positive or negative. Subjective norm relates to the perceived social pressure, or what important others think about the behavior. Perceived behavioral control concerns the person's belief in their ability to perform the behavior, based on the resources and opportunities they have. Together, these factors shape behavioral intentions, which in turn guide actual behavior.

Based on TPB, was the Behavioral Reasoning Theory (BRT) developed by Westaby (2005). These new theory also had influences of the Theory of Reasoned Action (TRA). TRA, introduced by Ajzen and Fishbein (1975), suggests that behavior is driven by behavioral intentions, which are shaped by a person's attitude toward the behavior and subjective norms, the perceived social pressure to perform or not perform the behavior. BRT expands on both theories by introducing reasons for and reasons against a behavior, which influence these global motives. It emphasizes the role of context-specific reasoning and personal values (Sahu et al. 2020).

These theories collectively show that travel decisions are influenced by both rational evaluations and psychological factors. A clear understanding of this complexity is crucial for designing policies that effectively align with real-world commuter behavior.

### 3.2.6. Employers role in mode choice

As mentioned earlier, individuals typically make their own decisions about how they commute. However, these choices can be significantly influenced when employers actively encourage or facilitate specific modes of transportation. Employers can do this in different ways, with soft and with hard measures. Soft measures are primarily focused on non-material aspects such as changing attitudes and perceptions, whereas hard measures involve tangible interventions, such as physical infrastructure or financial incentives (Marquez et al. 2024).

#### Hard measures

Financial measures are some of the most effective tools employers can use to influence commuting behavior. Employees who are reimbursed for a specific mode of transport, such as driving, cycling, or using public transit, are more likely to include that mode in their daily routine (Ton et al. 2020).

However, many employers remain hesitant to offer strong financial incentives for sustainable transport (Shin 2020). Some may not even be aware that they can provide commuter benefits such as pre-tax payroll deductions. This points to a need for transit agencies and policymakers to conduct outreach and marketing campaigns to increase awareness and promote these opportunities (Shin 2020).

Additional financial strategies include offering direct subsidies, tax credits, or grants for employees who use sustainable transportation modes (Baker 2023). Transit subsidies, in particular, have been shown to be one of the strongest indicators of a positive employer stance toward green commuting. They are directly linked to higher transit use and reduced reliance on private cars (Ding et al. 2014).

In contrast, car parking policies also act as a financial lever. Charging for parking instead of offering it for free serves as a powerful disincentive for car use and signals an organizational effort to discourage car dependence (Ding et al. 2014).

Facilities and services at the workplace can significantly influence commuting behavior. For instance, providing shuttle buses, secure bike parking, e-bike charging points, high-quality showers, and locker facilities can make cycling and public transport more appealing and practical (Soder & Peer 2018) (Baker 2023). Similarly, installing charging stations for electric vehicles can support a shift toward cleaner driving options (Baker 2023).

Beyond financial and physical resources, workplace policies also contribute to shaping commuting habits. One of the most impactful approaches is offering flexible working arrangements. When employees are free to adjust their schedules, they become less dependent on private vehicles and more likely to explore sustainable commuting alternatives (Baker 2023).

#### Soft measures

Employers can also support green commuting through broader awareness campaigns and policy adjustments. These might include coordinated work-time schemes, support for teleworking, and internal communication that promotes the environmental and personal benefits of sustainable commuting (Soder & Peer 2018).

Marquez et al. (2024) stated that promoting a modal shift among workers who currently commute by car can be supported by making this group feel proud to commute by bike and by inspiring them. This can be achieved by implementing targeted incentive programs rather than relying on a one-size-fits-all approach.

#### Other measures

Finally, selecting office locations that are easily accessible by public transport is a fundamental strategy for encouraging sustainable travel. When public transport is a convenient option, employees are more likely to use it (Tsairi & Martens 2024).

### 3.2.7. Bike adaptation

A primary concern for potential cyclists is safety. People are more likely to adapt to cycling if they feel secure on the road. This necessitates high-quality infrastructure, including separate bike lanes that shield cyclists from vehicular traffic and secure parking facilities to protect their bikes from theft or damage (Jessiman et al. 2023). The importance of robust infrastructure and safety measures is echoed in research, which highlights that their absence can significantly limit bike usage (Gentiletti et al. 2019). For faster electric bikes, such as speed pedelecs, dedicated cycle highways can further enhance safety and efficiency (Rybels et al. 2024).

Traditionally, longer travel times compared to other transport modes posed a disadvantage for bike commuting. However, the advent of e-bikes and speed pedelecs has revolutionized this aspect. These electric-assist bicycles significantly reduce travel time, making longer distances more feasible and attractive for cycling (Rybels et al. 2024). E-bikes also make areas with hilly terrain more accessible, expanding the potential for bike adaptation in diverse geographical settings(Gentiletti et al. 2025).

A person's existing travel habits heavily influence their willingness to adapt to cycling. Individuals who primarily rely on cars tend to be more reluctant to switch to cycling. In contrast, those who frequently use public transport are often more open to combining cycling with public transport options. Experienced cyclists, who already integrate biking into their routines, tend to focus more on safety regulations and improvements that enhance their existing cycling experience (Molin et al. 2016).

Bike adaptation is not typically an overnight shift but rather a gradual, integrated process involving small steps (Gentiletti et al. 2025). When individuals choose to cycle for certain journeys instead of driving, it doesn't necessarily mean they abandon car use entirely. Instead, cycling becomes one of several transport options, selected based on the specific context of each trip. User trials play a vital role in this transition. Even minor improvements in perceived trust or ease of use can significantly alter attitudes towards cycling (van der Steen et al. 2025).

While financial incentives can initially encourage cycling by providing an additional motive, their long-term effectiveness can be limited once the incentive is removed (Zeiske et al. 2021). Therefore, focusing on inherent benefits and positive experiences is crucial. Cyclists often report positive experiences, including stress relief and a better mood, compared to car commuters (Hansen & Nielsen 2014). Initiatives like bike-sharing programs can also lower the barrier to entry, making cycling more accessible to a wider population (Gentiletti et al. 2025).

## 3.3. Hospital profile and context

The academic hospital is centrally located on a shared campus that houses several other organizations. These include universities, high schools, other medical institutions, a variety of other companies and a lot of student housing. As a result, the area becomes highly congested during peak hours, especially in the evening. This congestion often causes frustration, as even short distances can take a long time to travel. During the morning peak, traffic congestion on the roads is less severe, but finding an available parking spot becomes more challenging.

There are several parking garages available. The main and largest parking garage is accessible to both employees and visitors. Parking in this garage costs €3 per day if someone enters between 06:30 and 12:00. Outside of these hours, parking is free (Academic hospital 2025). This policy is in place because many employees work irregular or on-call shifts and therefore rely on the car for their commute. Other garages or parking areas are reserved for employees only, although these are smaller in size, often further away from the hospital and not always covered. A Park and Ride (P+R) facility is also located within walking distance, at approximately a 10-minute walk to the hospital (Google Maps n.d.). The parking fee for this location is €2 per drive-in.

Visitors and staff who use public transport can reach the hospital by bus or fast tram. There are several train stations in the area, including one major station and several smaller ones. The main station is centrally located and serves as a key transfer hub for the wider region, making it highly accessible from various directions. However, the smaller stations are not directly connected to the hospital by bus or tram. Commuters arriving at these stations must first travel to the main station or a nearby tram stop before transferring to a bus or fast tram to reach the hospital.

The hospital is also surrounded by several bicycle parking facilities. Some of these are partially covered, while others are fully exposed. The indoor bicycle garages are equipped with charging points for e-bikes. Some parking facilities are reserved for employees, while others are accessible to both employees and hospital visitors. According to Zadeits (2024), there is currently a shortage of charging points for e-bikes, and many of the existing charging stations are too narrow to accommodate larger bicycles, such as speed pedelecs or cargo bikes. Furthermore, has the hospital addressed the perception among bicycle commuters that there is an overall shortage of bicycle parking spaces.

The hospital offers various programs and initiatives to make commuting as convenient and pleasant as possible for its employees. One example is the bicycle purchase plan. Through this program, employees can purchase a bicycle and receive financial reimbursement, making cycling a more accessible and attractive commuting option. This reimbursement can be repaid over a period of three years through deductions from the employee's salary. Since employees pay taxes on their salary, this creates a tax advantage on the purchase of the bicycle. Employees who commute by public transport are fully reimbursed for their travel costs. However, if an employee travels less than 7 kilometers per single trip, they receive a travel allowance of 18 cents per kilometer instead. This same rate applies to employees who commute by car or bicycle. The reimbursement policy has a maximum limit of 80 kilometers per day (Academic hospital 2025).

## 3.4. General conceptual model

Based on all the information gathered from the literature review, a conceptual model was developed, as shown in Figure 3.1. This model presents an overarching view of the key insights identified in the literature and serves as the framework within which this research will take place. While some factors are specifically related to a hospital context, others factors are generalizable and can also be applied to commuting frameworks in other settings.

### Conclusion from literature

The existing literature reveals a multitude of factors influencing mode choice and the potential for bike adaptation. Transportation modes vary significantly, and individual preferences largely dictate the selection of a specific alternative. Many sociodemographic and psychosocial characteristics contribute to these differences among people, with context further shaping the decision-making process. However, choices aren't solely made by individuals; external factors like employers or government regulations can also play a significant role.

It is important to note that much of the information found in the literature is specific to the context of each individual study. Different populations, countries, and circumstances are examined, which may not directly align with the hospital setting in this research. Therefore, it is essential to test the factors identified in the literature within the context of this specific population. This approach allows us to assess whether the findings from previous studies also hold true for this group.

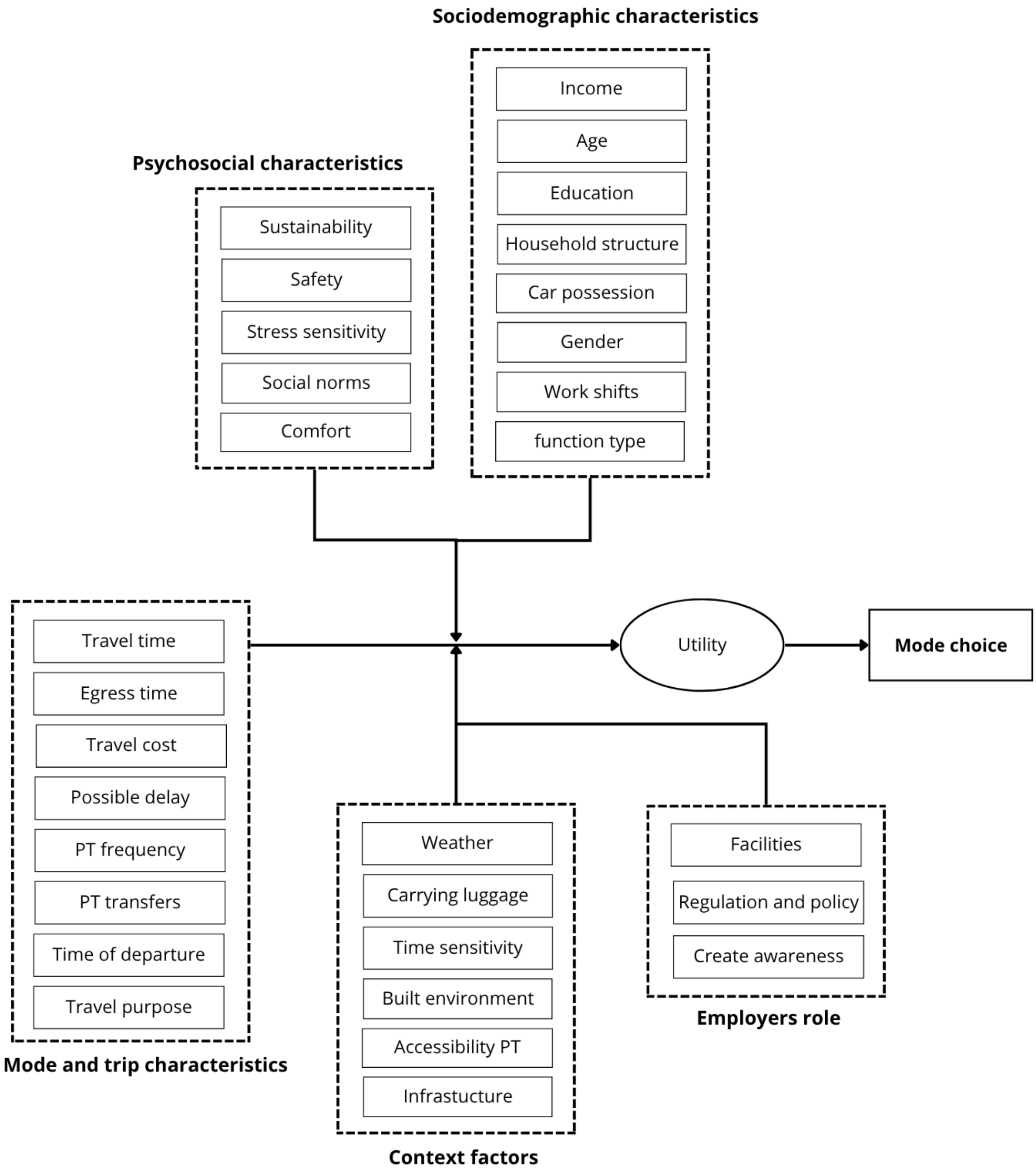



**Figure 3.1:** General conceptual model

# 4 Operationalization Survey

## 4.1. Experiment development

### 4.1.1. Alternatives development

In the previous study conducted by van der Meulen (2024), several different modes of transportation were examined.This follow-up study is specifically focused on understanding what motivates individuals to start cycling.

Because there are different types of bikes, and each type may be more attractive depending on the distance traveled, two distinct bike alternatives were defined: the city bike and the e-bike. This separation was made in close consultation with Pon and the academic hospital, as they wanted to clearly distinguish between the two options. It was also taken into account that most people already own a bike. Some have an electric bike, others have a regular city bike, and some even own both. Additionally, there are many differences between these two alternatives, such as price, speed, and the required facilities. Therefore, it is important to treat them as separate options.

These two alternative bicycles are compared to the current way of commute of hospital employees. For this, a distinction is made between people who travel to the hospital by car and those who use public transport. This separation is important because certain attributes used in the experiment (such as parking costs and parking time) only apply to car users and not to those who commute by public transport. This means that the three alternatives that will be compared are:

1. City bike
2. E-bike
3. (a) Car
   (b) Public transport

Furthermore, the experiment does not focus specifically on multi-modal transportation, such trips are addressed in a simplified manner. The emphasis is placed on the mode of transport used to access the Science Park, which is typically the final leg of a multi-modal journey. If this last leg is by public transport, the respondent's mode will be classified as: *Public Transport*. Conversely, if the final segment involves driving onto the hospital grounds, it will be recorded as: *Car*.

#### Target group

Because of this, the initial target group consisted of people who currently commute to work by car, public transport or multi-modal. The reason for including current car users in the study is linked to the hospital's sustainability goals. From a sustainability perspective, the car is the least favorable option. In addition, car commuters often face significant congestion during peak hours around the hospital. Public transport users were also included to better understand their views on bicycle commuting. A person's current travel mode is not always based on preference. It may be due to practical limitations, such as not owning a car or a bicycle. If they did have access to these modes, their commuting behavior might change. Including public transport users allowed the study to explore this possibility. Another reason for their inclusion is that some employees use both car and public transport in their daily commute. For these individuals, it is useful to compare the public transport part of their journey with a possible bike alternative. Finally, including both groups helped expand the respondent pool. If the study had focused only on car users, there would have been a higher risk of not recruiting enough participants, which could have resulted in insufficient data for meaningful conclusions.

However, the target group was later expanded to also include people who currently travel to the hospital by (electric) bike. These individuals can still make thoughtful decisions about what makes a specific alternative attractive or not. They were included because they may not currently have access to a car or public transport in their area, but might still prefer these options if they were available. To gain a clearer understanding of the broader group of respondents and to ensure the findings would be applicable to the entire hospital population, it was decided to include all travelers, not just those currently commuting by car or public transport.

However, participants who travel more than 30 kilometers for a single commute to work are excluded from the experiment. This decision was made because individuals living more than 30 kilometers from the hospital are unlikely to consider commuting by bike or e-bike, as the distance is generally too great for these modes of transport.

### 4.1.2. Attributes development

The literature review provided a broad overview of various attributes that can influence mode choice. However, it was not feasible to include all of these attributes in the Discrete Choice Experiment (DCE), as this would have increased the complexity and reduced the comprehensibility of the study. Additionally, the academic hospital had specific preferences regarding the inclusion or exclusion of certain attributes. Therefore, the decision on which attributes to incorporate in the experiment was made in close coordination with the hospital. This was done because the academic hospital aimed to investigate specific relationships relevant to the current challenges they are facing. For example, there is frequent congestion around the Science Park, prompting the hospital to explore how employees would respond to an increase in parking charges. Due to overcrowding in the parking garage, it is sometimes full, requiring people to park in a different garage farther from the hospital. These issues illustrate the rationale behind the selection of certain attributes.

Another focus was on understanding which attributes cause someone to deviate from their current mode of transport. Furthermore, Molin and Kroesen (2023) have indicated that combining both positive and negative incentive contributes effectively to motivating or demotivating the use of certain modes of transport. For this reason, efforts were made to explore how cycling could be made more attractive, while also considering ways to make car use less attractive, and public transport to a lesser extent.

The following section provides an overview of all variables used in the experiment. Although not all variables are varied, it is still important to include them to ensure that respondents fully understand the context and can make informed decisions.

#### Bicycle facilities

As indicated in the literature, the addition of good cycling facilities can significantly influence the number of people who choose to cycle to work (Soder & Peer 2018). Currently, the hospital already offers several cycling-related amenities, such as e-bike chargers and partially covered bike parking. Therefore, it is valuable to test the impact of expanding these facilities.

As mentioned in Chapter 3.3, there is currently a shortage of chargers. Participants in the Living Lab also expressed a strong demand for additional facilities, particularly lockers,as they allow users to store rain gear or other cycling clothing. Showers are already available to employees at the hospital and are therefore not included as an additional facility in the experiment.

Based on the requests from Living Lab participants and insights from the interview of Zadeits (2024), it was decided to include both lockers and additional chargers as attribute levels in the experiment. Lockers can benefit both city bike and e-bike users, while additional chargers are expected to have a positive influence specifically for e-bike riders.

### Purchase cost

Not everyone currently owns a city bike or an electric bike; some may already have a city bike but not an e-bike. Since the aim of this research is to explore what might encourage people to shift from their current mode of transport to cycling, it is important to recognize that some individuals may need to purchase a bicycle in order to make that shift. Because the choice sets represent a situation in which a new bicycle is being bought, respondents are asked to disregard their current possessions and not let these influence their decision-making. They are advised to simply compare the alternatives presented and evaluate them independently of their current situation.The academic hospital has a bike plan that allows employees to purchase a bicycle at a reduced cost through tax benefits. Using this scheme, along with the average purchase price of a city bike and an e-bike, the monthly costs were calculated.

The average price of a new e-bike in 2023 was €2575, while a new city bike cost €824 on average (RAI Vereniging 2024). Only new bikes were considered in this study, as the bicycle scheme of the hospital cannot be used for second-hand bicycles. Previously, the reimbursement offered was €1500, repayable over three years. However, this year the hospital increased the reimbursement to €2500. Despite this change, not all employees are aware of the update, as the employee platforms and official communication still mention the €1500 amount (Academic hospital 2025). Therefore, it was decided to define the attribute levels for the purchase price based on three reimbursement options: €1500, €2000, and €2500.

The monthly cost of purchasing a bicycle are then calculated based on the average price of the bike minus the monthly tax deduction. An average tax deduction rate of 37.48% was used for these calculations (Belastingdienst 2025). Taxes can only be deducted from the reimbursed amount, not from the remaining portion of the purchase price. For this reason, the total monthly costs were calculated as the repayment of the reimbursed amount minus the tax benefit, plus the remainder that must be paid directly by the employee. These calculations resulted in estimated monthly costs of €45, €50, and €55 for the reimbursement of respectively €2500, €2000 and €1500. The costs were presented on a monthly basis, as tax decisions are also based on the employees' monthly salaries.

The purchase cost for the city bike is also calculated according to the hospital's bike plan. However, since the average cost of a city bike is lower than the minimum reimbursement level, the full amount can be tax-deducted. Therefore, there is no need to vary the levels in the experiment. A detailed breakdown of the monthly cost calculations for each reimbursement level is provided in Appendix B.

The purchase costs of a car are deliberately not included in the experiment. Car costs can vary greatly and there are different types of ownership, which makes cost calculations complex and unreliable. In addition, there are many other associated costs, such as insurance, maintenance and periodic inspections. To keep the overview clear and the survey understandable for respondents, it was decided not to include these costs. However, this also means that in the actual situation, the cost difference between car use and bicycle alternatives is likely even greater than represented in the experiment.

### Parking and walking time

This attribute is mainly relevant for employees who currently commute to the hospital by car. There are several parking garages near the hospital, with some located closer than others. Most people prefer to use the garage closest to the hospital; however, this garage is often very busy during peak hours. As a result, it can take time to find a parking spot. If no spaces are available, employees may need to park in a garage further away from the hospital.

The time required to park the car and walk to the hospital entrance can therefore be considerable. According to data from Google Maps n.d. walking distances from these garages range from 3 to 11 minutes. Additionally, searching for a parking spot can further increase the total time. Due to these factors, the attribute levels were set at 10, 15, and 20 minutes. This range captures all possible scenarios and accounts for both parking availability and the walking time to the hospital.

The biggest bicycle parking garage is located directly next to the main entrance of the hospital. However, it may take a few minutes to find a parking spot for a bike. Therefore, an average of 5 minutes is used to account for both parking and walking to the hospital entrance, for both e-bike and city bike users. This value is not varied within the experiment and is fixed at 5 minutes.

There are several ways to reach the hospital by public transport, with different routes leading to different end-stations, each varying in distance from the hospital entrance. The most frequently used stop is the bus and tram station directly in front of the hospital, which is approximately a 3-minute walk away. Other nearby bus stops require up to 9 minutes of walking. As a result, an average walking time of 6 minutes is used for the public transport alternative Google Maps n.d. This value is also fixed and will not be varied within the experiment.

### Parking cost

Employees of the hospital are required to pay for parking in the garages at Science Park. This rate is reduced compared to the parking fee for visitors. In contrast, parking in the bicycle facilities is always free, the hospital does not charge any costs for it. Currently, parking a car at the hospital costs €3 per day if an employee enters the garage between 06:30 and 12:00 (Academic hospital 2025). However, if they park outside of this time window, parking is free. This policy applies to two garages: P-North and P-South.

The cost of parking at the nearest Park & Ride facility, is €2 per entry. Since the goal of the study is to combine both disincentives and positive incentives, it was decided, in collaboration with the hospital, to vary the attribute levels by increasing parking charges. Therefore, employee sensitivity to higher parking fees will be tested by varying the attribute at levels of €3, €5, and €7 per day.

### Delays

Delays can occur both on the road, due to congestion, and in public transport, due to disruptions. Since the current mode of transport is treated as a single alternative, which includes both car and public transport as sub-options, it was decided to apply the same delay levels to both. The average delay for a bus or tram is approximately 6 minutes (Rietveld et al. 2001). However, if a traveler misses a transfer due to a delay, the total delay can increase significantly. According to Zadeits (2024), congestion can be particularly severe when people leave the hospital, with delays reaching up to 45 minutes. To strike a balance between road and public transport delays, delay levels of 0, 10, and 20 minutes were used in the experiment. No delays for bicycles were taken into account, as earlier studies did not mention any issues related to crowding on bicycle paths.

### Travel time

Travel time was calculated for each mode of transport and is based on the average distance to the hospital per experiment. The average distances are shown in Table 4.1. The travel times for public transport and car were determined using points on the map located to the north, south, east, and west of the hospital. These points were placed at distances that correspond to the average commuting distance used in each experiment. All four directions were included to avoid bias and to account for variations in accessibility, as not all areas have the same level of connectivity to the hospital.

The travel times were not calculated based on fixed average speeds, as there are significant differences between various public transport modes (e.g., metro, tram, bus, train), and car travel times also vary depending on road type and surrounding traffic conditions. Therefore, it is more reliable to use the area surrounding Science Park as a reference. Google Maps automatically incorporates realistic average speeds for specific public transport modes and road types, providing more accurate travel time estimates. The specific travel time calculations are explained in Appendix B.

Travel times for city bikes and e-bikes were calculated using average cycling speeds. An average speed of 14 km/h was used for city bikes and 21,8 km/h for e-bikes (SWOV 2025; Molnár 2002). The combination of average distance per experiment and average speed was used to determine the total travel time for each bicycle type.

**Table 4.1:** Average distance per experiment

| Experiment | Categories (km) | Average distance (km) |
|---|---|---|
| Exp 1 | <= 7,5 | 3,75 |
| Exp 2 | 7,6 – 15 | 11,25 |
| Exp 3 | 15,1 – 30 | 22,50 |

**Table 4.2:** Travel time per transport mode per experiment

| *Experiment* | *Regular bike* | *E-bike* | *Car* | *Public transport* |
|---|---|---|---|---|
| Exp 1 | 16 min | 10 min | 9 min | 19 min |
| Exp 2 | 48 min | 31 min | 14 min | 37 min |
| Exp 3 | 96 min | 62 min | 21 min | 56 min |

### Travel allowance

The travel allowance is fixed at €0,18 per kilometer for both biking and driving. There is no travel allowance for public transport, as this mode is fully reimbursed by the hospital. The travel allowance was recently increased to €0,18 per kilometer and is fixed under the new collective labor agreement. Based on this recent adjustment and in consultation with the hospital, it was decided not to further vary the travel allowance in the experiment, as the hospital wanted to avoid giving employees the wrong impression or suggesting a possible increase in travel allowance in the future. The total travel allowance are calculated based on the average distance per experiment.

### Fuel cost

Fuel costs are important for employees who travel by car, as they represent fixed expenses that are inevitably incurred when commuting to the hospital by car. However, fuel costs vary depending on the type of vehicle. Therefore, an average fuel cost was used. This average is based on the distribution of vehicle types in the Netherlands, specifically electric, diesel, and petrol cars (CBS 2025). By combining the cost per kilometer for each vehicle type with their respective market share, an average cost of €0,11 per kilometer was calculated (RVO) 2024). The full calculation details can be found in Appendix B.

### Weather

Weather plays a crucial role in mode choice decisions. It can influence the likelihood of choosing active transportation and also affect the share of car and public transport use (Molin & Timmermans 2010). Research has shown that the presence or absence of rain is a particularly important factor, more so than temperature alone. To create a clear distinction between weather conditions in the experiment, a combined approach was used that considers both rain and temperature. As a result, two weather conditions were defined: "rainy and cold" and "warm and dry." The weather condition was identical across all alternatives within a single choice set but varied between different choice sets.

### Total variable overview

Table 4.3 shows all the attributes that were included and how they are varied across all choice sets. Furthermore, shows Table 4.4 the variables that are incorporated into the experiment but are not varied and have a fixed value. Lastly, there is Table 4.5 which shows the contact variables which will be included per choice set.

**Table 4.3:** Attribute and attribute levels

| **Alternative** | **Attribute** | **Values** |
|---|---|---|
| *City bike* | Bicycle facilities | Current facilities, Current facilities + lockers, Current facilities + lockers and additional charging points |
| *E-bike* | Purchase cost<br>Bicycle facilities | €45, €50, €55/month<br>Current facilities, Current facilities + lockers, Current facilities + lockers and additional charging points |
| *Car* | Parking and walking time<br>Parking cost<br>Delays | 10, 15, 20 min<br>€3, €5, €7/day<br>0, 10, 20 min |
| *PT* | Delays | 0, 10, 20 min |

**Table 4.4:** Fixed attributes

| Alternative | Attribute | Value |
|---|---|---|
| *City bike* | Travel time | Table 4.2 |
| | Parking and walking time | 5 min |
| | Travel allowance | €0,18/km |
| *E-bike* | Travel time | Table 4.2 |
| | Parking and walking time | 5 min |
| | Travel allowance | €0,18/km |
| *Car* | Travel time | Table 4.2 |
| | Travel allowance | €0,18/km |
| | Fuel cost | €0,11/km |
| *PT* | Travel time | Table 4.2 |
| | Travel allowance | 100% reimbursed |

**Table 4.5:** Context variable

| Alternative | Variable | Value |
|---|---|---|
| *All* | Weather | Rainy and cold, Warm and dry |

### 4.1.3. Utility functions

Given all the different attributes incorporated for each alternative, the utility function for each alternative can be calculated. The Beta coefficients will be estimated based on the selected model. However, the equations below provide an overview of the utility function for each alternative. Each choice set contains three alternatives, with the third being either the car or public transport. Separate utility functions are used for these alternatives, as not all attributes apply to both. For example, parking costs and walking time are attributes that are only relevant for the car alternative and are not varied for public transport. Furthermore, the weather coefficients are assessed separately for each alternative, as weather conditions could have a very different impact on the attractiveness of car use versus public transport. However, the models are always estimated based on three alternatives, with the availability of the third alternative taken into account.

$$
\begin{gathered}
U\ (\text{city bike}) = \beta_{\text{fac}} \cdot \text{fac} + \beta_{\text{weather1}} \cdot \text{weather} \\
U\ (\text{e-bike}) = ASC_{\text{ebike}} + \beta_{\text{fac}} \cdot \text{fac} + \beta_{\text{cost}_e} \cdot c_{\text{ebike}} + \beta_{\text{weather2}} \cdot \text{weather} \\
U(\text{car}) = ASC_{\text{car}} + \beta_{\text{park}_t} \cdot t_{\text{park}} + \beta_{\text{park}_c} \cdot c_{\text{park}} + \beta_{\text{delay}} \cdot t_{\text{delay}} + \beta_{\text{weather3}} \cdot \text{weather} \\
U(\text{pt}) = ASC_{\text{pt}} + \beta_{\text{delay}} \cdot t_{\text{delay}} + \beta_{\text{weather3}} \cdot \text{weather}
\end{gathered}
$$

### 4.1.4. Choice sets development

#### Composition choice sets

To ensure a manageable but robust experiment, is a D-efficient design employed. Unlike full factorial designs, which include every possible combination of attribute levels and often result in an unfeasible large number of choice sets. D-efficient designs strategically select a subset that maximizes information gain (Alamri et al. 2023). This approach significantly reduces the number of choice sets required, lowering the cognitive burden on respondents while still allowing for precise estimation of model parameters. However when using D-efficient design this means that priors have to estimated for the attributes. The priors where calculated based on different other studies. More explanation on what studies where used and how these priors are calculated is given in the Appendix C.1.

However, since there are three alternatives: city bike, e-bike, and the employee's current mode of transport, there is a risk that many respondents will consistently choose their current travel mode. If this occurs, there may be insufficient data to properly assess the trade-offs between the two bike alternatives. To address this issue, respondents will be asked to indicate both their first and second choice. Each choice set contains three alternatives. By asking for a second choice, respondents are encouraged to compare the two bike alternatives, even if their first choice remains the same.

### Number of choice sets

The number of choice sets presented to respondents depends on several factors. Equation 4.1 provides an overview of the minimum number of choice sets required (Molin 2023). The number of parameters refers to the total of all attributes and constants estimated in the model.

$$CS > \left(\frac{p}{A-1}\right) + 1 \tag{4.1}$$

$CS$ The minimal amount of choice sets
$p$ The amount of parameters
$A$ The amount of alternatives

In total, six attributes are varied within the choice sets. This number came down to six because the bicycle facilities are identical for both bike alternatives, however facilities can have a different affect on people using the city bike or e-bike, therefore is decided to estimate different priors and add them as separate parameters. As a result, these attributes correspond to six parameters. However, since the effect of some attributes may not increase linearly with higher levels, it may be necessary to estimate two parameters per attribute, to test for non-linearity. This would bring the total to twelve parameters.

Additionally, since there are three alternatives, one serves as the reference category, meaning that two alternative-specific constants need to be estimated. This means that the amount of parameters for the constants are two. This means a total of 14 parameters.

According to the equation provided in 4.1, the minimum number of choice sets required is eight. However, since all attributes have three levels, it is important to ensure attribute level balance. Each level should appear an equal number of times to avoid bias in the experiment. To achieve this, the minimum number of choice sets must be increased to nine, as this number is divisible by three and ensures proper balance.

Since the experiment includes a context variable, all conditions must be tested. Although there is only one context variable with two levels, this means that each choice set must be presented under both weather conditions. As a result, the experiment would include a total of 18 choice sets, because originally there were nine choice sets.

To avoid respondent fatigue and maintain the quality of the responses, the design is divided into blocks. Each respondent is assigned to one block only. In one block, the nine choice sets are presented with a specific weather condition, while in the other block, the same choice sets are shown with the opposite weather condition. Furthermore, the weather conditions alternate with each choice set: if choice set 1 presents good weather, then choice set 2 presents bad weather, and so on. For the other block, this order is reversed. This method ensures that the influence of weather can still be accurately measured, while keeping the number of choice sets per respondent limited and manageable.

## 4.1.5. Visual representation

When designing the survey and constructing the choice sets, several important aspects were taken into consideration. First and foremost, it was essential to ensure that the survey would not be too long, as lengthy surveys can lead to a loss of interest and concentration among respondents. The goal was to keep the total completion time under 12 minutes (Wigmore 2021). In addition to this, creating a pleasant and engaging experience for respondents was also a priority. This was achieved by incorporating color and images into the survey interface. Research suggests that visuals can enhance clarity and make scenarios more relatable and enjoyable for participants (Maptionnaire 2022). For this reason, the choice sets included color images of the travel alternatives, along with weather conditions relevant to each option.

Furthermore, considering that the survey would be completed by individuals with diverse educational and professional backgrounds, special attention was given to the clarity and simplicity of the language used (Zimba & Gasparyan 2023). The aim was to make the survey accessible and easy to understand for all participants. Finally, there is a clear and consistent structure in how the information is presented: travel time is shown first, followed by costs, and then facilities. This order ensures that respondents can easily understand and follow how the total value of each alternative is calculated.

Examples of a choice set are provided in Figure 4.1 and Figure 4.2. The question asked for each choice set was as follows:

*Which alternatives would you choose for your trip in this scenario, give your first and second choices?*

| **Weersomstandigheden:** |
|---|
| Het is een warme en droge dag |

| | **Stadsfiets** | **E-bike** | **Auto** |
|---|---|---|---|
| |  |  |  |
| Reistijd | 1u 36 min | 1u 2 min | 21 min |
| Parkeer en looptijd | 5 min | 5 min | 10 min |
| Vertraging | | | 0 min |
| Totale reistijd | 1 u 41 min | 1 u 7 min | 31 min |
| Reiskostenvergoeding | + €4,28/dag | + €4,28/dag | + €4,28/dag |
| Aanschafkosten* | - €14,3/maand | - €55/maand | - |
| Brandstofkosten | - | - | - €4,50/dag |
| Parkeerkosten Science Park | - | - | - €3/dag |
| Totale reiskosten | + €3,57/dag | + €1,53/dag | - €3,22/dag |
| Fiets faciliteiten UMC Utrecht | Huidige faciliteiten | Huidige faciliteiten | - |

*Aflossingsperiode van 3 jaar

**Figure 4.1:** Example choice set, version 1 car

| **Weersomstandigheden:** |
|---|
| Het is een warme en droge dag |

| | **Stadsfiets** | **E-bike** | **OV** |
|---|---|---|---|
| |  |  |  |
| Reistijd | 1u 36 min | 1u 2 min | 56 min |
| Parkeer en looptijd | 5 min | 5 min | 6 min |
| Vertraging | - | - | 0 min |
| Totale reistijd | 1 u 41 min | 1 u 7 min | 1 u 2 min |
| Reiskostenvergoeding | + €4,28/dag | + €4,28/dag | 100% vergoed |
| Aanschafkosten* | - €14,3/maand | - €55/maand | - |
| Totale reiskosten | + €3,57/dag | + €1,53/dag | €0,00/dag |
| Fiets faciliteiten UMC Utrecht | Huidige faciliteiten | Huidige faciliteiten | - |

*Aflossingsperiode van 3 jaar

**Figure 4.2:** Example choice set, version 1 public transport

## 4.2. Statements development

As discussed in the literature review, psychosocial characteristics can influence individuals' mode choice. To explore these characteristics and underlying attitudes, respondents are presented with a series of statements to assess how much they relate to each one. These statements are grouped into key themes: safety, health, activity, employer, sustainability, and delays. The themes were selected in close consultation with, and at the request of, the hospital. They reflect both current commuting experiences and attitudes toward potential future policies.

Table 4.6 presents the full list of statements. It shows that statements three to five relate to possible future policies or behavioral change, while statements one, two, and six focus more on current issues that employees may experience in their daily commute.

The target group for the discrete choice experiment differs from the target group for the attitudinal statements. While the discrete choice experiment focuses on employees who travel less than 30 kilometers per trip, this limitation does not apply to the attitudinal statements. These statements will be presented to all employees who complete the survey. This broader approach is chosen because the statements cover a wider range of topics that are not solely focused on cycling. As a result, employees who live farther away from the hospital are also considered relevant for this part of the study.

| | |
|---|---|
| 1. I experience the route I take to and from work as safe. | **Safety** |
| 2. My vitality and health make cycling to work less appealing to me. | **Health** |
| 3. I would like to be more physically active. | **Activity** |
| 4. I expect my employer to actively promote sustainable commuting. | **Employer** |
| 5. I am willing to accept slightly longer travel time if it is more sustainable. | **Sustainability** |
| 6. I have recently experienced problems with traffic congestion or delays in public transport. | **Delay** |

**Table 4.6:** Statements and themes

The statements were developed based on the findings from previous research as well as through consultation and discussions with the hospital. The first statement was included to explore concerns related to commuting safety, which had been raised in recent years. This allows us to assess whether employees themselves experience commuting as unsafe.

The health statement was designed to understand both the physical capabilities of employees and whether certain groups face limitations that prevent them from using specific modes of transport. At the same time, it is important to identify whether there are employees who would like to be more physically active. Commuting by bike could contribute to meeting that need for increased physical activity, that is why the activity-statement was included.

The sustainability and employer-related statement aim to assess the level of support among employees for more sustainable commuting. They also provide insight into whether there is a willingness to change behavior or if sustainability is only supported in theory. Comparing general attitudes with specific scenarios helps determine whether there is a gap between what employees say and what they are willing to do. For example, some may want the employer to promote sustainability but are not themselves willing to travel longer distances for that purpose.

The final statement addresses a recurring theme from earlier studies, in which many participants mentioned frequent delays and congestion in the area. Including this statement allows us to determine whether this issue is widespread among all employees or if it mainly affects a specific group.

## 4.3. Sociodemographic characteristics

Sociodemographic characteristics are included in the survey to estimate possible segmentation within the employee pool. However in discussions with Pon and the hospital regarding the previous study and its results, it became clear that certain questions about sociodemographic characteristics were less well received by respondents. For this reason, some highly personal characteristics have been excluded from the current survey.

However, other sociodemographic characteristics will still be included. For more sensitive questions, such as gender, a "Prefer not to say" option is provided to respect the respondent's privacy. Below is a complete overview of the characteristics that will be included in the questionnaire:

- Travel mode
- Travel distance
- Gender
- Function family
- Work shift
- Time of arrival at work
- Possession of transport modes
- Use multiple transport modes

It is important to understand the current sociodemographic characteristics of the respondents in order to establish a baseline measurement. This provides insight into the current distribution of travel modes and travel distances. Additionally, other characteristics, such as arrival time and work shifts, are more closely related to parking issues and congestion around the Science Park.

To gain a better understanding of these dynamics, it is valuable to know when most people arrive and which modes of transport they use. Their time of arrival may be directly related to their work shifts and functional roles within the hospital. These factors could also influence their travel behavior, such as choosing to travel in the evening or bringing a large amount of luggage.

Furthermore, information about the possession of different transport modes is included to assess whether having or lacking access to a specific mode influences their commuting choices. Individuals might make very different decisions if they had access to certain alternatives.

Lastly, it is important to know whether people occasionally use different transport modes. If they already switch modes from time to time, they may be more open to adopting new commuting options. All of these factors are considered relevant and have therefore been incorporated into the survey.

For the analysis that will be performed, all the answered coded. The full overview of the questions of the survey and all the codes of the answers are given in Appendix D.1

## 4.4. Data handling

All data collected through the survey will be processed to ensure that the appropriate analyses can be conducted. Two main data files have been prepared for this purpose. The first file will be used in SPSS and contains the results related to personal characteristics and responses to the attitudinal statements for all respondents. The second file is created in Excel to facilitate use in Python. This file includes all respondents who participated in the DCE, along with their personal characteristics, statement responses, and the choice sets.

For both data files, coding was applied to all personal characteristics and statements, based on dummy coding. A complete overview of the codes used for each variable level is provided in Appendix D. In the Excel file used for the DCE, the actual values of the attributes were used unless this was not feasible, in which case dummy coding was applied. Therefore will the parameter estimates be based on the actual values of the attribute levels.

## 4.5. Living Lab and open questions

In addition to questions about respondent characteristics and preferences, several other questions have been included. During the Living Lab, a significant amount of information was collected. To enable a meaningful comparison with that data, specific questions have been added for participants of the Living Lab. These questions are identical to those previously asked during their participation. This makes it possible to determine whether participants still report the same experiences or if their opinions have changed over time. These questions focused on the experiences of people when traveling by bike and which specific aspects of their trips they found more favorable than expected.

Furthermore, at the end of the survey, respondents are asked which sustainable transport modes they feel are needed. This is a open question where respondents can fill in anything they want. The question was included to establish a link between the quantitative survey responses and a potential qualitative follow-up, in which participants could share their ideas and opinions in more detail.

In Appendix D.2, the questions and possible answers related to the Living Lab participants are presented. These responses did not require coding, as several questions allowed participants to select multiple answers. However, whether or not someone participated in the Living Lab was coded as a separate variable.

## 4.6. Respondents selection

The selection and recruitment of respondents is a crucial part of the survey process and can have a significant impact on the results. All post and e-mails sent about the survey were sent twice to give people a reminder about the survey, a week after the first message was sent. An overview of the respondents who were recruited and in what way this was done, is given in table 4.7.

### Participants Living Lab

A base group of approximately 280 employees who participated in the previous research by van der Meulen (2024) will be contacted again. This group has been gathered in a dedicated Microsoft Teams channel and email list. These individuals were approached through both email and Teams to invite them to participate in the new survey. These are employees who willingly volunteered to sign up for the Living Lab and therefore demonstrated their interest in commuting sustainably.

### New targeted participants

In addition, the hospital has a dedicated SharePoint page focused on sustainability-related initiatives and articles. This page includes an audience of around 500 employees. A post was published on this platform introducing the survey and its objectives, encouraging participation. These employees also consider sustainability, although it remains uncertain whether this influences their choice of transportation mode.

### Recruiting random participants

Beyond the sustainability page, the hospital's general intranet platform is accessible to all employees, approximately 12.000 in total. While the platform allows for both large announcements and smaller updates, permission was not granted by the hospital to post a large announcement. However, approval was given to share a smaller update to draw attention to the survey and encourage broader participation.

Additionally, a physical set-up was arranged within the hospital to engage with employees directly, this was done three times in the restaurant of the hospital. This set-up will allow for personal interaction, creating opportunities to explain the survey, encourage participation, and collect valuable informal feedback from employees regarding their commuting experiences and opinions. This group of respondents was selected randomly, which means their views on their current commuting situation are not known in advance. Including this group is essential to ensure an even distribution across the total sample and to reduce bias. It allows for the inclusion of both employees who are sustainability-minded and aware of their commuting options, as well as those who may not actively consider sustainability or reflect on their commuting choices.

**Table 4.7:** Respondent recruitment

| Respondent type | Recruitment method |
|---|---|
| Living Lab participants | • Direct e-mail<br>• Post in Living Lab Teams channel |
| Targeted participants | • Post on Sustainability Sharepoint page |
| Random requirement | • Post on general Intranet page<br>• Physically recruitment in lunch restaurant |

# 5 Descriptive statistics

This chapter presents the initial results from the survey. Section 5.1 outlines how the data was prepared and how the analyses were conducted. Section 5.2 provides descriptive statistics of the respondents and explores possible relationships between their characteristics. Section 5.3 examines the attitudinal statements to assess respondents' views, corresponding to sub-question 3. The overall aim of this chapter is to understand who the respondents are, what defines them, and how their characteristics may relate to their attitudes.

## 5.1. Data processing

In total, *270* employees participated in the survey. Of this group, 161 respondents belonged to the target group for the Discrete Choice Experiment (DCE), as they travel less than 30 kilometers one way to the hospital.

The results will be analyzed based on two different target groups and, therefore, two separate datasets. The first dataset includes all respondents, along with their personal characteristics and answers to the attitudinal statements. The second dataset contains the same variables, but additionally includes all information related to the DCE. This second dataset is limited to respondents who fall within the target group for the DCE. The first dataset will be analyzed using SPSS, while the second dataset will is worked out in Excel en will be analyzed using Python with Biogeme package.

During the data processing, it became clear that some respondents were non-traders, meaning individuals who consistently chose their current mode of transport in the DCE, regardless of the alternatives presented. These non-traders were further examined to gain a better understanding of their behavior.

The analysis revealed a total of 83 respondents who showed no variation in their answers and were therefore labeled as non-traders. Among these 83 non-traders, 39 commute by city bike, 27 by e-bike and only 17 commute by car or public transport. Non-traders who already cycle are less of a concern in the context of this study, as the primary objective is to understand what could motivate more people to switch to cycling.

However, this also means that approximately 50% of all responses came from non-traders. The presence of such a substantial portion of non-traders, especially among those who are not yet cycling, is noteworthy. It raises important questions about what barriers prevent these individuals from considering alternative, more sustainable commuting options.

## 5.2. Descriptive statistics

**Table 5.1:** Overview frequencies en percentages

| Variable | Categories | Amount | Share % |
|---|---|---|---|
| Gender | Female | 180 | 66,7 |
| | Male | 84 | 31,1 |
| | Non-binary | 4 | 1,5 |
| | Prefer not to say | 2 | 0,7 |
| Participation Living Lab | Yes | 160 | 59,3 |
| | No | 110 | 40,7 |
| Single travel distance | Until 7,5 km | 40 | 14,8 |
| | 7,6 until 15 km | 57 | 21,1 |
| | 15,1 until 30 km | 78 | 28,9 |
| | More than 30 km | 95 | 35,2 |
| Mode of transport | City bike | 65 | 24,1 |
| | E-bike | 52 | 19,3 |
| | Public Transport | 98 | 36,3 |
| | Car | 55 | 20,5 |
| Car possession | Yes | 228 | 84,4 |
| | No | 42 | 15,6 |
| E-bike possession | Yes | 91 | 39,6 |
| | No | 179 | 60,3 |
| City bike possession | Yes | 195 | 72,2 |
| | No | 75 | 27,8 |
| Arrival time | Before 07.00 | 17 | 6,3 |
| | 07.00-08.00 | 113 | 41,9 |
| | 08.00-09.00 | 114 | 42,2 |
| | 09.00-10.00 | 16 | 5,9 |
| | 10.00-16.00 | 7 | 2,6 |
| | Na 16.00 | 3 | 1,1 |
| Shifts | I do not work in shifts | 126 | 46,7 |
| | Night, evening, weekend and on-call shift | 68 | 25,2 |
| | Day shift | 76 | 28,1 |
| Bike plan knowledge | Yes, fully familiar | 106 | 39,3 |
| | Yes, kind of familiar | 88 | 32,6 |
| | Yes, I have used it | 30 | 11,1 |
| | Yes, I'm planning on using it | 10 | 3,7 |
| | No, I'm not familiar | 36 | 13,1 |
| Function family | Scientific support and education | 37 | 13,7 |
| | Nursing and care | 38 | 14,1 |
| | Staff and administration and secretarial | 56 | 20,7 |
| | Medical specialists | 9 | 3,3 |
| | Management | 27 | 10,0 |
| | Clinical support | 18 | 6,7 |
| | Clinical (co-)treatment | 22 | 8,1 |
| | In training | 6 | 2,2 |
| | Facility staff | 20 | 7,4 |
| | Medical residents and junior doctors | 10 | 3,7 |
| | Analytical staff | 27 | 10,0 |

Table 5.1 presents the number of respondents per category and the corresponding percentages. For each variable, the percentages represent the relative share of each category. It is clear that almost every category within the variables is represented. In addition, some notable patterns emerge, such as the gender distribution. There are significantly more female respondents than male respondents, which is likely due to the fact that more women work in the healthcare sector than men (Langenberg et al. 2023).

Overall, the respondent group is divided into approximately 60% who participated in the Living Lab and 40% who did not. This distribution may be explained by the recruitment method. Participants in the Living Lab were targeted directly via email, which likely increased their response rate. Other participants were recruited through physical outreach and messages posted on internal intranet platforms.

The distribution of travel distances shows that, within the group of respondents, a larger portion lives more than 15 kilometers from the hospital compared to those living closer. The division by mode of transport reveals that most people commute by public transport, followed by city bike. The number of respondents using an e-bike or a car is nearly the same. Figure 5.1 shows the relationship between mode of transport and commuting distance. The data reveals that when people live close to work, nearly 90% use a bicycle alternative, with the majority choosing a city bike. This share decreases in the group between 7,5-15 kilometers, although around 70% of respondents in that group still opt for a bicycle alternative. In this group, the use of e-bikes gains more traction. Public transport use remains relatively stable, while car usage shows a big increase.

For the distance group between 15 and 30 kilometers, the use of bicycle alternatives drops significantly to below 40%. The most notable increase is in public transport use, while car use remains relatively stable. This group shows the most even distribution across all transport modes. Among respondents who travel more than 30 kilometers per trip, public transport becomes the dominant mode. Interestingly, some individuals in this group still choose to commute by bike. Notably, the number of city bike and e-bike users is nearly equal. Car use increases slightly compared to those traveling up to 30 kilometers but does not show a major shift.

Overall, car use remains relatively the same across all distance groups above 7,5 kilometers. Public transport is the preferred mode for distances above 15 kilometers, while bicycles, particularly city bikes, are most common for trips under 15 kilometers.

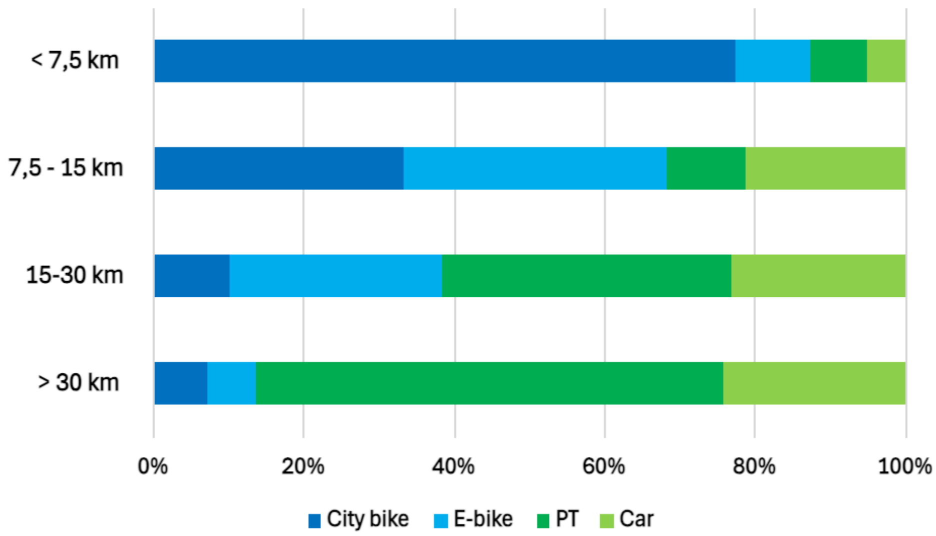



**Figure 5.1:** Distribution current mode of transport and the travel distance

As given in Table 5.1 shows the distribution of mode ownership that almost all respondents own a car, with only 15% indicating they do not. In comparison, 40% own an e-bike and 70% own a city bike. To gain deeper insight into this, the relationship between mode ownership and the mode of transport currently used for commuting was examined. Figure 5.2 shows that ownership of a specific mode of transport influences its use, this figure compares the ownership of a mode and if an employee then uses this as their current mode of transport. Among those who own a city bike, approximately 35% use it for their commute. Interestingly, nearly 50% of people who own an e-bike do not use it for commuting to the hospital. Instead, they opt for public transport or a car, and a small number even choose the city bike despite owning an e-bike. Furthermore, many people who own a car still choose to commute by public transport or by bike. In fact, around 75% of respondents who own a car most often do not use it to travel to the hospital.

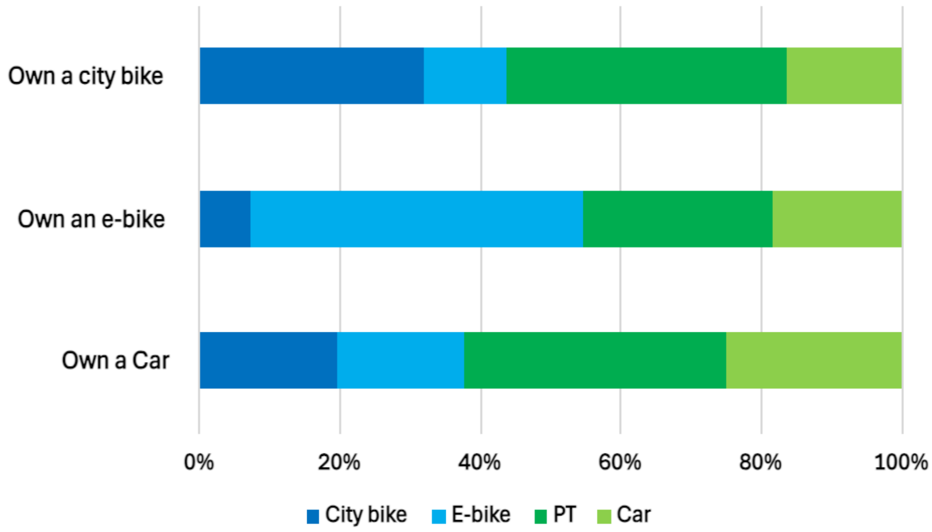



**Figure 5.2:** Distribution current mode of transport and possession of modes

A further distinction can be made based on e-bike ownership in relation to commuting distance. It is also relevant to identify potential groups who do not own an e-bike but do live within a feasible e-bike commuting range. Figure 5.3 shows that 60% of individuals who do not currently own an e-bike live within e-bike distance (less than 30 kilometers). For this group, using the bike plan which is offered by the hospital or lease an e-bike could be attractive, as it would enable them to acquire an e-bike and use it for their daily commute.

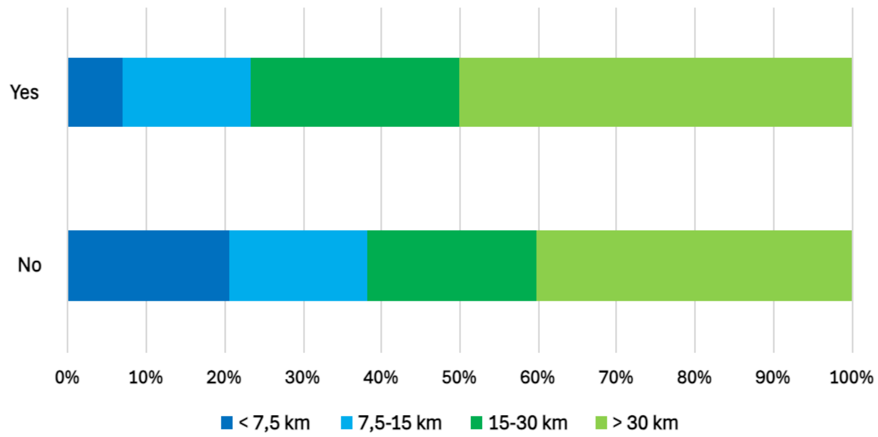
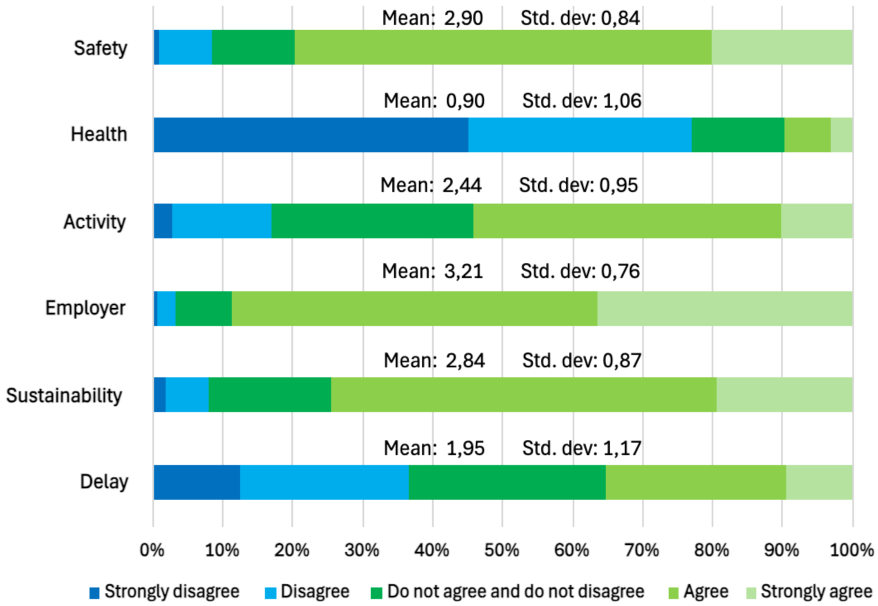



**Figure 5.3:** Distribution current mode of transport and travel distance

## 5.3. Attitude behavior

This aims to discuss the results found in relation to sub-question 3. Several statements, each linked to specific themes, were presented to the respondents in the survey. These were included to gain insight into respondents' attitudes toward various commute-related topics. Table 4.6 provides an overview of the statements and their corresponding themes. The names of these themes are used throughout the analysis to refer to the statements.

In Figure 5.4, is the distribution of responses shown, along with the mean and standard deviation. These statistics are based on a coding scheme where 0 represents "Strongly Disagree" and 4 represents "Strongly Agree." Several points immediately stand out in the figure. In the safety statement, it's often indicated that people perceive their journey as safe. 80% of respondents feel their trip is safe and therefore the mean comes down to 2,90 which represent that people agree with the question statement that the route is safe. In contrast, just under 80% of people indicate that fitness and physical condition aren't an issue for a bike ride. However, 10% state this might be a problem for them. The next statement addresses whether people would like to exercise more. Here, answers are somewhat divided. Nevertheless, the majority indicates agreement, while a large portion expresses no preference, and almost 20% disagrees.




| Statement answer | Value |
|---|---|
| Strongly disagree | 0 |
| Disagree | 1 |
| Neutral | 2 |
| Agree | 3 |
| Strongly agree | 4 |

**Figure 5.4:** Distribution of answers to statements

Both sustainability statements, one concerning longer travel time due to a more sustainable transport method and the other on whether employers should encourage sustainable travel, received high ratings. The same trend is evident: the vast majority agrees with both statements. However, the number of neutral responses is lower for encouraging sustainable travel than for longer travel times. For this reason, both statements have an average around three, which indicates that people agree. The last statement concerns road congestion and public transport delays. The answers to this question are highly dispersed, suggesting considerable individual variation in travel delays. Consequently, the average response is approximately 2, and this statement exhibits the highest standard deviation among all the statements.

### 5.3.1. Attitudinal relationships

To gain insight into how respondents' attitudes toward commuting are related, a correlation analysis was conducted on all presented statements. This method helps to identify patterns or clusters of agreement, revealing which perceptions tend to co-occur. From this analysis, three statements showed significant correlations above 0,25 with each other, indicating a noteworthy association. These key results are presented in Table 5.2. The full correlation matrix is available in Appendix E.

The two sustainability-related statements show a moderate correlation of 0,422. This indicates that respondents who score high on one of these statements often also score high on the other. The correlation between the safety statement and the two sustainability statements is 0,266 and 0,251, respectively. While these relationships are not as strong, they still indicate a positive association. These results provide an initial indication of what might emerge in the PAF analysis.

**Table 5.2:** Correlations statements

| Statements | | Safety | Employer | Sustainability |
|---|---|---|---|---|
| Safety | $r$ | 1 | ,266 | ,251 |
| | Sig. | - | <,001 | <,001 |
| Employer | $r$ | ,266 | 1 | ,422 |
| | Sig. | <,001 | - | <,001 |
| Sustainability | $r$ | ,251 | ,422 | 1 |
| | Sig. | <,001 | <,001 | - |

**Table 5.3:** Factor Matrix PAF

| Statement | Factor 1 |
|---|---|
| Employer | 0,649 |
| Sustainability | 0,649 |

Next, the Principal Axis Factoring (PAF) was performed. After running the model several times and removing statements that did not meet the minimum criteria, two statements were identified that both loaded highly on a single factor. Choosing a rotation method was not necessary, as rotation is not applicable when only one factor is extracted. The factor loadings from the final PAF run are presented in Table 5.3.

All analyses from now on will use the factor score rather than the individual scores of these two statements and be referred to as the "Sustainability Factor". The factor score was calculated by taking the average of each respondent's answers to both statements. The other statements did not load strongly on any specific factor. Therefore, they will be analyzed separately rather than grouped into a factor. In total, this results in four individual statements and one combined factor. In Appendix E is the whole process of the PAF given.

Although six statements were included in the analysis, only two showed strong loadings on the extracted factor. This suggests that the remaining four statements do not share sufficient common variance and likely do not reflect a shared underlying construct. Their low communalities indicate they are either measuring different concepts, are too heterogeneous in content. As such, these four statements did not load strongly on any specific factor and will be analyzed separately rather than grouped into a factor. The fact that these statements did not load highly on the identified factor is not surprising, given that the themes of the statements were all quite different. In total, this results in four individual statements and one combined factor. The full process of the PAF is detailed in Appendix E.

### 5.3.2. Attitude and sociodemographics

In the previous section, the averages of the attitudinal statements were discussed. However, attitudes may vary depending on specific characteristics of the respondents. Therefore, it is important to examine the relationship between respondent characteristics and their responses to the statements, as this can provide deeper insight into the reasoning behind their answers. To explore these relationships, statistical tests such as the Independent Samples T-Test and One-Way ANOVA were conducted to assess whether there are significant differences between groups of respondents. A full overview of all the results of these test are presented in Appendix E.2.1.

#### Delay and Mode

Figure 5.5 provides insight into how respondents experience delays based on their current mode of transport. It shows the distribution of agreement per current mode of transport. This gives insight into whether specific modes experience more delays than other. The statement made concerning delays is: *"I have recently experienced problems with traffic congestion or delays in public transport"*.

The mean for city bikes is the lowest, followed by e-bikes, indicating that e-bike users experience more delays compared to city bike users. This mean difference of 0,22 is notable given that both alternatives use the same roads. This might relate to the speed of an e-bike; stopping at a traffic light or waiting for people could be more annoying for faster riders because the speed difference is then greater compared to a city bike. However from the distributions it becomes clear that in both cases only around 78% of respondents agreed with the delay statement. The difference is mainly caused by the amount of people who answers strongly disagree and disagree.

Public transport has an even higher mean than the bike alternatives, and cars have the highest. The difference between car and public transport shows that people traveling by car experience more congestion problems than those facing delays in public transport, the difference is almost 0,4. The agreement percentages also show a notable difference: 35% for public transport users compared to 55% for car users.

The One-Way ANOVA revealed a significant difference between active modes of transport (city bike and e-bike) and public transport and cars. However, no significant difference was found within these two groups. This means there's a definitive difference in how people experience delays based on their mode of transport. Respondents using cars and public transport experience significantly more delays than those who commute by bike.

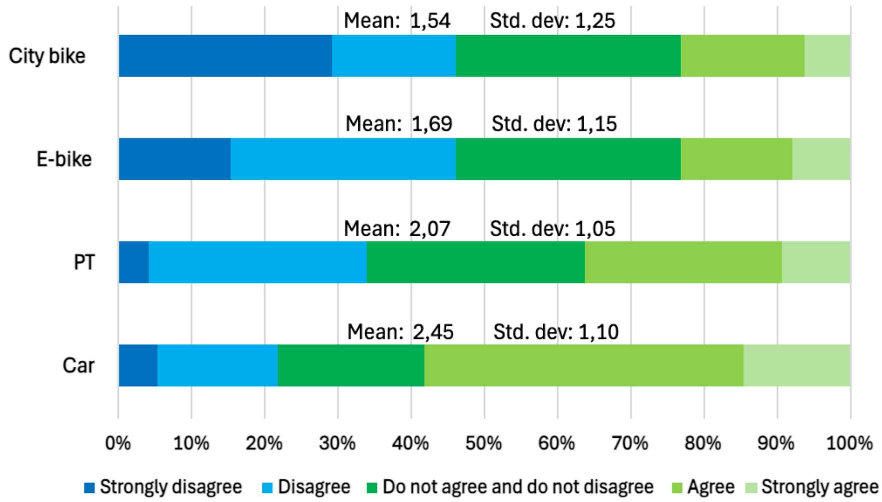



**Figure 5.5:** Relationship between the current mode of transport and the attitude towards delay

### Sustainability and Living Lab participation

An important aspect to consider when examining the respondent group of this research is that a large portion consists of individuals who participated in the Living Lab. This Living Lab specifically involved people who voluntarily applied to participate. These individuals likely sought to enjoy the project's benefits while also contributing to sustainable transportation initiatives. This voluntary participation could introduce potential biases in their responses compared to other respondents, as they may already be more sustainably oriented. Because of this, it's crucial to assess the relationship between Living Lab participation and respondents' attitudes towards the sustainability factor.

Figure 5.6 presents the results of the attitudes toward the sustainability factor. It becomes clear that the difference in sustainability attitudes between people who participated in the Living Lab and those who did not is not substantial, with a mean difference of only 0,14. However, the standard deviation for non-participants is higher than for participants, indicating a wider spread of answers among non-participants. The proportion of employees who strongly agree are approximately the same for both groups. Yet, the "Agree" group is larger for living Lab participants than for non-participants. Additionally, it's visible that the group who (strongly) disagree totals approximately 10% for non-participants, compared to under 5% for participants.

To test these differences, an Independent Samples T-test was performed. It became clear that equal variances cannot be assumed between the non-participant and participant groups. After accounting for this, the significance of the T-test turned out to be insignificant. This means that despite the observed difference in means, it cannot be definitively stated that there is a real difference in sustainability attitudes between Living Lab participants and non-participants.

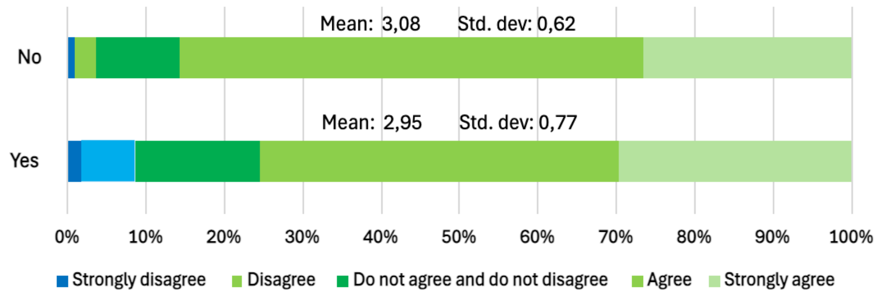



**Figure 5.6:** Relationship between participation of the living lab and attitude towards sustainability

### Sustainability and Mode

Figure 5.7 offers insight into differing attitudes towards the sustainability factor across various modes of transport. The mean values decrease from city bike to car, with a maximum difference of 0,47. This indicates that city bike users have a more sustainable outlook than e-bike users, who, in turn, are more sustainable-minded than public transport users, and finally, car users. The difference between city bike and e-bike is 0,22, suggesting that e-bike users are less sustainability-oriented than city bike users. Furthermore, the average scores for e-bike and public transport are quite close. All three alternatives (city bike, e-bike, and public transport) are better for the environment than a car, which is reflected in attitudes towards sustainability. Additionally, all standard deviations are relatively similar.

Based on the ANOVA results, a significant difference was found only between city bike and car. While clear differences in means are observed for other comparisons, these could not be confirmed by statistical significance. What can be definitively stated is that city bike users have a significantly more positive view of the sustainability statements than car users.

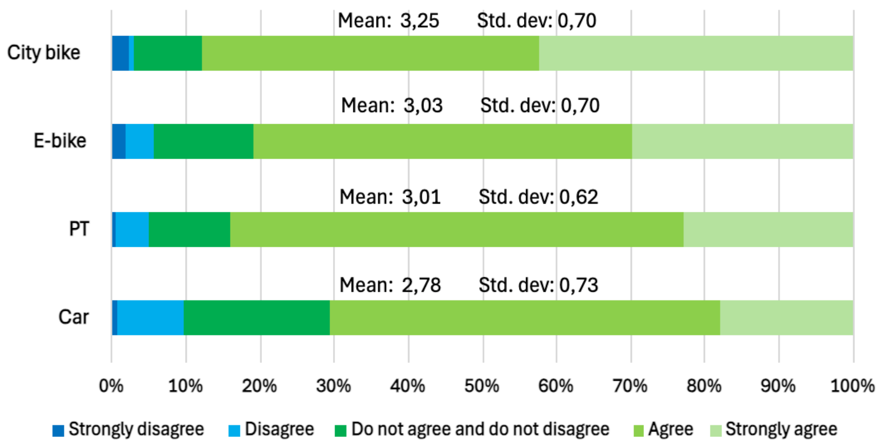



**Figure 5.7:** Relationship between current mode of transport and attitude towards sustainability

### Safety and Gender

Working in shifts or needing to be at the hospital early often means people must travel in the dark, which can significantly impact their perceived feeling of safety. Because of this, are respondents' attitudes tested, toward safety during their trips, particularly looking for a difference between men and women. For this analysis, only 'Man' and 'Woman' genders were considered, as the limited representation of other options prevented drawing significant conclusions. The safety statement is: *"I experience the route I take to and from work as safe"*.

The mean difference for the safety-related statement is 0,325 higher for men than for women. This aligns logically with the general understanding that women, overall, tend to feel less safe during transportation than men, especially at night. Despite this difference, both genders still scored high on the statement, with their values closely approaching 'Agree'. Figure 5.8 also illustrates that the values are more spread out for women than for men, indicated by a lower standard deviation for men. The biggest difference between the two distributions can be seen in the 'disagree' category, which is much bigger for women than for men.

After performing an Independent Samples T-test, it was determined that equal variances could not be assumed between men and women. Nevertheless, the mean difference for this test proved to be significant. This means that with certainty can be stated that women feel less safe than men during their commute.

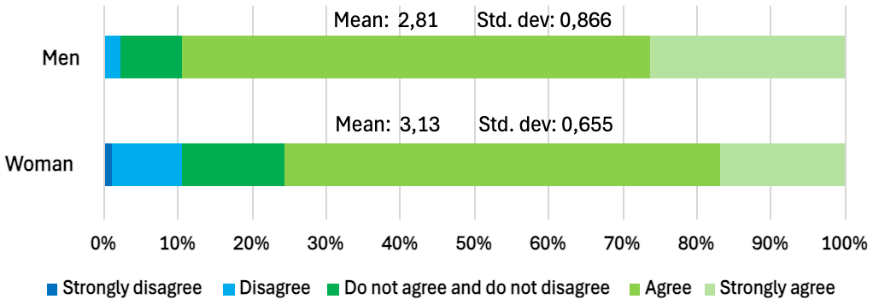



**Figure 5.8:** Relationship between gender and attitude towards safety

## Main insights

This chapter provides insight into the characteristics and behavior of the respondents who participated in the study. It becomes evident that commuting distance plays a major role in mode choice. Bicycles are predominantly used for trips under 15 kilometers, while public transport and cars are more common for longer distances. Although vehicle ownership does influence usage, simply owning a mode of transport does not guarantee it will be used for commuting.

Respondents generally perceive their commute as safe, although women feel less safe than men. Most people feel physically capable of cycling to work, yet they do not necessarily believe they should be more physically active. Sustainability appears to be a valued factor, especially among cyclists and participants of the Living Lab, though the difference between participants and non-participants is relatively small. Finally, delays are more frequently reported by those using public transport and cars, highlighting a pain point in these modes. Together, these findings offer a clearer picture of commuting behavior and preferences.

# 6 Commuting behavior continuity

The chapter aims to find the results to sub-question 1 and follows a logical progression to ensure that both the results and their context are clearly evaluated. First, the current status will be examined, focusing on how Living Lab participants are currently commuting. This provides a factual basis and highlights the concrete outcomes of both the Living Lab and the new survey. Next, the participants' experiences with their commuting trips will be explored, offering insight into their satisfaction levels and perceptions. After evaluating the current situation, the analysis considers what is still needed to further support and improve cycling as a commuting option. Finally, awareness of the cycling plan is assessed, since visibility and understanding of available programs are essential for long-term success and participation.

By following this structure, the analysis moves from reflection on outcomes, to evaluation of experiences, to identification of future needs, and concludes with an insight into the awareness of the cycling plan. The aim of this chapter is to assess whether past interventions have had a lasting impact on sustainable mode choice. In addition, it explores which new interventions are frequently requested by respondents, providing insight into other factors that could support a potential modal shift.

### Current travels

During the Living Lab, participants were asked how their travel behavior had changed as consequence of the project. This question was asked again in the current survey, to the Living Lab participants. It provides insight into whether people have continued traveling in the same way, whether sustainable travel behavior has decreased, or whether it has increased. Respondents could select from several options, which are presented in Table 6.1. The percentages shown in this table indicate the proportion of respondents who selected each option within that category. However, it is important to keep in mind that not all Living Lab participants responded to the new survey. Therefore, the percentages reported for 2025 are based on a smaller sample size. The results focus on three main categories: people who started traveling more sustainably, people who were already traveling sustainably, and people who have not adopted more sustainable travel behavior.

**Table 6.1:** Travel behavior changes

| Category | Answer options | % 2024 | % 2025 |
|---|---|---|---|
| Increased sustainability | More often by public transport | 42,4 | 33,1 |
| | More often by city bike | 11,7 | 5,6 |
| | More often by speed pedelec or e-bike | 26,9 | 13,3 |
| | More often a combination of public transport and bike | 6,4 | 18,8 |
| | **Total** | **87,5** | **70,6** |
| No change | **I always traveled sustainably** | **4,5** | **11,25** |
| No increased sustainability | Just as sustainable as before | 6,8 | 9,38 |
| | Now more often by car/motorbike/scooter | 1,1 | 8,75 |
| | **Total** | **8,0** | **18,1** |

The results clearly show that the proportion of people commuting sustainably has decreased since the end of the Living Lab. At the same time, more respondents now report that they were already traveling sustainably before the Living Lab. In theory, this percentage should remain consistent over time. This shift may partially explain the decrease in the first category. However, the data also shows an increase in the number of people who no longer commute more sustainably compared to during the Living Lab. This means that a significant portion of participants who adopted sustainable travel habits during the Living Lab have since reverted to their previous behavior, resulting in a 10% decrease compared to the end of the project.

On the other hand, it is clear that almost a year after the Living Lab ended, 83% of respondents still travel sustainably, and 70% indicate that the Living Lab influenced their travel behavior. This strongly suggests that providing people with the opportunity to try new, more sustainable travel modes, along with targeted interventions, can be an effective way to stimulate long-term changes in commuting behavior.

### Cycling experience

Another question that was included in this study, as well as during the Living Lab, asked respondents whether their experience with bicycle commuting matched their expectations. This question was only asked to people who stated that they traveled by bike. The response options ranged from "much better than expected" to "much worse than expected." However, since no respondents selected the last option, this response was excluded from the analysis. The specific question posed was: *"How do you feel about using the bicycle as part of your commute to the hospital?"*

As shown in Table 6.2(a), the overall experience with cycling has improved. Fewer people found the experience worse than expected, and a significant number even reported that the trip was better than they had anticipated. To gain deeper insight into what respondents liked or disliked most, they were presented with a list of factors and asked whether each had been better than expected in relation to their cycling trip. Respondents who indicated that their experience was worse than expected were also asked which specific factors had contributed negatively.

In 2024, all respondents who had a negative experience cited the weather as the main reason. In 2025, the only person who reported a worse-than-expected experience mentioned both the weather and travel time as contributing factors. Table 6.2(b) shows the percentage of respondents who felt that each factor was better than they had expected beforehand.

There are noticeable differences between certain factors. More respondents reported that they feel like their mode of transport is better for the environment and many experienced health benefits. Travel time and flexibility were also perceived more positively in 2025 compared to the 2024 results. This suggests that the support for certain aspects of cycling has increased and that positive experiences have spread more widely across the group of respondents. However, the perception of cost has declined, with fewer people indicating that it was better than expected.

**Table 6.2:** Expectations and positive experiences of bike commute

(a) Expectation Cycle Journey

| Answer | % 2024 | % 2025 |
|---|---|---|
| Much better than expected | 27,1 | 37,7 |
| Better than expected | 10,4 | 18,9 |
| Exactly as expected | 56,3 | 43,3 |
| Worse than expected | 6,3 | 1,9 |

(b) Better Than Expected Factors

| Answer | % 2024 | % 2025 |
|---|---|---|
| Cost | 24,4 | 17,0 |
| Flexibility | 13,3 | 26,4 |
| Travel time | 15,6 | 30,2 |
| Parking facilities | 4,4 | 0,0 |
| Environment | 2,2 | 26,4 |
| Health | 4,4 | 43,4 |
| Comfort | 4,4 | 11,3 |
| Weather | 6,7 | 5,7 |

### Possible improvements

All employees who completed the survey for this research were asked what could potentially improve their experience if they were to use a bicycle for commuting. This question was posed to everyone, also including those who currently commute by public transport or car. The main goal of this research is to identify factors that could help encourage a shift toward more bicycle commuting. This question provided a qualitative and quantitative insight into that issue. Respondents were presented with several predefined options, but an open-ended question was also included to allow them to suggest any sustainable commuting improvements they found relevant. For the purpose of this analysis, only the bike-related answers were taken into account.

Table 6.3 presents the predefined options shown to respondents, along with the percentage of respondents who indicated that these improvements are needed. Table 6.4 displays the ideas suggested by respondents themselves and how the percentage of how frequently each idea was mentioned. All results are shown as percentages to show what share of the total population supports this interventions. It makes sense that the percentages for the predefined options are higher than those for the self-suggested ideas. This is expected, as it is easier for respondents to agree with suggestions that are already presented, while open-ended responses require them to come up with ideas themselves.

The difference in opinions is particularly relevant when comparing respondents who already commute by bicycle to those who currently travel by public transport or car. For those who already cycle, the suggested improvements would primarily enhance their existing experience. However, for people who currently commute by car or public transport, these improvements could serve as incentives to switch to cycling. Therefore, a distinction is made between the level of support among the entire respondent group and among those who currently travel by car or public transport.

The results show that rain gear and the ability to dry wet clothing are the most frequently requested interventions. Additionally, more charging stations for e-bike batteries and facilities to freshen up or change clothes are also strongly supported. Among the self-suggested options, shared e-bikes are commonly mentioned, along with a general desire for access to a high-quality (electric) bike. Respondents did not specify whether this should be through leasing, purchasing, or sharing.

**Table 6.3:** Predefined improvements for bicycle commuting

| Improvement option | % Total group | % Car and PT |
|---|---|---|
| Facilities to change clothes or freshen up | 17,4 | 13,2 |
| Compensation/contribution for purchasing rain gear | 24,4 | 11,8 |
| Option to dry wet clothes | 20,0 | 11,2 |
| Lockable storage for items such as bike batteries | 11,5 | 9,9 |
| More chargers for bike batteries | 17,4 | 11,8 |
| Safer routes to the bicycle parking facility | 4,8 | 2,6 |
| Camera surveillance in the bicycle parking area | 11,1 | 3,2 |
| Wider parking spaces for e-scooters and electric cargo bikes | 4,4 | 3,9 |
| Nothing can improve this | 24,1 | 36,2 |

**Table 6.4:** Self-suggested improvements for bicycle commuting

| Improvement option | % Total group | % Car and PT |
|---|---|---|
| Larger and covered bicycle parking with wider bike racks | 6,2 | 1,3 |
| Shared e-bikes and public transport bicycles at stations | 9,6 | 17,1 |
| Higher travel expense reimbursement for cycling | 2,2 | 1,9 |
| Lease options with a trial period | 2,6 | 1,3 |
| Higher reimbursement within the bicycle plan | 2,9 | 5,2 |
| Travel expense reimbursement for all modes used in a multimodal journey | 0,7 | 0,6 |
| Compensation/contribution for bicycle maintenance | 1,4 | - |
| Compensation/contribution for bicycle subscription at train stations | 2,6 | 2,6 |
| Overall need for a good quality bicycle or e-bike | 13,0 | 5,9 |

Focusing on people who currently commute by car or public transport, it becomes clear that shared e-bikes receive significantly higher support compared to the overall respondent group. This suggests that most of the support for this option comes from individuals who do not currently cycle. The same pattern is observed for the option *"Higher reimbursement within the bicycle plan"*, which also receives notably more support from this subgroup. Overall, only 24% of all respondents stated that nothing could improve their bicycle commute. This suggests that the vast majority remain open to cycling, provided that additional facilities are offered. Even among current car and public transport users, only 36% indicated that nothing could improve the cycling experience.

### Program knowledge

As mentioned in Section 4.1, the hospital has a bicycle plan that allows employees to purchase a bicycle and receive monthly tax benefits on the cost. However, it is important to assess the level of awareness surrounding this program to ensure that all employees are informed and that no one is missing out on this opportunity. Knowledge about the bicycle plan was first assessed among the participants during the Living Lab. Later, the same question was posed to all respondents in the new survey. This was done to determine whether knowledge of the bicycle plan is limited to sustainability-focused circles or if it is more broadly known throughout the organization. A clear difference can be observed, as shown in Table 6.5. The percentage of people who are fully aware of the bicycle plan is much higher among Living Lab participants than among the broader employee population. At the same time, the proportion of respondents who are completely unaware of the plan is also significantly higher in the broader group. However, it is important to note that the data sources are not entirely comparable. The response options "Yes, I have used it" and "Yes, I'm planning on using it" were not included in the survey last year. Nevertheless, it can be assumed that respondents who selected these options in the new survey would likely fall into the category of being fully aware of the plan, which makes the differences between the two groups somewhat more balanced. However, there is a clear difference between the group of people who are not aware of the plan. This group is higher in the wider population of the hospital compared to the participants of the Living Lab. the share is almost doubled.

**Table 6.5:** Knowledge of bike plan

| Anwser | % 2024 | % 2025 |
|---|---|---|
| Yes, fully familiar | 87,9 | 38,9 |
| Yes, kind of familiar | 4,9 | 33,5 |
| Yes, I have used it | 0,0 | 12,4 |
| Yes, I'm planning on using it | 0,0 | 2,5 |
| No, I'm not familiar | 7,2 | 12,7 |

## Main insights

From this chapter can be concluded that most participants of the Living Lab still commute in a sustainable way, with 70% indicating that they now travel more sustainably than they did before the Living Lab. This demonstrates that the interventions and opportunities offered during the pilot were effective in supporting a long-term shift toward more sustainable commuting behavior. Many participants found the experience of sustainable travel to be more pleasant than expected, especially in terms of health benefits and travel time.

To ensure that more employees make the shift to sustainable modes of transport, or further strengthen existing sustainable behavior, several additional interventions could be introduced, specifically focused on cycling and what measures could improve the experience of commuting by bike. This showed a lot of on-site facilities which would be attractive for employees. Among those who currently commute by car or public transport, shared e-bikes stood out as the most appealing intervention. This suggests that shared mobility solutions can be an effective way to encourage modal shift among less sustainable commuters. This indicates that they would be open to using a shared e-bike for the last part of their journey.

One of the current measures in place is the hospital's bicycle plan. While it is relatively well-known, still 13% of respondents reported being unaware of it. These individuals represent a clear opportunity for further outreach, as raising awareness could potentially lead to greater participation. Encouragingly, 3% of all respondents explicitly mentioned that they plan to use the bicycle plan in the future.

# 7
# Model estimates

This chapter focuses on the results of the Discrete Choice Experiment. The outcomes and the model estimations provide insight into the answers to sub-questions 3 and 4.

## 7.1. Modal split

Figure 7.1 provides an overview of the distribution of chosen alternatives in the Discrete Choice Experiment (DCE), also referred to as the modal split. The results show relatively small differences among the three presented alternatives. The e-bike is the most frequently chosen option, accounting for 37% of selections, followed closely by the city bike and the non-active modes, with 32% and 31% respectively. The two non-active modes are grouped together in the analysis, as they were never presented in the same choice set; only one was included at a time. The figure also includes the current modal split to highlight the differences between respondents' actual travel behavior and their choices in the experiment. It is important to note that this distribution is not the same as the one presented in Table 5.1, as it only includes respondents who participated in the DCE.

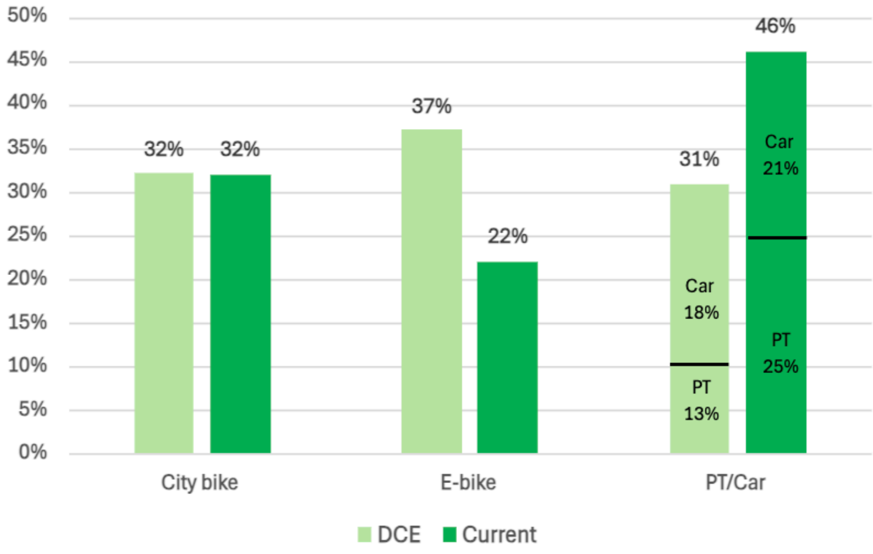



**Figure 7.1:** Modal split

The e-bike was chosen more frequently in the DCE than its current usage suggests. The share for the city bike remained the same, indicating a high likelihood that current city bike users consistently chose that alternative in the experiment as well. In contrast, both car and public transport were chosen less often in the DCE compared to their actual usage. This suggests that respondents who currently commute by car or public transport may have preferred the e-bike when presented with alternative options in the experiment. It is particularly noteworthy that while car usage declined by only 3%, public transport usage decreased significantly, by 12%. This suggests that a considerable number of individuals who currently rely on public transport opted for the e-bike alternative in the DCE. In contrast, people who commute by car appeared less open to switching to one of the bicycle alternatives. Notably, only the e-bike alternative gained a higher share, likely indicating that those who chose a bike over car or public transport almost exclusively selected the e-bike rather than the city bike.

Overall, these findings highlight the fixed commuting patterns among employees, particularly those who travel by car or city bike, as they tended to stick with their existing mode of transport. However, employees who currently use public transport appear more open to changing their travel behavior and exploring alternative modes. However, this modal split allows for a deeper analysis of how current travel modes influence mode choice, as well as what other factors may potentially impact these decisions. These analyses and results will be further explored in the following sections.

## 7.2. Different models

Several models were estimated to gain the most accurate insight into the choices respondents made. First of all were the Multinomial Logit (MNL) model and a Nested Logit (NL) model estimated. To assess whether estimating additional models would provide more insights, several focused models were developed. Therefore, a separate model was estimated that included only the bicycle alternatives, excluding the third option, car or public transport. This approach allowed for a more precise assessment to compare both bike alternatives and gain insight into the trade-offs made between the two alternatives.

Additionally, a model was estimated that focused exclusively on the current car and public transport users. This group was originally the target group of the study before it was expanded to include cyclists. For that reason, this specific subgroup was still analyzed to explore whether there are actual differences in trade-offs compared to the full models that included the entire respondent group.

Since a large number of non-traders were present among the responses, two additional sub-models were estimated without non-traders. These were based on the full MNL model and the car and public transport model. The aim was to assess the impact of non-traders and to determine whether the results significantly change when they are excluded.

Furthermore, a model was estimated that included interactions between different attributes to explore potential relationships. Lastly, a Latent Class Choice Model was estimated to identify whether distinct respondent groups with homogeneous preferences could be distinguished. Hereby an overview of all models which were estimated:

1. Multinominal Logit model
2. Nested Logit model
3. Bike model
4. Car and public transport model
5. Multinominal Logit model without non-traders
6. Car and public transport model without non-traders
7. Interaction model
8. Latent Class Choice model

## 7.3. Model selection

Each model had its own purpose and therefore it is important to evaluate what each model contributed to understanding choice behavior. After assessing their impact, several model will be selected for further investigation to gain deeper insights and clarity.

### MNL and NL comparison

Table 7.1 shows the model fit of the MNL and NL model. The comparison reveals that the differences between the MNL model and the NL model are small. Although the AIC and BIC values are slightly lower for the MNL model, the differences are not substantial. Therefore, based on model fit alone, it cannot be concluded that one model clearly outperforms the other. As a result, the added complexity of incorporating the nesting parameter in the NL model is not supported by improvements in model fit. This is confirmed by the results of the Likelihood Ratio Test (LRT). The difference in log-likelihood between the models was not large enough to yield a statistically significant result, indicating that the added complexity of the NL model does not improve the model's fit to the data.The LRT calculations are given in Appendix F.1.1.

**Table 7.1:** Model fit comparison MNL and NL

| Model | Sample size | LL | $\rho^2$ | AIC | BIC |
|---|---|---|---|---|---|
| Full MNL | 1449 | -1468,31 | 0,08 | 2958,62 | 3016,68 |
| Full Nested | 1449 | -1468,22 | 0,08 | 2960,44 | 3023,78 |

In the NL model, the two bicycle alternatives are grouped into a separate nest, unlike the MNL model, where all alternatives are assumed to be evaluated independently. The fact that the NL model does not significantly improve model fit indicates that introducing a nesting structure for the bicycle alternatives does not provide a better representation of the respondents' choice behavior. This suggests that, despite their similarities, respondents do not evaluate the bicycle alternatives in a way that reflects shared unobserved preferences or correlated decision-making. This finding implies that all alternatives, including the two bicycle options, are treated by respondents as sufficiently distinct choices. As a result, the assumption of independence between alternatives, as imposed by the MNL model, appears to hold in this context. Because of these results will be continued with the MNL model as this is more straightforward for interpretation.

### Additional filtered models

Appendix F, Table F.4 provides an overview of the MNL models estimated with and without non-traders. This comparison was conducted to assess the impact of non-traders. However, the models showed that removing non-traders had very little effect on the attribute beta values. The only notable differences appeared in the alternative specific constants, which increased across all alternatives, indicating a stronger preference for the city bike among non-traders. This is not surprising, as the non-trader group primarily consisted of current city bike users. Overall, the differences between the models were not substantial enough to justify selecting the MNL model without non-traders as the main model.

The same applies to the comparison between the car and public transport model with and without non-traders. In Appendix F in Table F.6 are the model estimates for both versions presented. The estimated beta values show minimal differences, with the model excluding non-traders generally having slightly higher values for the attributes and context parameters. This suggests that traders may be more sensitive to the attributes. However, since most attributes remain statistically insignificant and the differences are minor, there is no clear improvement in explaining choice behavior.

# 7.4. Multinominal Logit model

## 7.4.1. Interaction estimation process

Interaction effects reveal how preferences for attributes can vary across variables, resulting in a more realistic understanding of decision-making. The interaction effects are estimated based on the MNL model. This approach ensures that all respondents are considered, allowing for a more comprehensive and well-rounded interpretation of the results. Three types of interactions are considered; between attributes themselves, with attitudes and with sociodemographic characteristics.

When logically considering the variables, the hypothesis was that some variables could influence one another, potentially strengthening or weakening their overall effects. Based on this assumption, different models were estimated. The process began by sketching specific relationships, and each interaction was tested in a separate model to assess whether it was significant on its own and whether it improved model fit, as measured by the LL, $\rho^2$, AIC and BIC. Once it was confirmed that an interaction met all these criteria, it was included in the full model. In the end, the final model combined all interactions that contributed positively.

It was expected that only interactions involving delay and weather would improve model fit and yield significant results, as the other attributes were not significant in the models' main effects. This expectation was confirmed: the only interaction that improved model fit was between delay and weather. All interaction effects which were estimated but that did not lead to increased model fit or were statistically significant are listed in Appendix F.3.

### 7.4.2. Estimation of model

Table 7.2 presents the model that includes several interaction effects. The alternative specific constants (ASCs) reflect the utility differences between alternatives when all other attributes are held constant. These constants indicate which alternative would be preferred as the base option in such cases. The reference category is the city bike, and its ASC is therefore set to 0. The results show that the e-bike is less preferred base on base preference compared to the city bike. However, the car emerges as the most preferred alternative, followed by public transport. This order differs from the main effects model, where public transport was the most preferred alternative.

The coefficients of the attributes have either increased or decreased in magnitude, suggesting a stronger or weaker impact on utility compared to the MNL model without interaction terms. Notably, parking cost, delay, and parking time show substantial changes. Parking cost, in particular, receives an illogical positive coefficient, suggesting that higher parking costs would increase utility. This counterintuitive result may be due to the inclusion of interaction terms, which might have clarified or distorted the underlying effects. Parking and walking time however, becomes more influential and statistically significant in this model, indicating that respondents are more sensitive to parking and walking time when these factors increase.

The weather-related parameters clearly show that, in good weather conditions, the utility of choosing an e-bike increases, while the utility of both the car and public transport decreases. The difference between the car and public transport is minimal, with a slightly larger disutility for the car. This could be because traveling in pleasant weather makes transfers (typically associated with public transport) more tolerable or even enjoyable.

The parameters for the interaction effect are given as: ATTRIBUTE_statement. Individuals who perceive sustainability as important for their trip are more sensitive to delays, suggesting they may be more conscious of the total impact of their travel. Similarly, those who have recently experienced delays are also more delay-averse, possibly because they are more aware of the inconveniences involved. Interestingly, users of city bikes and e-bikes show higher delay sensitivity compared to car or public transport users. Those who recently experienced congestion or delay also show increased sensitivity to parking costs. This may be because individuals who have already spent a long time in traffic or faced congestion on the hospital grounds become more focused on the overall burden of their trip, including the cost of parking.

Furthermore, individuals who report that their vitality and health make cycling less appealing (health) are more sensitive to parking and walking time. This likely reflects a greater reliance on car use. For these respondents, having to walk a longer distance from the parking garage to the hospital can be particularly inconvenient and burdensome, making it a more significant factor in their mode choice.

Finally, respondents who expect their employer to actively promote sustainable commuting (employer) are more sensitive to the cost of an e-bike, possibly reflecting the expectation that such initiatives should be employer-supported. A decrease in price would be attractive for them in case this is caused by the employer. However it is also visible that women are more focused on the monthly expenses of the e-bike then men.

The model fit improved significantly with the inclusion of interaction terms. The LL value became much less negative compared to the main model, and both the AIC and BIC values decreased. The McFadden R-square ($\rho^2$) has increased reasonably from 0,08 to 0,19. These findings underscore the relative importance of accounting for attitudinal differences when evaluating preferences in sustainable mobility choices. However, it is important to keep in mind that certain parameters are not statistically significant at the 95% confidence level, meaning that the interpretation of these parameters cannot be made with certainty.

**Table 7.2:** Model estimates interactions

| | Interaction model | | Main model | |
|---|---|---|---|---|
| **Parameter** | **Value** | **Rob. t-test** | **Value** | **Rob. t-test** |
| *Alternative Specific Constants* | | | | |
| ASC_e-bike | -0,64 | -0,81* | -0,52 | -0,67* |
| ASC_car | 1,87 | 3,107 | 0,97 | 1,91* |
| ASC_pt | 1,49 | 7,06 | 1,38 | 8,52 |
| *Parameters* | | | | |
| COST_E | 0,03 | 1,58* | 0,01 | 0,67* |
| C_PARK | 0,16 | 1,07* | -0,06 | -1,08* |
| DELAY | -0,15 | -2,87 | -0,02 | -3,00 |
| FAC | 0,08 | 0,88* | 0,06 | 0,83* |
| T_PARK | -0,09 | -2,79 | -0,01 | -0,32* |
| *Context Parameters* | | | | |
| WEATHER_e-bike | 0,25 | 1,86 | 0,25 | 1,92* |
| WEATHER_car | -2,27 | -7,47 | -1,56 | -7,27 |
| WEATHER_pt | -2,02 | -7,71 | -1,67 | -9,09 |
| *Attribute interaction* | | | | |
| DELAY_WEATHER | 0,01 | 0,36* | | |
| *Attitude interaction* | | | | |
| DELAY_sustainability | -0,03 | -3,16 | | |
| DELAY_delay | -0,02 | -2,67 | | |
| T_PARK_health | 0,05 | 7,41 | | |
| C_PARK_delay | 0,07 | 3,52 | | |
| COST_E_employer | -0,01 | -2,57* | | |
| *Sociodemographic interaction* | | | | |
| COST_E_woman | -0,42 | -3,03* | | |
| COST_E_men | -0,38 | -2,73* | | |
| DELAY_citybike | -0,24 | -5,19 | | |
| DELAY_e-bike | -0,21 | -4,17 | | |
| DELAY_pt | -0,08 | -1,65* | | |
| DELAY_car | -0,01 | -0,15* | | |

* Not significant for 95%

**Table 7.3:** Model fit MNL interaction model

| **Model** | **Parameters** | **Sample size** | **LL** | $\rho^2$ | **AIC** | **BIC** |
|---|---|---|---|---|---|---|
| Main model | 11 | 1449 | -1468,31 | 0,08 | 2958,62 | 3016,68 |
| Interaction model | 23 | 1449 | -1285,76 | 0,19 | 2617,52 | 2728,93 |

### 7.4.3. Utilities an probabilities

To identify which alternative is most attractive in a choice set and has the highest portability of being chosen, can the utility functions and probability be assessed. The utility functions shown below are based on the results of the MNL model. Although the interaction model has a better model fit, it is in this case more practical to estimate the utility function based on the MNL model, as no respondent-specific variables are needed then. These represent the utilities for the reference categories of all attributes. The reference levels reflect the current situation at the hospital for specific attributes best, such as parking prices, available facilities and e-bike purchase cost. Other attributes, such as delays and parking/walking time, may however vary from day to day. To ensure consistency and comparability, all attribute values used in this analysis are set to their reference levels. Additionally, a distinction is made between the utilities under good weather and bad weather conditions, as the model estimates indicate that weather has the biggest influence on mode choice. On the right are the attributes values given, which are used to calculate the utilities for all reference categories.

**Reference values**
COST_E = €45/month
C_PARK = €3/day
DELAY = 0 min
FAC = 0 (current facilities)
T_PARK = 10 min

**Bad weather**
U(city bike) = 0,06 · 0 = 0,00
U(e-bike) = -0,52 + 0,01 · 45 + 0,06 · 0 + 0,25 · 0 = -0,07
U(car) = 0,97 - 0,06 · 3 - 0,02 · 0 - 0,01 · 10 - 1,56 · 0 = 0,69
U(pt) = 1,38 - 0,02 · 0 - 1,67 · 0 = 1,38

**Good weather**
U(city bike) = 0,06 · 0 = 0,00
U(e-bike) = -0,52 + 0,01 · 45 + 0,06 · 0 + 0,25 · 1 = 0,18
U(car) = 0,97 - 0,06 · 3 - 0,02 · 0 - 0,01 · 10 - 1,56 · 0 = -0,87
U(pt) = 1,38 - 0,02 · 0 - 1,67 · 1 = -0,29

Based on the utility functions, it is clear that in the case of bad weather, the most preferred option is public transport. The utility for this alternative is nearly twice as high as that of the car, which is the next preferred mode. The difference between the e-bike and the city bike is very small, with a slight preference for the city bike.

In contrast, the order of preferences changes significantly in good weather. The e-bike becomes the most preferred option, followed by the city bike, then public transport, and finally the car. The preference for the e-bike in good weather is likely related to the enjoyment of the surroundings and the overall experience of the trip. In pleasant weather, people may perceive their journey as more relaxing. Since riding an e-bike requires less physical effort than a city bike, this likely contributes to its increased attractiveness.

A complete overview of the calculated utilities and probabilities per choice set can be found in Appendix F.2. The order of the utility rankings for both good and bad weather remains consistent across all choice sets. Meaning that in case of bad weather public transport is always most attractive followed by the car. The only variation is between the city bike and e-bike, which switch places in terms of lowest utility under bad weather conditions. The same patterns is visible for good weather, the e-bike is then always most attractive, followed by the city bike, public transport and lastly the car. The fact that this utility order does not change across different choice sets indicates that the model is not very sensitive to variations in attribute levels only to the weather conditions.

Blocks were used in the experiment to make sure the weather context could be correctly inserted, the utilities for both blocks were calculated separately. The probabilities, however, are based on the average utility values across both blocks. Additionally, the probabilities are split between car and public transport scenarios. This is done because each choice set always included three alternatives, with either the car or public transport as one of them. Therefore, there is no mutual dependency between these two alternatives, and they must be calculated separately.

From the probability results, is concluded that in all choice sets where the car was included, the e-bike had the highest probability of being chosen. In contrast, when public transport was included, it had the highest probability of selection. These probabilities demonstrate that the outcome of the choice was highly dependent on whether car or public transport was shown as the third alternative. Nevertheless, even though people who currently commute by car were always presented with the car option, many still chose other modes. This explains why the e-bike consistently emerged as the alternative with the highest probability of being selected.

## 7.5. Latent Class Choice Model

A Latent Class Choice Model (LCCM) was estimated to explore whether there are distinct groups of respondents with homogeneous characteristics. This estimation is based on the MNL model, incorporating various sociodemographic characteristics of the respondents to determine whether these factors influence class membership.

### 7.5.1. Estimation process

In Table 7.4, the model fit statistics are presented for models with one class (the MNL model), two classes, and three classes. From this table, it can be seen that the model with three classes has the best Log-Likelihood value and, consequently, the highest McFadden's $R^2$.

To arrive at these results, a model with two classes was first estimated to assess its performance. Based on this two-class model, a selection was made regarding which variables to include for determining the latent classes. Once this specification was finalized, a model with three classes was estimated to see whether it would result in an improved model fit. Finally, a model with four classes was also estimated, but unfortunately, this did not yield reportable results and was therefore not used. Since the three-class model showed the best fit, it was decided to use this model for interpretation. Furthermore is Class 3 the reference class.

Several sociodemographic characteristics were tested to examine whether they would positively affect the model fit. Attitudinal factors were also considered. Among these, only the employer-related statement contributed to an improved model fit and statistical significance. The other attitude variables did not show a meaningful effect.

In addition, the variables for current mode of transport, commuting distance, and knowledge of the bicycle plan were included in the model. While other variables were also tested, their inclusion made the model overly complex and introduced the risk of multicollinearity, leading to insignificant results. The variables "MODE" and bike plan knowledge "BP" were categorical and therefore needed to be converted into dummy variables. These were estimated per attribute level, using "Other" as the reference level for transport mode and "Somewhat familiar" (1) as the reference level for bike plan knowledge. Dummy coding the distance variable "DIST" was not necessary as it has a ordinal scale. The bike plan knowledge levels are represented in the table according to their coding. These coding can be found in Table D.6 in the Appendix.

Table 7.5 presents the model estimates. In Table 7.4 it becomes clear that the model fit has improved significantly. McFadden's R-squared ($\rho^2$) reaches a value of 0,51, which is much higher than in the MNL model. In addition, both the AIC and BIC values have decreased substantially, further indicating a better model fit.

**Table 7.4:** Model fit LCCM

| Model | Parameters | Sample size | LL | $\rho^2$ | AIC | BIC |
|---|---|---|---|---|---|---|
| MNL | 11 | 1449 | -1468,31 | 0,08 | 2958,62 | 3016,68 |
| LCCM_2 | 34 | 1449 | -960,76 | 0,40 | 1989,52 | 2168,99 |
| LCCM_3 | 57 | 1449 | -785,54 | 0,51 | 1685,09 | 1985,97 |

### 7.5.2. Class interpretation

#### Class 1: Sensitive mixture

The ASCs reveal a notable pattern: the value for the e-bike is exceptionally high, while the differences between car, public transport, and city bike are relatively small. This suggests that if all other attributes were held constant, this group would have a strong inherent preference for the e-bike.

Furthermore, this class is highly sensitive to trip attributes, especially when compared to the main MNL model. They respond strongly to both purchasing and parking costs, and also consider walking and parking time, indicating that they are particularly sensitive to the broader context of a trip.

The weather parameters, however, appear counterintuitive. In good weather, the utility of the e-bike highly decreases, while that of car and public transport decreases less. This implies that the city bike becomes more attractive in relative terms during favorable weather conditions. This pattern may be explained by the composition of the class.

This group primarily consists of individuals who live close to the hospital and are aware of the bike plan. Although their mode use is mixed, the majority appear to be city bike users. Interestingly, the negative utility for e-bike mode may reflect that city bike users dominate the class and experience the city bike as the most attractive option, especially in good weather, thus potentially explaining the unexpected weather effects.

**Table 7.5:** LCCM estimated

| | *Class 1* | | *Class 2* | | *Class 3* | | *Main* | |
|---|---|---|---|---|---|---|---|---|
| Individuals per class | 52 | | 55 | | 54 | | | |
| Class share | 32,2% | | 34,4% | | 33,4% | | | |
| **Parameter** | **Value** | **T-test** | **Value** | **T-test** | **Value** | **T-test** | **Value** | **T-test** |
| *Alternative Specific Constants* | | | | | | | | |
| ASC_e-bike | 48,41 | 5,02 | 6,35 | 2,85 | 3,41 | 1,52* | -0,52 | -0,67* |
| ASC_car | 0,03 | 1,92* | 10,86 | 9,16 | 2,79 | 1,87* | 0,97 | 1,91* |
| ASC_pt | -0,39 | -0,38* | 12,42 | 12,76 | 2,26 | 4,65 | 1,38 | 8,52 |
| *Parameters* | | | | | | | | |
| COST_E | -1,09 | -5,27 | 0,03 | 0,65* | -0,02 | -0,36* | 0,01 | 0,67* |
| C_PARK | -0,61 | -2,59 | -0,10 | -0,77* | -0,07 | -0,42* | -0,06 | -1,08* |
| DELAY | -0,03 | -0,66* | -0,03 | -1,47* | -0,03 | -1,18* | -0,02 | -3,00 |
| FAC | 0,23 | 0,49* | 0,09 | 0,58* | 0,11 | 0,68* | 0,06 | 0,83* |
| T_PARK | -1,30 | -7,12 | 0,01 | 0,27* | -0,01 | -0,25* | -0,01 | -0,32* |
| *Context parameters* | | | | | | | | |
| WEATHER_e-bike | -11,11 | -18,03 | -6,22 | -8,91 | 0,01 | 0,02* | 0,25 | 1,92* |
| WEATHER_car | -1,49 | -4,01 | -8,86 | -13,58 | -11,16 | -19,27 | -1,56 | -7,27 |
| WEATHER_pt | -3,69 | -2,18 | -10,56 | -10,28 | -1,77 | -2,95 | -1,67 | -9,09 |
| *Class membership* | | | | | | | | |
| INTERCEPT | 3,92 | 0,90* | 25,53 | 3,85 | | | | |
| DISTANCE | -2,05 | -5,13 | 2,26 | 4,04 | | | | |
| BP_0 | 0,96 | 1,61* | 2,63 | 1,76* | | | | |
| BP_2 | -0,59 | -0,87* | 7,16 | 2,31 | | | | |
| BP_3 | -0,15 | -0,21* | 2,93 | 0,65* | | | | |
| BP_4 | -1,51 | -1,51* | -1,64 | -1,67* | | | | |
| MODE_citybike | 8,12 | 5,66 | -18,46 | -4,68 | | | | |
| MODE_e-bike | -8,95 | -3,78 | -42,04 | -5,40 | | | | |
| MODE_pt | 3,79 | 2,04 | -10,23 | -4,95 | | | | |
| MODE_car | 3,46 | 2,16 | -11,77 | -4,70 | | | | |
| S4_Employer | -1,85 | -2,45 | -5,84 | -3,72 | | | | |

* Not significant for 95%

### Class 2: Rigid motorized patterns

The baseline tendency, as indicated by the ASCs, shows that if all other attributes are set to zero or not considered, individuals in this class would prefer the car and public transport over the e-bike. The e-bike, in turn, is clearly preferred over the city bike.

All attribute parameters are not statistically significant, meaning no firm conclusions can be drawn without uncertainty. However, it is evident that this class is less sensitive to these attributes compared to Class 1, but still somewhat more sensitive than the population in the main MNL model. Delay, parking cost, and parking time are all attributes to which this class is sensitive. However, the purchase cost of the e-bike has a counterintuitive sign, suggesting that this may not be an attribute they consider important.

The class membership intercept for Class 2 is very high, indicating that, all else being equal, individuals have a strong baseline probability of being assigned to this class. This could explain why the mode-related class membership parameters are highly negative, a strong positive intercept could then still result in reasonable overall class membership utility. Furthermore, individuals who currently commute by city bike or e-bike are relatively less likely to be part of this group. The probabilities are relatively higher for those using car or public transport, suggesting that these users are more likely to belong to this class.

Overall, this group is clearly characterized by individuals who tend to travel longer distances. They are fully aware of the hospital's bicycle programs, may have even used it or plan on using it.

### Class 3: Influenceable e-bikers

The ASCs show that, when no attributes are considered, individuals in this class have a baseline preference for the e-bike. While the differences between the ASCs are relatively small, the city bike appears to be the least attractive of the alternatives.

This preference for the e-bike is also reflected in the current mode distribution of individuals in this class. Since e-bike users are largely absent from Classes 1 and 2, it is likely they are concentrated in Class 3. This may explain the higher baseline utility for the e-bike in this group.

Although none of the attribute parameters are statistically significant, they mostly show logically consistent directions. Compared to Class 2, individuals in Class 3 are slightly less sensitive to the attributes, though still more sensitive than those in the main MNL model. No single attribute stands out strongly, but the parameter for bike facilitates (FAC) nearly doubles compared to the main MNL model, suggesting some sensitivity to this feature. However, since FAC is dummy coded, its overall impact remains limited. The weather-related parameters also show intuitive effects: the e-bike becomes more attractive in good weather, and the city bike does as well, especially when compared to the car. This aligns well with the overall e-bike preference observed in this class.

The intercepts for Class 1 and Class 2 are both positive, implying that the intercept for Class 3 is likely much lower or even negative, though this cannot be directly estimated. Indicating that, when all membership functions are not taken into account, there is a lower probability of an employee falling into this class. Similarly, the travel distance for this group likely falls somewhere between Class 1 (short distances) and Class 2 (longer distances), reflecting a mix of commute patterns.

It is also clear that people in this class are generally not aware of the hospital's bike plan. However, many of them already use or prefer the e-bike, meaning they may have missed out on tax advantages and the support the hospital offers. Interestingly, individuals in this group tend to believe that the hospital should take a more active role in encouraging sustainable commuting. Combined with their lack of awareness of existing programs, this reveals an opportunity for improved communication.

### Class comparison

The classes can be compared based on several characteristics. One of these is the relative influence of the attributes. This was calculated by examining the effect of each attribute based on its range, relative to the maximum range across all attributes. Based on this, it is possible to estimate the relative importance of each attribute compared to the others.

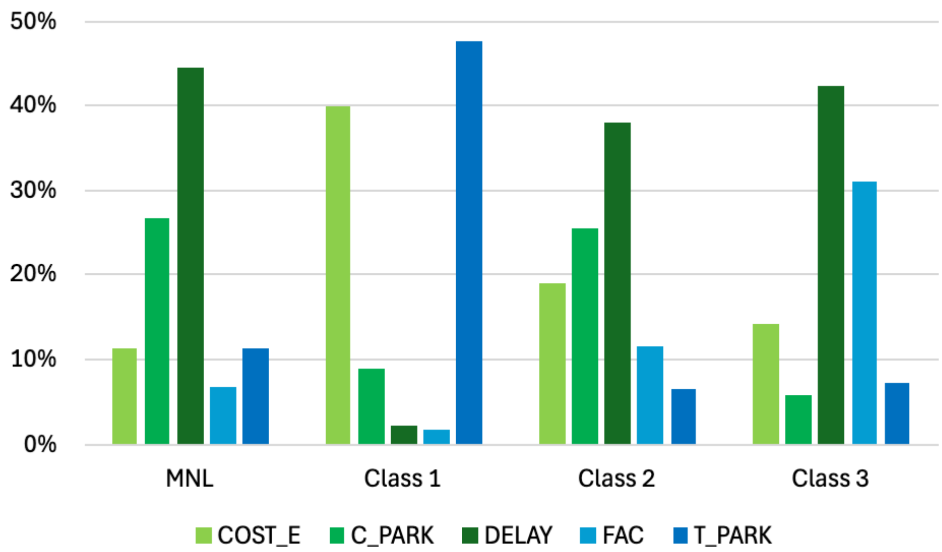



**Figure 7.2:** Relative importance attributes

Figure 7.2 shows the relative impact of the attributes. It reveals that for both the MNL model and Classes 2 and 3, delay has the greatest influence on utility. At the same time, other differences are also apparent. It can be observed that Class 2 and the MNL model are quite similar in how attribute importance is distributed: aside from delay, there are no extreme highs or lows, and all other attribute have some form of influence. In Class 3, facilities stand out as having a relatively high impact on utility, which is not seen in the other classes. This may be because a large portion of this group already uses an e-bike and therefore places more value on good cycling facilities. The remaining attributes in this class have limited influence. Class 1 shows a different pattern, with e-bike purchase cost and walking and parking time having the strongest impact. These attributes are relevant for different modes of transport, which suggests that this is a group where multiple transport modes are actively considered.

The weather variable was analyzed separately, as it is not mode-specific, given in Figure 7.3. From this can be observed that in good weather, the number of bicycle and e-bike choices increases significantly, while the probability of choosing alternatives such as the car or public transport decreases considerably. This trend is confirmed by the weather-related parameters in the MNL model. However, this pattern is not clearly reflected in the parameters of, for example, Class 1 and 2.

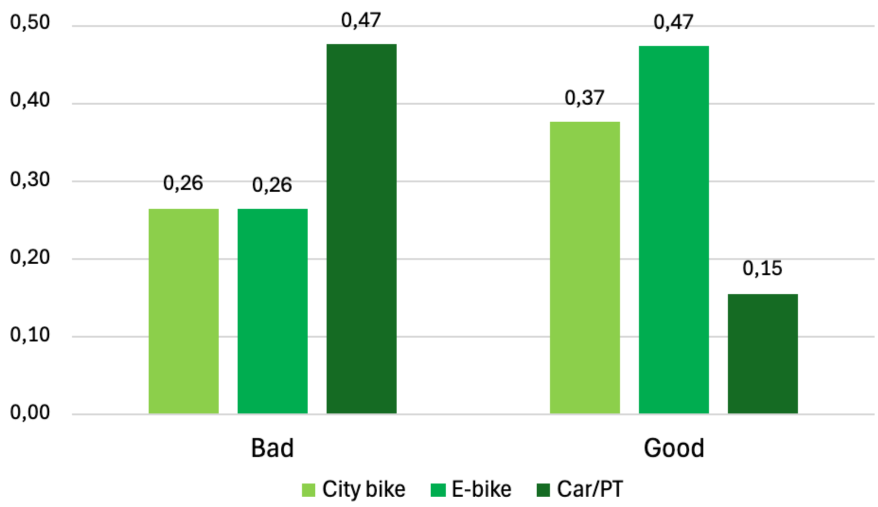



**Figure 7.3:** Relationship weather and alternative choice

This study primarily focuses on identifying which factors influence a potential shift towards bicycle use. For that reason, the probability of choosing a bicycle alternative was examined for each class. Table 7.6 presents these probabilities. It is clear from the table that Class 2 shows the lowest probabilities of selecting a bicycle, which aligns with the current travel behavior of this group, as most of them travel by car or public transport. This class stands out in particular, as the probability of them choosing a bicycle alternative is 11%.

In contrast, the probabilities for Class 1 and Class 3 are much higher. In Class 1, the city bike is most frequently chosen, while in Class 3, the e-bike is clearly preferred. This pattern reflects the current travel behavior of the individuals in those groups. However, the main interest lies in the potential shift among individuals who do not currently cycle. Therefore, can specifically be estimated what the probability is that car and public transport users would choose a bicycle or e-bike alternative in at least one of the presented choice scenarios. Table 7.7 shows that for these groups, the e-bike is significantly more attractive than the city bike. Notably, 42% of car users and 50% of public transport users opted for a bicycle in at least one scenario. This suggests that a considerable portion of these individuals is open to switching to cycling.

**Table 7.6:** LCCM probabilities

| Mode | Class 1 | Class 2 | Class 3 |
|---|---|---|---|
| City bike | 28,2% | 1,8% | 2,0% |
| E-bike | 0,4% | 9,1% | 27,7% |
| Total | 28,6% | 10,9% | 29,7% |

**Table 7.7:** Bike probabilities per mode

| Mode | Car | Public transport | City bike | E-bike |
|---|---|---|---|---|
| City bike | 8,2% | 8,3% | 85,2% | 5,7% |
| E-bike | 33,3% | 42,0% | 9,11% | 77,2% |
| Total | 41,5% | 50,3% | 94,3% | 82,8% |

# 8 Synthesis

This chapter integrates the findings from the sub-questions discussed in the previous chapters to assess their interrelations and determine whether they strengthen or weaken each other's explanatory power. Figure 8.1 presents the estimated conceptual model, which displays all the variables that influence utility and mode choice as found in this research.

The first sub-question focused on the long-term impact of the Living Lab intervention. The results demonstrate that a substantial share of participants, over 80%, continued to travel sustainably after the conclusion of the intervention. Moreover, their evaluation of the experience had improved over time. This suggests that opinion is not static and that the perceived utility of sustainable commuting modes may increase through continued use.

Despite this promising continuation of cycling behavior, respondents mentioned many positive aspects of the bicycle trip. However, none of them stated that the provided cycling facilities met their expectations. This suggests that there is still significant room for improvement, both for people who already cycle and for those who do not yet. In the Latent Class Choice Model, it became clear that only the class primarily composed of e-bike users (Class 3) was sensitive to the cycling facilities offered. This implies that the facilities presented in the experiment were mainly suited to current bicycle users. This interpretation is supported by the fact that car and public transport users gave very different suggestions when asked what could improve their potential cycling experience. This indicates that other types of interventions may be more effective for encouraging these groups to shift toward cycling.

The second sub-question explored participants' attitudes regarding health, sustainability, safety, and the need for physical activity. Overall, the attitude data painted a supportive picture: most participants perceived their route as safe, had no physical barriers to cycling, and expressed strong agreement with sustainability goals. These attitudes serve as an important source of information, as they can highlight potential barriers and challenges that may arise when implementing interventions. The conceptual model accounts for this by including attitudes as a determinant of latent class membership. This is especially relevant for understanding the distinctions between groups. For instance, current cyclists tended to express stronger sustainability values, whereas car users were more likely to report dissatisfaction with delays but where less emphasized with environmental concerns. This distinction helps explain why car users are more often represented in Class 2, where motorized modes are preferred and sensitivity to positive cycling attributes is minimal.

The attitudinal findings also reveal a potential for change. Although many car users identified less strong with sustainability, they did express frustration with delays. Delay was also one of the most influential attributes in the discrete choice experiment, especially for Classes 2 and 3. This convergence between reported attitudes and modeled sensitivities supports the internal consistency of the conceptual framework. It suggests that while some individuals may not actively seek sustainable alternatives, they are still influenced by the negative aspects of their current commuting mode. This implies that shifts in mode choice may occur not only through motivation but also through dissatisfaction.

The third sub-question focused on contextual factors influencing travel behavior. Across all estimated models, good weather significantly increased the attractiveness of cycling, while bad weather led to greater reliance on public transport and the car. The conceptual model anticipated this through the inclusion of contextual interaction effects, and the empirical findings confirm its relevance. However, the degree to which weather influenced behavior varied across classes. Class 1 responds less strongly to weather compared to classes 2 and 3, where weather effects overshadow the other attributes. This highlights that context does not affect all travelers equally.

In conclusion, the sub-questions addressed different components analysis and these are combined in the conceptual model and, when considered together, provide a coherent and layered understanding of commuting behavior in the hospital context. The model's components: attitudes, context, characteristics, and latent segments, are all reflected in the empirical findings, demonstrating that sustainable behavior can be promoted, but that its maintenance and expansion depend on how well different determinants are aligned with individual needs and circumstances.

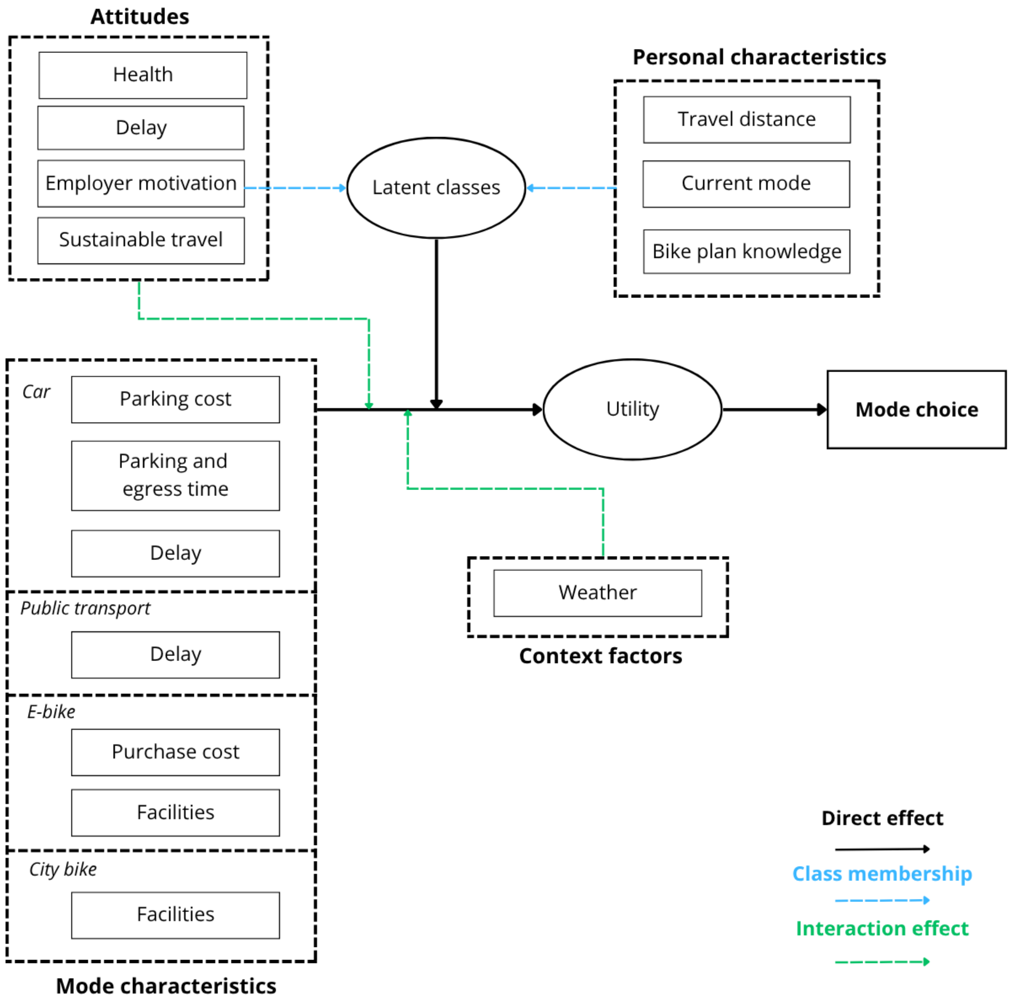



**Figure 8.1:** Estimated conceptual model

# 9 Conclusion and Discussion

## 9.1. Conclusion

### 9.1.1. Research overview

This research, conducted with an academic hospital and Pon Holdings, explored employee commuting behavior to identify factors influencing mode choice and opportunities for encouraging more sustainable travel, namely cycling.

It builds on a previous Living Lab, where 300 employees committed to sustainable commuting for seven months. Participants received incentives like shared e-bikes and additional travel allowances. A Discrete Choice Experiment (DCE) during that pilot showed a strong preference for leased e-bikes, prompting further study. Building on these results, this study focuses on exploring the potential for a modal shift towards cycling, marking the starting point of the current research.

A new Discrete Choice Experiment was introduced in this study to assess the trade-off between bike and other modes. It compared city bikes, e-bikes, and employees' current modes of transport, focusing on car and public transport users. The survey later on also included current bike commuters to capture the full range of decision-making dynamics and maximize the amount of respondents. In the experiment, different attributes were varied, including the purchase cost of an e-bike, car parking costs, parking time for the car, possible delays for both car and public transport, and the available bicycle facilities, in addition to the weather conditions. The Discrete Choice Experiment was analyzed using multiple modeling techniques, including Multinomial Logit and Latent Class Choice Models, to capture preference differences within the population. Additionally, survey sections evaluated whether Living Lab participation had a lasting impact on sustainable travel and gathered ideas through open-ended questions on how to improve the cycling experience.

The combination of quantitative results from the Discrete Choice Experiment, and the comparison with the Living Lab, together with the qualitative insights from the open-ended responses created a broad and well-rounded set of findings. The conclusions, findings, implications, and limitations derived from these results will be presented in the following sections.

### 9.1.2. Answering main research question

The results and conclusions drawn throughout the duration of this study formed the basis for answering the following main research question:

*To what extent do transportation mode attributes influence the choice of (electric) bicycle commuting over alternative modes among employees in the healthcare sector?*

This research question can be answered in two ways: through the results of the Discrete Choice Experiment and the suggested interventions provided by respondents in the open-ended questions. This allows conclusions to be drawn from both quantitative and qualitative data.

The results of the Discrete Choice Experiment reveal that commuting preferences among employees are highly diverse. There is no single commuter profile; rather, distinct behavioral patterns exist, each with its own sensitivities and motivations. The segmentation provided by the Latent Class Choice Model offers a valuable framework for interpreting this variation. Three latent classes were identified, each containing approximately 52 to 55 respondents, reflecting an almost even distribution of one-third per group. These groups were mainly distinguished by their current mode of transport and their sensitivity to the various attributes. Overall, the findings confirm that travel behavior is shaped by a dynamic interplay of personal experience, motivation, infrastructure, and broader contextual factors.

Among all attributes tested, delay emerged as the strongest contributor to utility across the overall respondent group. While delay plays a significant role, especially in influencing the decision to move away from car and public transport alternatives, weather was found to have an even stronger effect on bike choice. Good and dry weather significantly increases the probability of choosing a bicycle mode. However, unlike delay, weather is not mode-specific and affects all alternatives. Still, the way weather is experienced depends on the mode of transport.

Furthermore, the occurrence of delay was particularly influential for current cyclists, but its effect was less pronounced for those who currently use a car or public transport. This is remarkable, as these are the groups that most frequently experience delays. A possible explanation is that they have become accustomed to these delays and therefore take them less into account when choosing a travel mode. In contrast, attributes like the purchase cost of the e-bike had some influence across all classes, especially for Class 1, which mostly exists out of city bike users. Cycling facilities, however, only had a significant effect on current e-bike users and had little impact on those using other modes. This suggests that the facilities presented in the experiment may not have been attractive to car and public transport users, something that was reflected in the qualitative responses, where participants proposed other types of interventions they considered more effective.

From this all can be concluded that, the mode of transport that respondents currently use strongly influences how they perceive the choice sets. People tend to focus more on attributes that affect their current mode rather than on features that could make other alternatives more attractive. Despite this, the probability results show clear potential for change. For example, there is a 42% probability for car users and 50% for public transport users that they would select one of the bicycle alternatives in a given choice set scenario. This indicates genuine interest and opportunity for behavioral change. It has become clear that the e-bike offers more potential than the city bike, since almost everyone prefers the e-bike, except for those who currently use the city bike.

However, the qualitative responses, given in the open-end questions, make it clear that such a shift is not likely to result from the interventions presented in the experiment, such as adding lockers or charging stations. Instead, respondents pointed to broader issues, like the delays in public transport or road traffic, as key reasons for reconsidering bike alternatives. While the quantitative findings highlighted the importance of disincentives like delay and cost, the qualitative feedback emphasized the need for positive incentives that actively encourage cycling as a viable and appealing commuting option.

Based on the number of participants in the experiment and their estimated probabilities of choosing a bicycle alternative, 24 out of 73 current car and public transport users appear open to switching to cycling. When current bike users are also included, the total number of respondents with a likely preference for cycling rises to 111 out of 161, which is approximately 70%. This represents a 15% increase compared to the current modal split.

### 9.1.3. Policy recommendations

Based on all the findings found in this research and the conclusions draw on that are specific policy recommendation suggested to step into these results and possibly use them for better.

#### Shared bike hubs

During the Living Lab, several hubs were in use with shared bikes. It is recommended to reintroduce these hubs. From the open-end question was found that there is a high demand among former participants, as they already know the benefits, but interest is also strong among non-participants. Delay was found to be one of the strongest contributors to utility. This delay mainly occurs in the final part of the journey, particularly around the hospital area. It could potentially be avoided if people used shared bikes for the last few kilometers. Furthermore should the implementation of this initiative happen during the summer and spring months. People are significantly influenced by weather conditions, making it crucial to introduce them to this new method of transport when the weather is favorable. As observed from the Living Lab, once individuals have adapted to a new travel method, there is a high probability they will continue using it. Therefore, by the time winter and autumn arrive, people may have already gotten used to it, and consequently, be less deterred by bad weather.

The highest demand is for a hub at the Central train station. However it is known that implementing this would involve substantial costs. Therefore, two possible approaches could be considered. The first option is to create one central hub at the main station, as most public transport users cross this station. From this station it is only a 20 minute bike on the city bike compared to appropriately 15 minutes by e-bike.

The second option is to establish three smaller hubs. Both Driebergen-Zeist and Bilthoven stations have Park and Ride (P+R) facilities, making them attractive options for both public transport users and car drivers. From Bilthoven, it is approximately a 15-minute e-bike ride to the hospital, compared to about 20 minutes from Driebergen-Zeist station. The third hub could then be places at Bunnik, this station however does not have a nearby P+R facility and would therefore primarily serve public transport users. From this station, the cycling distance to the hospital is around 10 minutes on a regular bike and approximately 7 minutes on an e-bike.

For all of these hubs, it would be crucial for employees to have comprehensive information regarding the e-bikes and their availability. This could be facilitated through an app that also unlocks the bikes and continuously tracks the number of available e-bikes. This real-time availability is important as it allows individuals currently traveling by car or public transport to make an informed decision about whether to continue with their present mode of transport.

Alternatively, reimbursing the public transport bicycle (OV-fiets) is another option for shared e-bikes. However, this would necessitate a designated return point for these bikes on the hospital grounds. Currently, if we consider the locations where these bikes are already available, this option covers all the previously mentioned stations, including smaller stations like Vaartsche Rijn and Lunetten.

### Expand bike plan

Another attribute that respondents in Class 2 were particularly sensitive to was the purchase cost of an e-bike. This class mainly consists of people who currently travel by car or public transport. In addition to their sensitivity to price, respondents also shared a wide range of ideas and suggestions for the bicycle plan in response to the open-ended question. For this reason, it would be a good idea to revise and expand the current bicycle plan. This expansion could take several forms:

Firstly, considering an even higher reimbursement for the bicycle plan is advisable. The price of electric bicycles has increased significantly in recent years, making a higher reimbursement more relevant. The current per-kilometer allowance could be maintained alongside this change (Authorities 2025).

Another option is for the hospital to offer a loan to employees for purchasing a bicycle. In this case, the hospital would initially cover the cost of the bike, and the employee would gradually repay the amount. However, this would mean that the bike remains the property of the hospital until it is fully paid off. The current plan still requires employees to pay a substantial portion of the bicycle cost themselves, and some simply do not have the immediate funds to do so. If the entire amount were loaned to the employee interest-free, they could gradually pay it back while the per-kilometer allowance is retained (Authorities 2025).

Finally, extending the bicycle plan to include second-hand bicycles should be considered. Not everyone prefer a new bike over a second-hand bike and there is a big market of second hand bikes. Currently, buying a second-hand bike is not possible within the bicycle plan, but second-hand bicycles are considerably cheaper and therefore much more appealing to many people.

### Awareness campaigns

As mentioned earlier, delay is a major contributor to disutility in commuting. Therefore, it is important to place more emphasis on helping employees avoid delays. One way to achieve this is by increasing awareness of the different commuting options available to them. Employees could be offered a personalized overview of their transport choices, including estimated travel times and costs for each option. This would allow individuals to discover alternatives they may not have considered before and to identify ways to avoid delays and possibly save time.

In addition to raising awareness about commuting options, attention should also be given to the current programs the hospital already provides. One example is the bicycle purchase plan, which should be familiar to all staff. To ensure this, an awareness campaign should be implemented to promote the bike plan more effectively. Some recent updates have been made, such as an increase in the reimbursement amount, but these changes are not yet widely known within the hospital. Several online documents still display outdated information, highlighting the need for clearer communication and better visibility of the current version of the bike plan.

These awareness efforts can also be included in the on-boarding process for new employees. Since new staff are not yet fully informed about the commuting options offered by the hospital, providing clear and accessible information at an early stage can encourage them to make more sustainable travel choices. This moment is especially important, as new employees are still forming their commuting habits and may be more open to exploring different possibilities.

#### Improve facilities of bicycle parking

The facilities around the bicycle parking garage should be enhanced by adding practical amenities, such as drying racks for rain gear and additional battery chargers. These functions could be combined in secure lockers that offer both drying and charging capabilities. It is recommended to place these lockers in a staff-only bicycle parking area, rather than one accessible to hospital guests, as the lockers may contain personal belongings. It's worth noting that many respondents also expressed interest in (partial) reimbursement for rain gear. However, since a plan for this is already underway, it is not included in this recommendation. These improvements will mainly focus on people who already commute by e-bike, as they showed the highest sensitivity to the provided facilities in the experiment for Class 2. However, the responses to the open-ended question revealed support for the need for additional facilities, although not necessarily the ones that were presented in the experiment.

#### Change travel allowance structure

Redesigning the travel allowance system is essential to ensure that employees can declare their full commute. Employees have stated in the open-end questions that it is not possible to register multi-modal travel, in case one part of the trip is less then 7 km. This can act as a barrier for switching to more sustainable or flexible commuting options for the last part of their journey. If employees choose to travel partly by car and partly by bike, the final segment of their journey is not reimbursed. As a result, some may opt to take the car for the entire trip, simply because switching to another mode would result in part of their commute not being compensated. For instance, if someone switches to the bike for the last 5 kilometers, that portion would go unreimbursed. However, if they remain in their car for the entire trip, the full distance is reimbursed. This creates a financial disincentive for multi-modal commuting. Focusing on removing that barrier can also help reduce delays, as most delays occur in the final few kilometers. By avoiding this part of the journey, commuters can save time and benefit from a more efficient travel experience.

To address this issue, the full commuting distance should be eligible for reimbursement, regardless of how it is divided between transport modes. The system should allow employees to indicate that they used a multi-modal commute. As long as the total commuting distance exceeds the minimum threshold for reimbursement, the method of division between travel modes should not affect compensation.

## 9.2. Discussion

### 9.2.1. Limitations

Although this research gave a lot of insightful findings, there are also some limitation which limited the results but also the operations. This chapter outlines the main limitations of the study, including design choices, data collection challenges, and restrictions in tested interventions. These factors may have influenced the results and should be considered when interpreting the findings.

The full respondent group, including those in the DCE, contains many participants from the Living Lab. These individuals are more familiar with both the benefits and drawbacks of sustainable travel. This differs from randomly recruited participants and may have introduced bias into the results. In addition, travel distance was unevenly distributed. Many respondents commuted over 30 kilometers, while shorter-distance groups were underrepresented. These long-distance commuters were excluded from the DCE but included in the attitude analysis, which may have affected the average results.

The combination of discouraging car and public transport use while encouraging cycling could not be fully tested in this study. The only incentive implemented for cycling was the addition of facilities, while financial incentives could not be included. This was because it was not permitted to vary travel allowance in the DCE, as the hospital did not want to present employees with potential interventions that might ultimately not be feasible. While understandable, this restriction removed the opportunity to assess whether people would actually respond to financial incentives, which is an important element in real-world behavioral change. The same applies to the lease bike option, which was initially considered for inclusion in the DCE but was later excluded due to the same concerns. As a result, the full range of possible interventions could not be evaluated en the main focus was on the dis-incentivizing of the car and public transport. Therefore, the experiment only provided the opportunity to test a limited number of positive incentives. This makes it more difficult to develop effective policies, as the model primarily highlights what people dislike. For example, delay was viewed very negatively by employees and is clearly a problem the hospital needs to address. However, potential solutions like building more roads or adding parking spaces contradict the hospital's goal of reducing car use. To properly assess whether people would find alternative modes of transport more attractive, it is essential to include positive incentives for those alternatives in future models.

Another limitation relates to how the choice sets in the DCE were visually presented. From the results was indicated that weather played a significant role in the decision making. While this may reflect genuine preferences, it could also be influenced by the way weather was presented in the choice sets. Unlike the other attributes, which were shown in a table format, the weather condition was illustrated using prominent images and colors. These visual elements naturally draw attention and may have unintentionally made weather the most salient factor, diverting focus from the other, less visually emphasized attributes.

Additionally, some respondents mentioned that it was sometimes difficult to spot the differences between the presented choice sets. In some cases, only one attribute was altered, making it hard to recognize what had changed and how the new set differed from the previous one. Comparing choice sets is not the goal in DCE but comparing alternatives is. This added cognitive load might have caused fatigue or confusion, making it harder for participants to compare all alternatives thoroughly. As a result, some may have defaulted to making decisions based primarily on the weather image, rather than evaluating all attributes equally. This could have influenced the outcomes and limited the depth of insight the DCE was intended to capture.

This could also be a reason why there were many non-traders among the respondents. These individuals significantly influenced the results, but it remains unclear whether their consistent choice for a single alternative truly reflects a strong preference or if it stems from not fully engaging with the choices. It is possible that some respondents did not take the time to carefully examine and compare all alternatives in each set, which raises concerns about the reliability of their responses. However, non-traders were mostly individuals who currently commute by city bike or e-bike. It is possible that these respondents interpreted the choice sets too literally in relation to their current bike and assumed they would need to purchase a new one. The intention of the choice sets, however, was to assess which bike alternative they found most attractive regardless of the condition or ownership of their current bicycle. This misunderstanding may have led some participants to make choices based on personal context rather than evaluating the general attractiveness of the alternatives as intended.

For simplicity and to focus on a bike modal shift, where car and public transport combined into one category in the study. However, these modes differ significantly in terms of user experience and relevant influencing factors. Grouping them together may have introduced bias, as certain variables, such as delays, may affect one mode more than the other. This can make interpretation of the results more difficult and less accurate. In future research, treating these modes separately would provide more detailed insights and support better-targeted policy decisions. This aligns with the fact that the attributes used in the experiment were mostly alternative-specific. As a result, it may have been more difficult to estimate the differences between alternatives. If more general (mode-independent) attributes had been included, such as travel allowance, it would likely have been easier to interpret specific differences between the modes.

### 9.2.2. Scientific relevance

This section discusses the scientific relevance of this thesis by comparing the results of the study with existing literature. By examining similarities and differences, this chapter highlights how the findings contribute to the current body of knowledge on commuting behavior and bicycle adoption. This reflection helps position the study within the broader academic context and identifies areas for further research.

According to Ha et al. (2020), trip duration plays an important role in mode choice. The descriptive statistics in this study support this finding: active modes of transport, such as cycling, are more commonly used for shorter distances, while car and public transport use increases with longer distances. A similar pattern was observed in the latent class analysis, where the group that mostly traveled shorter distances showed greater interest in using the city bike and e-bike. However, it has become apparent that public transport use only increases significantly after a distance of more than 30 kilometers, while car use remains relatively constant from 7,5 kilometers onward. This differs from the findings of Le and Teng (2023), who indicated increased public transport and car use for mid-length trips. Furthermore, did it became apparent in this research that the occurrence of delay also had a significant impact on the attractiveness of car and public transport. This was already noted by Nichols et al. (2024).

Molin et al. (2016) stated that these is a relation between bike adoption and the willingness to cycle based on individual's current mode of transport. This was confirmed by O'Reilly et al. (2024), who found that people with stronger environmental awareness are more likely to choose active modes of transport. These findings were supported by the results of this study, where it was shown that respondents who currently commute by bike were more likely to agree with sustainability-related statements. The results related to weather were also in line with what was stated in the literature. Where weather was indeed mentioned, and especially rain, as a highly influential factor making specially biking and walking less attractive (Böcker & Thorsson 2013; Klöckner & Friedrichsmeier 2011).

However, the findings of this study diverge from some of the existing literature. For example, a discrepancy was found regarding the role of facilities: although Soder and Peer (2018) and Baker (2023) argued that improving facilities significantly increases the attractiveness of cycling, the estimated models in this study showed very little impact from these attributes, aside from people who currently already use the e-bike. Interestingly though, this aligns with the qualitative data, as many respondents mentioned the need for improved facilities in the open-ended questions, suggesting that while facilities may not drive initial mode choice, they are still valued and could influence long-term adoption.

Aside from the attractiveness of different mode choices, Hartgen (1974) and McCarthy et al. (2017) state that possession also plays an important role. Specifically, owning a car strongly influences mode choice. However, this was not the case in this study, as 75% of respondents who own a car do not use it to commute to the hospital.

In the studies by Zadeits (2024) and van der Meulen (2024), the e-bike was frequently mentioned as a highly attractive option. These findings were confirmed in the present study, where the e-bike emerged as the most appealing mode of transport during good weather. However, unlike those earlier studies, public transport was found to be the most attractive option during bad weather. A direct comparison between these studies is difficult, as the previous research did not account for the effect of weather. Furthermore, the interest in shared e-bikes at stations and P+R locations, which was raised in this study, aligns with the findings of Zadeits (2024), where these options were often requested, and with van der Meulen (2024), where they were already in use. This repeated mention from both Living Lab participants and other employees highlights the potential value and demand for implementing shared e-bikes at key transfer points. The difference in public transport attractiveness could be due to the new regulation concerning fact that public transport is fully reimbursement whereas this was not the case for the study of Zadeits (2024).

These differences and similarities highlight the scientific relevance of this study. Many findings from the two previous studies conducted on this specific research group were confirmed, but also expanded upon. This shows that testing these factors among a broader population provides a more complete and nuanced understanding. It also reveals that while there is a segment of the population that remains highly unwilling to change, there is another group that is open to change, although it is still unclear what would truly motivate them to shift their commuting behavior.

### 9.2.3. Future research

Building on the insights from this study and the limitations mentioned in the previous section, this chapter explores some important directions for future research. The suggestions aim to fill remaining gaps, look into new strategies, and help make the results more widely applicable. The goal is to support more effective and scalable ways to encourage cycling among employees.

### Focus car and public transport users

Since the main goal of this research is to encourage a shift towards cycling, for the next research more focused attention should be given to current car and public transport users. To better understand their perspectives, it is recommended to organize separate focus groups: one consisting of people who currently commute by car and another of those using public transport. These groups would provide a space for participants to share experiences and barriers, while also allowing for direct testing and discussion of potential interventions. This is a way to test qualitative insights and see what their support is among a small group of employees. The results indicated a 42% probability that some current car users, and 50% for current public transport users, would choose a bicycle alternative. For this research, it is important to address the remaining 58% and 50% who are still unwilling to switch, and to explore the reasons behind their reluctance.

It is therefore suggested to hold several sessions, each with 5–10 participants, ensuring a group size that allows for dynamic discussion while still giving every participant the opportunity to be heard. These groups should be composed to ensure diversity in terms of professional background, job roles, and especially commuting distances. Such discussions could directly explore why people have not yet made a modal shift and provide valuable insights into their motivations and concerns.

Additionally, it may be wise to look beyond the current Living Lab participants. While their involvement has been very informative and their engagement high, the opinions of this group have become clear over the last year. To increase the applicability of the findings, it is more relevant at a new stage to focus on generalizability and gain insight from employees who have not yet engaged with sustainable commuting initiatives.

### Lease bike trials

Employees expressed interest in the option to temporarily try out an e-bike or speed pedelec. This idea could be implemented within a small group to assess how effective and attractive such a trial would be. By limiting the pilot to a small sample, it's easier to monitor outcomes, gather feedback, and evaluate whether the experience increases the likelihood of long-term adoption. Therefore, a lease bike trial could be offered to new employees. Since they haven't yet developed a fixed commuting routine, they may be more open to trying alternative travel options. This makes them an ideal group to test a lease system on a small scale and for a limited period. If the trial proves successful and the lease bike is well-received, it could later be expanded to the wider hospital staff.

Additionally, new employees are often not yet familiar with internal commuting policies or dependent on travel allowance income flows. This matters because when using a lease bike, employees are no longer eligible for the standard travel allowance due to tax regulations. For new staff, this might be less of an issue, as they have no previous experience with the travel reimbursement system at the hospital to compare it with.

### Insights into travel behavior

A valuable follow-up study could focus on analyzing people's travel patterns, specifically looking at how the last 7 kilometers of their journey are completed. By gaining insight into how this final segment is typically traveled, targeted strategies can be developed to encourage more sustainable modes of transport.

A cost analysis could be conducted to determine how expenses are currently distributed across the final part of employees' commutes by public transport. One example is the use of the fast tram, which provides a direct connection between the region's main train station and the hospital. If data can be gathered on how frequently this service is used, it would be possible to estimate the total cost involved. This, in turn, could help determine how much budget would become available if this segment were replaced by cycling.

These potential savings could then be reallocated, for instance, to fund shared bike hubs at stations where the most cost reductions can be achieved. Another option is to increase the travel allowance for employees who cycle, offering an extra incentive. Currently, public transport journeys are fully reimbursed. If employees switch to cycling, they could not only receive reimbursement for their partial public transport trip but also receive a travel allowance for their bicycle trip.

In addition to identifying the most frequently used public transport stations, it is also possible to analyze the popularity of Park and Ride (P+R) locations. While actual parking activity at these P+R sites may not be directly observable, it is still feasible to estimate which P+R locations are most often passed by or lie along employees' regular commuting routes. These estimations can be made based on home addresses and the likely routes employees take to reach the hospital, even if not directly tracked. Once these popular locations are identified, the hospital can take targeted action by placing shared e-bike hubs at these frequently passed P+R sites. If these bikes are reimbursed, it creates a extra incentive for employees: they benefit by not experiencing delay in the parking garages and receive a travel allowance for using the shared bikes. This combination can make the switch to multi-modal commuting more appealing.

### Revealed versus stated preference

Another valuable follow-up study would be to compare revealed preferences with stated preferences, particularly to validate the actual influence of weather conditions found in this study. This could be done by examining real commuting behavior on sunny versus rainy days. For example, by comparing the submitted travel allowance claims with the weather on those specific days, can be assessed whether fewer cycling trips occur on rainy days than on sunny ones. If such a pattern is observed, it supports the findings of this study. However, if no such difference exists, it may indicate that people overestimate the extent to which their travel choices are influenced by the weather.

# References


Ababio-Donkor, A., Saleh, W., & Fonzone, A. (2020). Understanding transport mode choice for commuting: The role of affect. *Transportation Planning and Technology*, *43*(4), 385–403. https://doi.org/10.1080/03081060.2020.1747203

Abdullah, S., Markandya, A., & Nunes, P. A. L. D. (2011). Introduction to economic valuation methods. In A. Batabyal & P. Nijkamp Eds., *Research tools in natural resource and environmental economics* pp. 143–187. World Scientific. https://doi.org/10.1142/9789814289238_0005

Academic hospital. (2025a). *Betaald parkeren medewerkers*. https://nieuwemedewerker.umcutrecht.nl/nl/betaald-parkeren-medewerkers

Academic hospital. (2025b, February). *Hoe umc utrecht medewerkers anders laat reizen*. https://www.umcutrecht.nl/nieuws/hoe-umc-utrecht-medewerkers-anders-laat-reizen

Academic hospital. (2025c). *Overzicht cao à la carte regelingen umc utrecht*. https://assets-eu-01.kc-usercontent.com/c5303bed-a69b-01c6-288b-5868950b8c3f/0d3b23fe-059e-4cf2-a9f5-1e291b786908/Overzicht%20CAO%20a%20la%20carte%20UMC%20Utrecht%20concept%20202408%20%282%29.pdf

Adamidis, F., Haddad, C. A., Abouelela, M., & Antoniou, C. (2025). Mode choices under car-reducing scenarios: Measurable factors and latent attitudes. *Transportation Behaviour and Society*, *40*(101001). https://doi.org/10.1016/j.tbs.2025.101001

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1975). A bayesian analysis of attribution processes. *Psychological Bulletin*, *82*(2), 261–277. https://doi.org/10.1037/h0076477

Akinc, D., Street, D. J., & Vandebroek, M. (2024). Varying choice set sizes in discrete choice experiments. *Journal of Choice Modelling*, *52*, 100493. https://doi.org/10.1016/j.jocm.2024.100493

Alamri, A. S., Georgiou, S. D., & Stylianou, S. (2023). Discrete choice experiments: An overview on constructing d-optimal and near-optimal choice sets. *Heliyon*, *9*(7). https://doi.org/10.1016/j.heliyon.2023.e18256

Alamri, A., Stelios, G., & Stella, S. (2023). Discrete choice experiments: An overview on constructing d-optimal and near-optimal choice sets. *Heliyon*, *9*, e18256. https://doi.org/10.1016/j.heliyon.2023.e18256

Alghamdi, R., & Bahari, G. (2025). Shift work, psychological health disorders, and job security among nurses: A cross-sectional study. *Healthcare*, *13*(3), 221. https://doi.org/10.3390/healthcare13030221

Authorities, T. (2025). *Mijn werkgever heeft een fietsplan – hoe werkt dat?* https://www.belastingdienst.nl/wps/wcm/connect/nl/personeel-en-loon/content/mijn-werkgever-heeft-een-fietsplan-hoe-werkt-dat

Baker, A. (2023). *Commute zero: Employer attitudes towards sustainable commuting and business travel*. Thinks: Insight Strategy. https://www.thinksinsight.com/reports/commute-zero-employer-attitudes-towards-sustainable-commuting-and-business-travel

Belastingdienst. (2025). *Box 1: Belastbaar inkomen uit werk en woning*. https://www.belastingdienst.nl/wps/wcm/connect/bldcontentnl/belastingdienst/prive/inkomstenbelasting/heffingskortingen_boxen_tarieven/boxen_en_tarieven/box_1/box_1

Ben-Akiva, M., & Lerman, S. R. (1985). Discrete choice analysis: Theory and application to travel demand. *Transportation Research Part B: Methodological*, *19*(5), 409–412. https://doi.org/10.1016/0191-2607(90)90037-7

Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., & Polydoropoulou, A. (1999). Integration of choice and latent variable models. *Massachusetts Institute of Technology*. https://mit.edu

Biernat, E., Krzepota, J., & Sadowska, D. (2020). Cycling to work: Business people, encourage more physical activity in your employees! *Work*, *65*, 391–399. https://doi.org/10.3233/WOR-203091

Böcker, L., & Thorsson, S. (2013). Integrated weather effects on cycling shares, frequencies, and durations in rotterdam, the netherlands. *Weather, Climate and Society*, *6*, 468–481. https://doi.org/10.1175/WCAS-D-13-00066.1

Boncinelli, F., Contini, C., Gerini, F., Romano, C., Scozzafava, G., & Casini, L. (2020). The role of context definition in choice experiments: A methodological proposal based on customized scenarios. *Wine Economics and Policy*, *9*(2), 49–62. https://doi.org/10.36253/web-7978

Booker, L. A., Spong, J., Hodge, B., Deacon-Crouch, M., Bish, M., Mills, J., & Skinner, T. C. (2024). Differences in shift and work-related patterns between metropolitan and regional/rural healthcare shift workers and the occupational health and safety risks. *Australian Journal of Rural Health*, *32*(1), 141–151. https://doi.org/10.1111/ajr.13075

Casier, C., & Witlox, F. (2022). An analysis of trip preferences among e-bike users in commuting: Evidence from an online choice-based conjoint experiment. *TU Delft OPEN*, *22*(1), 17–41. https://doi.org/10.18757/ejtir.2022.22.1.5971

CBS. (2023). *Hoeveel reisden inwoners van nederland van en naar het werk?* https://www.cbs.nl/nl-nl/visualisaties/verkeer-en-vervoer/personen/van-en-naar-werk

CBS. (2024, July). *Mobility; per person, modes of travel, purposes of travel and regions*. https://www.cbs.nl/nl-nl/cijfers/detail/84710ENG

CBS. (2025a). *Cijfers over broeikasgasemissies in nederland*. https://www.cbs.nl/nl-nl/cijfers/detail/84755NED

CBS. (2025b). Hoeveel personenauto's zijn er in nederland? https://www.cbs.nl/nl-nl/visualisaties/verkeer-en-vervoer/vervoermiddelen-en-infrastructuur/personenautos

CBS. (2025c). *Welke sectoren stoten broeikasgassen uit?* https://www.cbs.nl/nl-nl/dossier/dossier-broeikasgassen/welke-sectoren-stoten-broeikasgassen-uit-

Chen, C., Gong, H., & Paaswell, R. (2008). Role of the built environment on mode choice decisions: Additional evidence on the impact of density. *Transportation*, (35), 285–299. https://doi.org/10.1007/s11116-007-9153-5

Columbia University Mailman School of Public Health. (2025). *Exploratory factor analysis* [Accessed on March 10, 2025]. Retrieved March 10, 2025, from https://www.publichealth.columbia.edu/research/population-health-methods/exploratory-factor-analysis

Cranenburgh, S. (2023). Sen1221 statistical analysis of choice behaviour [Lecture presented at the Techincal University of Delft, 2023].

Ding, C., Liu, C., Lin, Y., & Wang, Y. (2014). The impact of employer attitude to green commuting plans on reducing car driving: A mixed method analysis. *Human-Transport Interacyion*, *26*(2), 109–119. https://doi.org/10.7307/ptt.v26i2.1350

Du, X., Du, Y., Zhang, Y., Zhu, Y., & Yang, Y. (2024). Urban and rural disparities in general hospital accessibility within a chinese metropolis. *Scientific Reports*, *14*(23359). https://doi.org/10.1038/s41598-024-74816-4

Dutch Association of Hospitals. (2023, March). *Nvz kiest met cao-akkoord voor medewerkers: 15% erbij*. https://nvz-ziekenhuizen.nl/actualiteit-en-opinie/nvz-kiest-met-cao-akkoord-voor-medewerkers-15-erbij

European Council. (2025). *Climate change: What is the eu doing*. https://www.consilium.europa.eu/en/policies/fit-for-55/#:~:text=The%20European%20climate%20law%20makes,EU%20climate%2Dneutral%20by%202050.

Felix, R., Moura, F., & Clifton, K. J. (2019). Maturing urban cycling: Comparing barriers and motivators to bicycle of cyclists and non-cyclists in lisbon, portugal. *Journal of Transport Health*, *15*(100628). https://doi.org/10.1016/j.jth.2019.100628

Feng, J., Zhu, X., Wang, F., Huang, S., & Chen, C. (2022). A learning framework for personalized random utility maximization (rum) modeling of user behavior. *IEEE Transactions on Automation Science and Engineering*, *19*(1), 510–521. https://doi.org/10.1109/TASE.2020.3041411

Forward, S. (2004). The prediction of travel behaviour using the theory of planned behaviour. In T. Rothengatter & R. D. E. Huguenin Eds., *Traffic and transport psychology: Theory and application*. Elsevier. https://www.researchgate.net/publication/281510103

Fraboni, F., Prati, G., Casu, G., de Angelis, M., & Pietrantoni, L. (2022). A cluster analysis of cyclists in europe: Common patterns, behaviours, and attitudes. *Transportation*, *49*, 591–620. https://doi.org/10.1007/s11116-021-10187-3

Friedel, J. E., Foreman, A. M., & Wirth, O. (2022). An introduction to "discrete choice experiments" for behavior analysts. *Behavioural Processes*. https://doi.org/10.1016/j.beproc.2022.104628

Gentiletti, M. G., Cahour, B., & Safin, S. (2019). Can an experience with no car use change future mode choice behavior? *Sustainability*, *11*(4698). https://doi.org/10.3390/10.3390/su11174698

Gentiletti, M. G., Cahour, B., & Safin, S. (2025). Abandoning the car to embrace the bicycle in urban france: A model of modal shift for daily commuting routines. *Sustainability (Switzerland)*, *17*(448). https://doi.org/10.3390/su17020448

Gibbs, G. R. (2012). *Analyzing qualitative data*. SAGE Publications, Ltd. https://doi.org/10.4135/9781849208574

Google Maps. (n.d.). https://www.google.com/maps

Göransson, J., & Andersson, H. (2023). Factors that make public transport systems attractive: A review of travel preferences and travel mode choices. *European Transport Research Review*, *15*(32). https://doi.org/10.1186/s12544-023-00609-x

Gundlach, A., Ehrlinspiel, M., Kirsch, S., Koschker, A., & Sagebiel, A. (2018). Investigating people's preferences for car-free city centers: A discrete choice experiment. *Transportation Research Part D: Transport and Environment*, *63*, 677–688. https://doi.org/10.1016/j.trd.2018.07.004

Ha, J., Lee, S., & Ko, J. (2020). Unraveling the impact of travel time, cost, and transit burdens on commute mode choice for different income and age groups. *Transportation Research Part A: Policy and Practice*, *141*, 147–166. https://doi.org/10.1016/j.tra.2020.07.020

Hamersma, M., & Roeleven, I. (2024). Acceptabele bereikbaarheid een reizigersperspectie.

Hansen, K. B., & Nielsen, T. A. S. (2014). Exploring characteristics and motives of long distance commuter cyclists. *Transport Policy*, *35*, 57–63. https://doi.org/10.1016/j.tranpol.2014.05.001

Hartgen, D. T. (1974). Attitudinal and situational variables influencing urban mode choice: Some empirical findings. *Transportation*, *3*, 377–392. https://link.springer.com/article/10.1007/BF00167967

Heinen, E., & Maat, K. (2012). The effect of work-related factors on the bicycle commute mode choice in the netherland. *Transportation*, *40*(1), 23–43. https://doi.org/10.1007/s11116-012-9399-4

Heiss, F. (2002). Structural choice analysis with nested logit models. *The Stata Journal*, *2*(3), 227–252. https://www.stata-journal.com/article.html?article=st0017

Hely. (2025). Transfer hub – duurzaam  efficiënt vervoer. https://hely.com/oplossingen/transfer-hub

Hensher, D. A., & Greene, W. H. (2002). Specifications and estimation of the nested logit model: Alternative normalisations. *Transportation Research Part B*, *36*(1), 1–17. https://doi.org/10.1016/S0191-2615(00)00035-7

Iseki, H., Taylor, B. D., & Miller, M. (2006). *The effects of out-of-vehicle time on travel behavior: Implications for transit transfers* tech. rep. Institute of Transportation Studies, University of California, Los Angeles. https://escholarship.org/uc/item/8tz2r8hg

Jessiman, P. E., Rowe, R. E., & Jago, R. (2023). A qualitative study of active travel amongst commuters and older adults living in market towns. *BMC Public Health*, *23*(840). https://doi.org/10.1186/s12889-023-15573-3

Jones, L. R., Bennett, C., MacArthur, J. H., & Cherry, C. R. (2024). Consumer purchase response to e-bike incentives: Results from a nationwide stated preference study. *Journal Name*, *129*. https://doi.org/https://doi.org/10.1016/j.trd.2024.104114

Kaczynski, A. T., Bopp, M. J., & Wittman, P. (2010). Association of workplace supports with active commuting. *Preventing Chronic Disease*, *7*(6). http://www.cdc.gov/pcd/issues/2010/nov/09_0193.htm

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2). https://courses.washington.edu/pbafhall/514/514%20Readings/ProspectTheory.pdf

KiM. (2023). Mobiliteitsbeeld 2023. https://www.kimnet.nl/mobiliteitsbeeld

Kipfer, N. (2024, June). *Substituting the traditional? examining usage patterns of e-bikers through discrete choice modeling* [Master's thesis, University of Basel]. https://stud.unibas.ch

Klöckner, C. A., & Friedrichsmeier, T. (2011). A multi-level approach to travel mode choice – how person characteristics and situation specific aspects determine car use in a student sample. *Transportation Research Part F: Traffic Psychology and Behaviour*, *14*, 261–277. https://doi.org/10.1016/j.trf.2011.01.006

Ko, J., Lee, S., & Byun, M. (2019). Exploring factors associated with commute mode choice: An application of city-level general social survey data. *Transport Policy*, *75*, 36–46. https://doi.org/10.1016/j.tranpol.2018.12.007

Lahoz, L. T., Pereira, F. C., G. Sfeir, I. A., Monteiro, T. M., & Azevedo, C. L. (2023). Attitudes and latent class choice models using machine learning. *Journal of Choice Modelling*, *49*, 100452. https://doi.org/10.1016/j.jocm.2023.100452

Langenberg, H., Melser, C., & Peters, M. J. (2023, November). Arbeidsmarktprofielvan zorg en welzijn in 2022. https://www.cbs.nl/nl-nl/longread/statistische%20trends/2023/arbeidsmarktprofiel-van-zorg-en-welzijn-in-2022/3-zorgmedewerkers

Le, J., & Teng, J. (2023). Understanding influencing factors of travel mode choice in urban-suburban travel: A case study in shanghai. *Urban Rail Transit*, *9*, 127–146. https://doi.org/10.1007/s40864-023-00190-5

Lim, S., Ahn, H., Shin, S., Lee, D., & Kim, Y. H. (2024). Investigating night shift workers' commuting patterns using passive mobility data. *Transportation Research Part A: Policy and Practice*. https://doi.org/https://doi.org/10.1016/j.tra.2024.104002

Lindsey, R., & Dahlman, L. (2024, January). *Climate change: Global temperature*. https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature

Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling*, *3*, 57–72. https://doi.org/10.1016/S1755-5345(13)70014-9

Lu, H., & Gan, H. (2024). Unraveling the influence of perceived built environment on commute mode choice based on hybrid choice model. *Applied Sciences (Switzerland)*, *14*. https://doi.org/10.3390/app14177921

Maptionnaire. (2022). *12 best practices in survey design to boost response rates and get quality data*. https://www.maptionnaire.com/blog/12-best-practices-in-survey-design

Marquez, L., Cantillo, V., & Paternina-Arboleda, C. D. (2024). Hard and soft measures for motivating workers to commute by bicycle: The case of bogota. *Case studies on Transport Policy*, *18*. https://doi.org/10.1016/j.cstp.2024.101299

McCarthy, L., Delbosc, A., Currie, G., & Molloy, A. (2017). Factors influencing travel mode choice among families with young children (aged 0–4): A review of the literature. *Transport Reviews*, *37*(6), 767–781. https://doi.org/10.1080/01441647.2017.1354942

McFadden, D. (1974). *Conditional logit analysis of qualitative choice behavior* P. Zarembka, Ed. Academic Press.

Mikhaylov, A., Moiseev, N., Aleshin, K., & Burkhardt, T. (2020, June). *Global climate change and greenhouse effect*. https://doi.org/10.9770/jesi.2020.7.4(21)

Milieu Centraal. (2025). Co2-uitstoot fiets, ov en auto. https://www.milieucentraal.nl/duurzaam-vervoer/co2-uitstoot-fiets-ov-en-auto/

Molin, E. (2023). Sen1221 statistical analysis of choice behaviour [Lecture presented at the Techincal University of Delft, 2023].

Molin, E., & Arentze, T. (2013). Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice*, *58*, 15–28. https://doi.org/10.1016/j.tra.2013.10.005

Molin, E., & Kroesen, M. (2023). Hoe motiveer je werknemers om met de fiets of ov naar het werk te gaan in plaats van met de auto? https://www.tudelft.nl/2023/tbm/hoe-motiveer-je-werknemers-om-met-de-fiets-of-ov-naar-het-werk-te-gaan-in-plaats-van-met-de-auto#:~:text=Onderzoek%20van%20TU%20Delft%20wetenschappers,niet%20met%20de%20auto%20komt.

Molin, E., Mokhtarian, P., & Kroesen, M. (2016). Multimodal travel groups and attitudes: A latent class cluster analysis of dutch travelers. *Transportation Research Part A: Policy and Practice*, *83*, 14–29. https://doi.org/10.1016/j.tra.2015.11.001

Molin, E., & Timmermans, H. J. P. (2010). Context dependent stated choice experiments: The case of train egress mode choice. *Journal of Choice Modelling*, *3*(3), 39–56. https://doi.org/10.1016/S1755-5345(13)70013-7

Molnár, H. (2002). Fietsend achterop. *Index, Centraal Bureau voor de Statistiek (CBS)*, (7).

Nardi, P. M. (2018). *Doing survey research: A guide to quantitative methods* 4th. Routledge. https://doi.org/https://doi.org/10.4324/9781315172231

Nichols, A., Ryan, J., & Palmqvist, C. (2024). The importance of recurring public transport delays for accessibility and mode choice. *Journal of Transport Geography*, *115*. https://doi.org/10.1016/j.jtrangeo.2024.103796

O'Reilly, R. K., Kollmann, A., & nd J. Reichl, J. C. (2024). Macro-factors driving bicycle adoption as a primary transport mode across europe. *Transport Behaviour and Society*, *34*(100669). https://doi.org/10.1016/j.tbs.2023.100669

Osborne, J. W. (2014). *Best practices in exploratory factor analysis*. CreateSpace Independent Publishing. https://www.researchgate.net/publication/209835856_Best_Practices_in_Exploratory_Factor_Analysis_Four_Recommendations_for_Getting_the_Most_From_Your_Analysis

Parmar, J., Saiyed, G., & Dave, S. (2023). Analysis of taste heterogeneity in commuters' travel decisions using joint parking– and mode–choice model: A case from urban india. *Transportation Research Part A*, *170*(103610). https://doi.org/10.1016/j.tra.2023.103610

Posner, R. A. (1997). Rational choice, behavioral economics, and the law. *Stanford Law Review*, *50*. https://chicagounbound.uchicago.edu/journal_articles/1880

RAI Vereniging. (2024). *Fietsbranche ziet omzet stabiliseren in 2023*. https://www.raivereniging.nl/actueel/nieuws/fietsbranche-ziet-omzet-stabiliseren-in-2023/

Rérat, P. (2021, February). *The rise of the e-bike: Towards an extension of the pratcice of cycling?* https://doi.org/10.1080/17450101.2021.1897236

Rietveld, P., Bruinsma, F. R., & Vuuren, D. J. (2001). Coping with unreliability in public transport chains: A case study for netherlands. *Transportation Research Part A*, *35*, 539–559. https://doi.org/10.1016/S0965-8564(00)00006-9

Rijkswaterstaat. (2024). *Rapportage rijkwegennet, 2023: 1 januari - 31 december*.

Rogers, E. (2003). *Diffusion of innovations*. Simon; Schuster Free Press.

Ross, A., & Willson, V. L. (2017). *Basic and advanced staistical tests*. Sense Publishers, Rotterdam. https://doi.org/10.1007/978-94-6351-086-8_5

Rungie, C. M., Coote, L. V., & Louviere, J. J. (2012). Latent variables in discrete choice experiments. *Journal of Choice Modelling*, *5*, 145–156. https://doi.org/10.1016/j.jocm.2013.03.002

RVO. (2023, May). *Rapportageverplichting werkgebonden personenmobiliteit)* [Last checked on 21st of January 2025]. Rijksdienst voor Ondernemend Nederland. https://www.rvo.nl/onderwerpen/rapportage-wpm

RVO). (2024, November). *Brandstofprijsvergelijking*. https://www.rvo.nl/onderwerpen/brandstofprijsvergelijking

Rybels, S., Vanoutrive, T., Corradi, D., & Coppens, T. (2024). Bicycle commuting beyond short distances: Built environment, socio-demographic factors and type of bicycle influencing the choice to cycle to three university campuses. *European Journal of Transport and Infrastructure Research*, *24*(4), 111–132. https://doi.org/10.59490/ejtir.2024.24.4.7013

Sabir, M., Koetse, M. J., & Rietveld, P. (2007). The impact of weather conditions on mode choice: Empirical evidence for the netherlands. *BIVEC Conference*. https://www.researchgate.net/publication/382563705

Sahu, A. K., Padhy, R. K., & Dhir, A. (2020). Envisioning the future of behavioral decision-making: A systematic literature review of behavioral reasoning theory [Open Access]. *Australasian Marketing Journal*, *28*(2), 145–159. https://doi.org/10.1016/j.ausmj.2020.05.001

Scheiner, J., & Holz-Rau, C. (2007). Travel mode choice: Affected by objective or subjective determinants? *Transportation*, *34*, 487–511. https://doi.org/10.1007/s11116-007-9112-1

Schwanen, T., Dijst, M., & Dieleman, F. M. (2006). The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. *Journal of Transport Geography*, *14*(5), 327–341. https://doi.org/10.1016/j.jtrangeo.2005.06.004

Sfeir, G., Rodrigues, F., & Abou-Zeid, M. (2022). Gaussian process latent class choice models. *Transportation Research Part C: Emerging Technologies*, *136*, 103552. https://doi.org/10.1016/j.trc.2022.103552

Sheard, J. (2018). Quantitative data analysis. In *Research methods: Information, systems, and contexts* pp. 429–452. Elsevier Ltd. https://doi.org/10.1016/B978-0-08-102220-7.00018-2

Shin, E. J. (2020). Commuter benefits programs: Impacts on mode choice, vmt, and spillover effects. *Transport Policy*, *94*, 11–22. https://doi.org/10.1016/j.tranpol.2020.05.001

Shuttel. (2025). Thuiswerkvergoeding zo geregeld. https://shuttel.nl/mobiliteitsoplossingen/thuiswerkvergoeding/

Smith, A., McDonald, A. D., & Sasangohar, F. (2020). Night-shift nurses and drowsy driving: A qualitative study. *International Journal of Nursing Studies*, *112*(103600). https://doi.org/10.1016/j.ijnurstu.2020.103600

Soder, M., & Peer, S. (2018). The potential role of employers in promoting sustainable mobility in rural areas: Evidence from eastern austria. *International Journal of Sustainable Transportation*, *12*(7), 541–551. https://doi.org/10.1080/15568318.2017.1402974

Spearman, C. (1904). General intelligence, objectively determined and measured. *The American Journal of Psychology*, *15*, 201–292. https://doi.org/10.2307/1412107

Statista. (2025, January). *Transportation emissions worldwide: Statistics and facts*. https://www.statista.com/topics/7476/transportation-emissions-worldwide/

SWOV. (2025). *Elektrische fietsen – 7. hoe snel wordt op een elektrische fiets en op een speed-pedelec gereden*. https://swov.nl/nl/fact/elektrische-fietsen-7-hoe-snel-wordt-op-een-elektrische-fiets-en-op-een-speed-pedelec-gereden

Tazliqoh, A. Z., Wigena, A. H., & Syafitri, U. D. (2019). Fractional factorial and d-optimal design for discrete choice experiments (dce). *IOP Conference Series: Earth and Environmental Science*, *299*, 012067. https://doi.org/10.1088/1755-1315/299/1/012067

Thurstone, L. L. (1927). A law of comparative judgment. *Psychological Review*, *34*(4), 273–286.

Tomlinson, K., & Benson, A. R. (2021). Learning interpretable feature context effects in discrete choice, 12. https://doi.org/10.1145/3447548.3467250

Ton, D., Bekhor, S., Cats, O., Duives, D. C., Hoogendoorn-Lanser, S., & Hoogendoorn, S. P. (2020). The experienced mode choice set and its determinants: Commuting trips in the netherlands. *Transportation Research Part A: Policy and Practice*, *132*, 744–758. https://doi.org/10.1016/j.tra.2019.12.027

Tsairi, Y., & Martens, K. (2024). Workplace responsibility for employee mobility? a review of sustainability reporting frameworks. *Transport Reviews*, *44*(5), 1077–1102. https://doi.org/10.1080/01441647.2024.2356030

Turney, S. (2023). *Chi-square ( $^2$) table | examples  downloadable table*. Scribbr. https://www.scribbr.com/statistics/chi-square-distribution-table/

Ulahannan, A., & Birrell, S. (2022). Designing better public transport: Understanding mode choice preferences following the covid-19 pandemic. *Sustainability*, *14*(10). https://doi.org/10.3390/su14105952

United Nations. (2025). *The paris agreement*. https://www.un.org/en/climatechange/paris-agreement

van Lierop, D., & Bahamonde-Birke, F. J. (2021). Commuting to the future: Assessing the relationship between individuals' usage of information and communications technology, personal attitudes, characteristics and mode choice. *Networks and Spatial Economics*, *23*, 353–371. https://doi.org/10.1007/s11067-021-09534-9

van der Meulen, N. (2024). Rethinking commuting: Sustainable mobility practices. https://resolver.tudelft.nl/uuid:16837f34-1c03-4aed-9ac6-090e985a5b8e

van der Steen, N., Cappelle, J., & Vanhaverbeke, L. (2025). Adoption of speed pedelecs as a commuting vehicle: Investigating the influence of a test period. *Transportation Research Part A: Policy and Practice*, *194*(104414). https://doi.org/10.1016/j.tra.2025.104414

Vedel, S. E., Jacobsen, J. B., & Skov-Petersen, H. (2017). Bicyclists' preferences for route characteristics and crowding in copenhagen – a choice experiment study of commuters. *Transportation Research Part A: Policy and Practice*, *100*, 53–64. https://doi.org/10.1016/j.tra.2017.04.006

Washbrook, K., Haider, W., & Jaccard, M. (2006). Estimating commuter mode choice: A discrete choice analysis of the impact of road pricing and parking charges. *Transportation*, *33*, 621–639. https://doi.org/10.1007/s11116-005-5711-x

Webb, E. J. D., Meads, D., Lynch, Y., Judge, S., Randall, N., Goldbart, J., Meredith, S., Moulam, L., Hess, S., & Murray, J. (2021). Attribute selection for a discrete choice experiment incorporating a best-worst scaling survey. *Value in Health*, *24*(4), 575–584. https://doi.org/10.1016/j.jval.2020.10.025

Westaby, J. D. (2005). Behavioral reasoning theory: Identifying new linkages underlying intentions and behavior. *Organizational Behavior and Human Decision Processes*, *98*(2), 97–120. https://doi.org/10.1016/j.obhdp.2005.07.003

Wigmore, S. (2021). *11 best practices for more effective survey designs*. https://www.kantar.com/inspiration/research-services/11-survey-design-best-practices-to-increase-effectiveness-pf

Willson, R. W. (1992). Commuter mode choice and free car parking. *Transportation Research Part A: Policy and Practice*, *26*(3), 169–185. https://doi.org/10.1016/0965-8564(92)90021-C

Zadeits, E. (2024). Moving towards a carless place of work: Qualitative research on hospital employees. https://resolver.tudelft.nl/uuid:6436aec3-ca1d-4394-8932-4a7f14dcb065

Zeiske, N., van der Werff, E., & Steg, L. (2021). The effects of a financial incentive on motives and intentions to commute to work with public transport in the short and long term. *Journal of Environmental Psychology*, *78*(101718). https://doi.org/10.1016/j.jenvp.2021.101718

Zhang, J., Wada, K., & Oguchi, T. (2021). Morning commute in congested urban rail transit system: A macroscopic model for equilibrium distribution of passenger arrivals. *Transportmetrica B*, *11*(2195582). https://doi.org/10.1080/21680566.2023.2195582

Zhou, J. (2012). Sustainable commute in a car-dominant city: Factors affecting alternative mode choices among university students. *Transportation Research Part A*, *46*(7), 1012–1029. https://doi.org/10.1016/j.tra.2012.04.001

Zimba, O., & Gasparyan, A. Y. (2023). Designing, conducting, and reporting survey studies: A primer for researchers. *Journal of Korean Medical Science*, *38*(48). https://doi.org/10.3346/jkms.2023.38.e403

# A
# Literature review

To gather all relevant literature that supports the background and information needs of this study, a thorough and extensive literature review was conducted. Various external platforms were used, including Google Scholar, Scopus, and ScienceDirect. In addition, internal platforms such as Brightspace and the TU Delft Repository were consulted. To ensure that a reasonable number of papers were found and that the selected papers were relevant to the study and the current state of transportation systems, specific inclusion and exclusion criteria were established. What was included and excluded is discussed below. Within Scopus, a combination of different search terms was applied in order to find the most relevant and high-quality selection of academic papers:

### Exclusion criteria
For the research conducted in Scopus, the focus was on literature published from 2013 onward. This time frame was chosen to ensure that outdated or no longer relevant information was excluded. Several topics were also deliberately left out, such as transport modes that are not legally permitted in the Netherlands, like Segways or e-scooters. All included literature had to be related to travel behavior or mode choice; studies focusing on other types of incentives were excluded. As a result, topics such as self-selection of residential location were not considered. Additionally, literature specifically related to the COVID-19 period and its effects on travel behavior was excluded, as the goal was to examine the current state of mobility, not temporary changes caused by the pandemic.

### Inclusion criteria
In the literature search, only open access articles were considered. Filtering out articles that later require paid access is unnecessary time-consuming and inefficient. In addition to commuting trips, studies related to travel to universities were also included. This was relevant because the research is based on an academic hospital, which attracts many students. Furthermore, many doctors are still in training and therefore attend educational programs on site. Finally, only English-language articles were considered, as other languages (except Dutch) are not accessible to the researcher.

### Exceptions
Due to the complex combination of topics, it was sometimes necessary to conduct additional research beyond the articles initially selected based on the predefined search terms. In addition, snowballing was used to identify other interesting and relevant articles. Table A.1 provides an overview of the articles identified through this method. For snowballing, the focus was placed less on the publication date and more on the relevance and added value of the article in relation to the subject. Based on these criteria, some articles were included in the literature review, even if they did not meet the original search criteria. This approach was not only applied to snowballing but also to other articles that proved relevant during the review process.

The timespan criterion was also not applied to articles related to methodologies. Many methodological foundations are found in older publications or were developed in earlier research. These methodologies are often still relevant today, as they have been refined and are now more widely used.

**Table A.1:** Snowballing in literature

| Initial source | Snowballed source |
|---|---|
| (Nichols et al. 2024) | (Chen et al. 2008) |
| (Marquez et al. 2024) | (Molin & Arentze 2013) |
| (Rybels et al. 2024) | (Hansen & Nielsen 2014) |
| (Fraboni et al. 2022) | (Felix et al. 2019) |
| (van der Meulen 2024) | (Parmar et al. 2023) |
| (van der Meulen 2024) | (Molin et al. 2016) |
| (Adamidis et al. 2025) | (Zeiske et al. 2021) |
| (Gentiletti et al. 2025) | (Gentiletti et al. 2019) |

# B

# Attribute calculations

## B.1. Purchase plan cost

The attribute levels for the purchase cost of the e-bike are based on the reimbursement scheme provided by the academic hospital's bicycle plan. These calculations are derived from different levels of reimbursement, resulting in varying monthly costs. The detailed calculations for each type of reimbursement for e-bikes and the city bike are presented in Table B.1.

**Table B.1:** Monthly cost per reimbursement level for e-bike

| Reimbursement | Personal contribution | Personal* contribution | Pay-off reimbursement* | Tax benefit* | Total cost* |
|---|---|---|---|---|---|
| **E-bike options** | | | | | |
| €1500 | €1075 | €30 | €41 | €16 | €55 |
| €2000 | €575 | €16 | 55 | €21 | €50 |
| €2500 | €75 | €2 | €69 | €26 | €45 |
| **City bike** | | | | | |
| €824 | €0 | €0 | €23 | €9 | €14 |

*Per month

## B.2. Travel time

Four points on the map were selected, located to the north, west, south, and east of the hospital. This selection was made three times for all experiments, with each point placed at distances of 3.25 km, 11.5 km, and 22.5 km from the hospital, based on the average distances used in the experiments. For each of these points, travel times were estimated for two modes of transportation (Google Maps n.d.).

For both car and public transport, travel times were not calculated using fixed speeds but were instead taken directly from Google Maps. This approach was chosen because travel speed varies significantly between different public transport modes (e.g., tram, bus, train), and car speed also depends heavily on the type of road and surrounding traffic conditions. Google Maps accounts for these factors and reflects average travel speeds in the area surrounding the hospital, because of this more realistic travel time estimates could be obtained.

**Table B.2:** Experiment 1: Travel times

| Region | Car | PT |
|---|---|---|
| N | 6 | 21 |
| E | 9 | 11 |
| S | 12 | 22 |
| W | 8 | 22 |
| **Average** | **9** | **19** |

**Table B.3:** Experiment 2: Travel times

| Region | Car | PT |
|---|---|---|
| N | 14 | 37 |
| E | 16 | 40 |
| S | 12 | 39 |
| W | 13 | 31 |
| **Average** | **14** | **37** |

**Table B.4:** Experiment 3: Travel times

| Region | Car | PT |
|---|---|---|
| N | 23 | 57 |
| E | 20 | 54 |
| S | 18 | 55 |
| W | 23 | 58 |
| **Average** | **21** | **56** |

# B.3. Fuel cost

Fuel costs are calculated based on the average prices of electricity, petrol, and diesel. Each fuel type has its own price, as well as a specific share in the current vehicle fleet in the Netherlands. Both the price and the share of each fuel type are used to calculate the average fuel cost.

**Table B.5:** Distribution cars

| Fuel | % |
|---|---|
| Electric | 17,8 |
| Diesel | 7,7 |
| Petrol | 74,5 |

**Table B.6:** Price per 100 km

| Fuel | € |
|---|---|
| Electric | 6,91 |
| Diesel | 9,29 |
| Petrol | 10,82 |

**Table B.7:** Prices per experiment

| | E1 | E2 | E3 |
|---|---|---|---|
| Electric | €0,26 | €0,78 | €1,55 |
| Diesel | €0,35 | €1,05 | €2,09 |
| Petrol | €0,41 | €1,22 | €2,44 |
| Average | €0,38 | €1,13 | €2,25 |
| | €0,75 | €2,25 | €4,50 |

# C

# Experiment development

## C.1. Ngene syntax and priors

Table C.1 shows the priors used for all attributes. The priors used in this research are based on several previous studies that included similar alternatives. An important source of input was the earlier research conducted by van der Meulen 2024, Molin and Arentze 2013 and Molin and Kroesen 2023. However, not all priors could be directly applied, as some differed in terms of attribute levels or the way specific aspects were handled in those studies.

Furthermore, since it could be of value to test for non-linearity, additional priors had to be introduced. No specific priors were available to represent potential non-linear effects at the attribute levels used in this study. Therefore, these priors were estimated based on logical assumptions and the expected direction of the effects.

There was also no directly applicable prior available for the specific combination of bicycle facilities included in this experiment. As a result, a combination of findings from different studies, each based on varying facility configurations, was used to estimate a suitable prior.

All parameters, except the constants are dummy coded, meaning that the priors correspond to the coding of the dummy variables. In Ngene, the coding used is (2, 1, 0), for example to represent delay levels of 20, 10, and 0 minutes. The reference level is placed last, and the prior for this level is not estimated, so it is not included in the syntax. The priors apply only to the other two levels.

**Listing C.1:** Ngene Syntax

```
design
;alts = BIKE, EBIKE, CURRENT_MODE
;rows = 9
;eff = (mnl, d)

;cond:
if(BIKE.FAC = 1, EBIKE.FAC = 1),
if(BIKE.FAC = 2, EBIKE.FAC = 2),
if(BIKE.FAC = 0, EBIKE.FAC = 0)

;model:
U(BIKE) = FAC_citybike.dummy[0.40|0.30] * FAC [2,1,0]
+ ASC_BIKE [0.75]

/
U(EBIKE) = cost_ebike.dummy [-0.62|-0.55] * COST_E [55,50,45]
+ FAC_ebike.dummy [0.76|0.39] * FAC
+ ASC_EBIKE [1.3]

/
U(CURRENT_MODE) = time_park.dummy [-0.79|-0.55] * T_PARK [20,15,10]
+ cost_park.dummy [-1.25|-0.75] * C_PARK [7,5,3]
+ delay_car/pt.dummy[-0.84|-0.28] * DELAY [20,10,0]
$
```

**Table C.1:** Attribute definitions and priors

| Attribute | Meaning | Alternative | Prior | Source |
|---|---|---|---|---|
| COST_E | Monthly cost e-bike | E-bike | -0.62 \| 0.55 | (van der Meulen 2024) |
| C_PARK | Parking cost per day | Car | -1.25 \| -0.75 | (Molin & Arentze 2013) |
| T_PARK | Time to find parking spot | Car | -0.79 \| -0.55 | (Molin & Arentze 2013) |
| DELAY | Delay car and PT | Car/PT | -0.84 \| -0.28 | (Molin & Kroesen 2023) |
| FAC | The bicycle facilities | Bike | 0.40 \| 0.30 | (Kaczynski et al. 2010) (Willson 1992) (Heinen & Maat 2012) |
| FAC | The bicycle facilities | E-bike | 0.76 \| 0.39 | (Casier & Witlox 2022) |
| ASC_citybike | Constant for bike | Bike | 0.75 | (Molin & Arentze 2013) |
| ASC_e-bike | Constant for e-bike | E-bike | 1.3 | (Molin & Kroesen 2023) |

**Table C.2:** Design of choice sets

| Choice | FAC_citybike | COST_E | FAC_e-bike | T_PARK | C_PARK | DELAY | WEATHER1 | WEATHER2 |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 45 | 0 | 20 | 3 | 0 | 0 | 1 |
| 2 | 2 | 50 | 2 | 15 | 7 | 0 | 1 | 0 |
| 3 | 2 | 45 | 2 | 10 | 3 | 10 | 0 | 1 |
| 4 | 0 | 55 | 0 | 10 | 7 | 20 | 1 | 0 |
| 5 | 1 | 55 | 1 | 20 | 7 | 10 | 0 | 1 |
| 6 | 2 | 55 | 2 | 20 | 5 | 20 | 1 | 0 |
| 7 | 0 | 50 | 0 | 15 | 5 | 10 | 0 | 1 |
| 8 | 1 | 50 | 1 | 15 | 3 | 20 | 1 | 0 |
| 9 | 1 | 45 | 1 | 10 | 5 | 0 | 0 | 1 |

### C.1.1. Choice set results

**Table C.3:** MNL efficiency measures

Part 1: Summary Statistics

| Measure | Value |
|---|---|
| D error | 9.361082 |
| A error | 19.31295 |
| B estimate | 22.641813 |
| S estimate | 1001.067573 |

Part 2: Attribute priors and estimates

| Variable | Fixed prior | Sp est | Sp t-ratio |
|---|---|---|---|
| FAC_citybike(d0) | 0.4 | 609.37087 | 0.079399 |
| FAC_citybike(d1) | 0.3 | 885.701401 | 0.065859 |
| COST_E(d0) | -0.62 | 29.809815 | 0.358985 |
| COST_E(d1) | -0.55 | 38.246636 | 0.316927 |
| FAC_e-bike(d0) | 0.76 | 165.58121 | 0.152318 |
| FAC_e-bike(d1) | 0.39 | 516.872363 | 0.086211 |
| T_PARK(d0) | -0.79 | 157.36638 | 0.156243 |
| T_PARK(d1) | -0.55 | 247.632789 | 0.124552 |
| C_PARK(d0) | -1.25 | 56.326865 | 0.261155 |
| C_PARK(d1) | -0.75 | 138.674705 | 0.166440 |
| DELAY(d0) | -0.84 | 139.164373 | 0.166147 |
| DELAY(d1) | -0.28 | 1001.067573 | 0.061948 |

# D
# Overview survey

## D.1. Survey questions

In this section are all the question in the survey given with the possible answers and their coding. Question 7 is coded in three different ways because, for each transport mode such as city bike, e-bike, and car or motorbike, it is important to determine whether the respondent has it in their possession.

1. Which mode of transport do you usually use to arrive at the Science Park?
2. What distance do you travel on a one-way trip to your workplace?
3. What is your gender?
4. At what time do you normally arrive at work?
5. Are you in possession of the following modes of transport?
6. Are you familiar with the bike plan the UMC Utrecht offers?
7. What is your function family?
8. What shifts do you work?

### D.1.1. Answer coding

**Table D.1:** Coding q1

| Answer | Code |
|---|---|
| City bike | 0 |
| E-bike | 1 |
| Public transport | 2 |
| Car/motor | 3 |
| Walking | 4 |
| Other | 5 |

**Table D.2:** Coding q2

| Answer | Code |
|---|---|
| Until 7.5 km | 0 |
| 7.5 until 15 km | 1 |
| 15.1 until 30 km | 2 |
| More than 30 km | 3 |

**Table D.3:** Coding q3

| Answer | Code |
|---|---|
| Woman | 0 |
| Man | 1 |
| Non-binary | 2 |
| Prefer not to say | 3 |

**Table D.4:** Coding q4

| Answer | Code |
|---|---|
| Before 07.00 | 0 |
| 07.00-08.00 | 1 |
| 08.00-09.00 | 2 |
| 09.00-10.00 | 3 |
| Later then 10.00 | 4 |

**Table D.5:** Coding q5

| Answer | | Code |
|---|---|---|
| Car/Motor | No | 0 |
| | Yes | 1 |
| E-bike | No | 0 |
| | Yes | 1 |
| City bike | No | 0 |
| | Yes | 1 |

**Table D.6:** Coding q6

| Answer | Code |
|---|---|
| Yes, fully familiar | 0 |
| Yes, kind of familiar | 1 |
| Yes, I have used it | 2 |
| Yes, I'm planning on using it | 3 |
| No, I'm not familiar | 4 |

**Table D.7:** Coding q8

| Answer | Code |
|---|---|
| Analytical staff | 0 |
| Medical residents and junior doctors | 1 |
| Facility staff | 2 |
| In training | 3 |
| Clinical (co-)treatment | 4 |
| Clinical support | 5 |
| Management | 6 |
| Medical specialists | 7 |
| Staff, administration and secretarial | 8 |
| Nursing and care | 9 |
| Scientific support and education | 10 |

**Table D.8:** Coding q9

| Answer | Code |
|---|---|
| I do not work in shifts | 0 |
| Night, evening, weekend and on-call shift | 1 |
| Day shift | 2 |

**Table D.9:** Coding statements

| Answer | Code |
|---|---|
| Strongly disagree | 0 |
| Disagree | 1 |
| Do not disagree, do not agree | 2 |
| Agree | 3 |
| Fully agree | 4 |

## D.2. Living Lab questions

First of all, the respondents will be ask if they participated in the Living Lab, in case they answer yes here. Then they will be referred to all the Living Lab related questions. Furthermore is there branching in this part of the survey. The answer they give decided the next question they will be receiving. In case the respondent answers something bike related in question 2 then he or she will be sent to question 3 and 4.

**Q1:** Did you participate in the Living Lab Sustainable Travel?
☐ Yes ☐ No

**Q2:** Have you been traveling in a more sustainable way to the hospital since the ending of the Living Lab?
☐ Yes, more often by public transport
☐ Yes, more often by city bike
☐ Yes, more often by e-bike/speed pedelec
☐ Yes, more often a combination of public transport and bike
☐ No, I always traveled sustainably
☐ No, just as sustainable as before
☐ No, now more often by car/motorbike/scooter

**Q3:** How do you feel about using the bicycle as part of your commute to UMC Utrecht?
☐ Much better than expected
☐ Better than expected
☐ Exactly as expected
☐ Worse than expected
☐ Much worse than expected

**Q4:** What aspects of your bike commute exceeded/did not exceed, your expectations? (Multiple answers possible)
☐ Cost
☐ Flexibility
☐ Travel time
☐ Bike parking facilities
☐ Feels better for nature
☐ Health
☐ Comfort
☐ Weather

# E

# Attitude analyses

## E.1. Relationship between attitudes

### E.1.1. Correlation table

In Table E.1 are all the correlations between the statements given. Here it is shown that not all correlations are significant. Furthermore it can be seen that many correlation do not show a high value because they are lower then 0,2.

**Table E.1:** Correlations statememts

| **Statements** | | Safety | Health1 | Health2 | Sustainability1 | Sustainability2 | Delay |
|---|---|---|---|---|---|---|---|
| Safety | $r$ | 1 | -,116 | ,153 | ,266 | ,251 | -,046 |
| | Sig. | - | ,058 | ,012 | <,001 | <,001 | ,448 |
| Health1 | $r$ | -,116 | 1 | ,113 | -,142 | -,122 | ,083 |
| | Sig. | ,058 | - | ,065 | ,019 | ,045 | ,172 |
| Health2 | $r$ | ,153 | ,113 | 1 | ,182 | ,176 | ,179 |
| | Sig. | ,012 | ,065 | - | ,003 | ,004 | ,003 |
| Sustainability1 | $r$ | ,266 | -,142 | ,182 | 1 | ,422 | -,022 |
| | Sig. | <,001 | ,019 | ,003 | - | <,001 | ,717 |
| Sustainability2 | $r$ | ,251 | -,122 | ,176 | ,422 | 1 | -,055 |
| | Sig. | <,001 | ,045 | ,004 | <,001 | - | ,369 |
| Delay | $r$ | -,046 | ,083 | ,179 | -,022 | -,055 | 1 |
| | Sig. | ,448 | ,172 | ,003 | ,717 | ,369 | - |

$r$ = Pearson correlation. Significance 2-tailed.

### E.1.2. Principal Axis Factoring steps

This section outlines the steps taken during the Principal Axis Factoring (PAF) procedure. In the first run, a Direct Oblimin rotation was applied. It immediately became clear that three items did not meet the minimum threshold for communalities ($> 0.25$): namely, the items 'Safety', 'Health', and 'Delay'. For this reason, these items were removed from further analysis.

In the second run, it became apparent that the communalities for the item 'Activities' also fell below the acceptable threshold. Consequently, this item was also excluded from the analysis.

In the final run, two items remained, both of which met the minimum communality criterion. These items were both related to sustainability and therefore conceptually aligned. To determine the most appropriate rotation method, the analysis was rerun using Varimax rotation. Both the Direct Oblimin and Varimax rotations produced identical results, which is expected when only one factor is extracted.

**Table E.2:** Estimation run 1, Direct Oblimin

KMO and Bartlett's Test

| Test | | Value |
|---|---|---|
| KMO | | 0,629 |
| Bartlett | Chi-Square | 120,287 |
| | Df | 15 |
| | Sig. | <,001 |

Communalities

| Statement | Initial | Extraction |
|---|---|---|
| Safety | 0,111 | 0,177 |
| Health | 0,056 | 0,116 |
| Activity | 0,110 | 0,512 |
| Sustainability | 0,222 | 0,428 |
| Employer | 0,214 | 0,392 |
| Delay | 0,045 | 0,093 |

**Table E.3:** Estimation run 2, Direct Oblimin

KMO and Bartlett's Test

| Test | | Value |
|---|---|---|
| KMO | | 0,561 |
| Bartlett | Chi-Square | 64,831 |
| | df | 3 |
| | Sig. | <,001 |

Communialities

| Statement | Initial | Extraction |
|---|---|---|
| Activity | 0,045 | 0,076 |
| Sustainability | 0,190 | 0,430 |
| Employer | 0,189 | 0,415 |

**Table E.4:** Estimation run 3, Varimax and Direct Oblimin

KMO and Bartlett's Test

| Test | | Value |
|---|---|---|
| KMO | | 0,500 |
| Bartlett | Chi-Square | 52,589 |
| | df | 1 |
| | Sig. | <,001 |

Communalities

| Statement | Initial | Extraction |
|---|---|---|
| Sustainability | 0,178 | 0,422 |
| Employer | 0,178 | 0,422 |

Factor Matrix

| Statement | Factor 1 |
|---|---|
| Sustainability | 0,649 |
| Employer | 0,649 |

# E.2. Relationship between attitudes and sociodemographic

## E.2.1. Independent Sample T-test and One-Way ANOVA

For the Independent Sample T-test is the Levene's test used to test for equality of variances. If Levene's test is not significant, then equal variances can be assumed and proceeded with standard post hoc tests like Tukey's. If Levene's test is significant, it indicates that the group variances are not equal. After this, the equality of means can be assessed. If the test for mean differences is not significant, we cannot assume that there is a meaningful difference between the groups in relation to the statement.

For the ANOVA is the Games-Howell post hoc test used. Games-Howell does not assume equal variances or equal sample sizes, making it ideal when those assumptions are violated. It compares all possible pairs of group means and adjusts for differences in variability, helping us identify which groups are truly different. Significant variables show that it can be assumed that there are difference between these two groups.

Table E.5 shows that equal variances cannot be assumed between the participants of the Living Lab and those who did not participate, as Levene's test is significant. Furthermore, the test for equality of means is not significant ($p = 0{,}145$), which is higher than the 0,05 threshold. This means it cannot be concluded that there is a significant difference in how participants and non-participants of the Living Lab perceive sustainability.

**Table E.5:** T-Test sustainability and Living Lab

| | *Levene's Test for Equality* | | *T-Test for Equality of Means* | | |
|---|---|---|---|---|---|
| | **F** | **Sig.** | **Mean Difference** | **Std. Error** | **Sig.** |
| Equal variance assumed | 5,770 | 0,017 | 0,130 | 0,085 | 0,129 |
| Equal variance not assumed | | | 0,130 | 0,089 | 0,145 |

Table E.6 again shows a significant value for Levene's test, meaning that equal variances cannot be assumed. However, the test for equality of means is highly significant, indicating that there is a clear difference in how women experience safety compared to men.

**Table E.6:** T-Test safety and gender

| | *Levene's Test for Equality* | | *T-Test for Equality of Means* | | |
|---|---|---|---|---|---|
| | **F** | **Sig.** | **Mean Difference** | **Std. Error** | **Sig.** |
| Equal variance assumed | 5,440 | 0,020 | -0,325 | 0,106 | 0,002 |
| Equal variance not assumed | | | -0,325 | 0,096 | $<$0,001 |

Table E.8 show different relation between the groups. A significant difference was found between the bike alternatives and car users. This means we can state with confidence that people who commute by car experience delays more often than those who use a bike. Another difference is seen between the public transport users and city bike users as this difference is also significant, meaning that people using public transport relatively experience more delays.

**Table E.7:** ANOVA mode and delay

| Mode 1 | Mode 2 | Mean difference | Std. Error | Sig. |
|---|---|---|---|---|
| City bike | E-bike | -0,154 | 0,222 | 0,900 |
| | PT | -0,534 | 0,188 | 0,027 |
| | Car | -0,926 | 0,213 | <0,001 |
| E-bike | City bike | 0,154 | 0,222 | 0,900 |
| | PT | -0,380 | 0,192 | 0,202 |
| | Car | -0,772 | 0,216 | 0,003 |
| PT | City bike | 0,534 | 0,188 | 0,027 |
| | E-bike | 0,380 | 0,192 | 0,202 |
| | Car | -0,392 | 0,181 | 0,140 |
| Car | City bike | 0,926 | 0,213 | <0,001 |
| | E-bike | 0,772 | 0,216 | 0,003 |
| | PT | 0,392 | 0,181 | 0,140 |

Table E.8 shows that many variables are not statistically significant, indicating no meaningful differences between most groups. However there is a significant difference found between people who travel by city bike and people who travel by car. As the ones on the city bike are presumed to be more sustainably focused.

**Table E.8:** ANOVA sustainability and mode

| Mode 1 | Mode 2 | Mean difference | Std. Error | Sig. |
|---|---|---|---|---|
| City bike | E-bike | 0,217 | 0,127 | 0,325 |
| | PT | 0,236 | 0,107 | 0,127 |
| | Car | 0,469 | 0,131 | <0,003 |
| E-bike | City bike | -0,217 | 0,127 | 0,325 |
| | PT | 0,019 | 0,113 | 0,998 |
| | Car | 0,252 | 135 | 0.250 |
| PT | City bike | -0,236 | 0,107 | 0,127 |
| | E-bike | -0,019 | 0,113 | 0,998 |
| | Car | 0,234 | 0,116 | 0,192 |
| Car | City bike | -0,469 | 0,131 | <0,003 |
| | E-bike | -0,252 | 135 | 0.250 |
| | PT | -0,234 | 0,116 | 0,192 |

# F

# Model estimates

## F.1. Additional models

### F.1.1. Nested Logit Model

**Table F.1:** Estimation results NL

| | | | | |
|---|---|---|---|---|
| Sample Size: | 1449 | | $\rho^2$ | 0,08 |
| Parameters | 12 | | AIC: | 2960,44 |
| Final Log Likelihood: | -1468,22 | | BIC: | 3023,79 |
| | **Value** | **Rob. S. E.** | **Rob. t-test** | **Rob. p-value** |
| *Alternative Specific Constants* | | | | |
| ASC_e-bike | -0,22 | 0,21 | -1,02 | 0,31 |
| ASC3_car | 0,56 | 0,54 | 1,05 | 0,30 |
| ASC3_pt | 0,94 | 0,27 | 3,44 | 0,00 |
| *Parameters* | | | | |
| COST_E | 0,00 | 0,00 | 1,00 | 0,32* |
| C_PARK | -0,07 | 0,05 | -1,21 | 0,22* |
| DELAY | -0,03 | 0,01 | -3,24 | 0,00 |
| FAC | 0,06 | 0,08 | 0,83 | 0,41* |
| T_PARK | -0,01 | 0,02 | -0,37 | 0,71* |
| *Context Parameters* | | | | |
| WEATHER_e-bike | 0,09 | 0,08 | 1,03 | 0,30* |
| WEATHER_car | -1,65 | 0,21 | -7,98 | 0,00 |
| WEATHER_pt | -1,76 | 0,18 | -9,53 | 0,00 |
| *Nest Parameter* | | | | |
| MU_BIKE | 3,01 | 3,05 | 0,99 | 0,32* |

* Not statistically significant for 95%

#### Likelihood Ratio Test

To compare the model fit of the NL model and the MNL model, a LRT was performed. This test assesses whether the added complexity of the NL model significantly improves the model fit compared to the simpler MNL model. The LRT value was calculated as 0,18. With one additional degree of freedom, the critical chi-square value at a 0,05 significance level is 3.84 (Turney 2023). Since the calculated value (0,18) is far below the critical threshold, the improvement in fit is not statistically significant. Therefore, the simpler MNL model is preferred over the more complex NL model.

$$LR = -2 \cdot \ (LL_{MNL} - LL_{NL})$$
$$LR = -2 \cdot (1468,31 - 1468,22) = 0,18$$

## F.1.2. Bike model

**Table F.2:** Estimation results bikes

| | | | | |
|---|---|---|---|---|
| Sample Size: | 1251 | | $\rho^2$ | 0,04 |
| Parameters | 4 | | AIC: | 1672,74 |
| Final Log Likelihood: | -832,37 | | BIC: | 1693,27 |
| | **Value** | **Rob. S. E.** | **Rob. t-test** | **Rob. p-value** |
| *Alternative Specific Constant* | | | | |
| ASC_e-bike | 1,14 | 0,73 | 1,56 | 0,12* |
| *Parameters* | | | | |
| COST_E | -0,01 | 0,01 | -0,74 | 0,46* |
| FAC | 0,00 | 0,00 | 0,04 | 0,97* |
| *Context Parameters* | | | | |
| WEATHER_e-bike | -0,28 | 0,12 | -2,44 | 0,02 |

* Not statistically significant for 95%

## F.1.3. MNL model comparison without non-traders

**Table F.3:** Model fit comparison MNL model with and without non-traders

| **Model** | **Parameters** | **Sample size** | **LL** | $\rho^2$ | **AIC** | **BIC** |
|---|---|---|---|---|---|---|
| Full MNL | 11 | 1449 | -1468,31 | 0,08 | 2958,62 | 3016,68 |
| MNL minus non-traders | 11 | 702 | -586,67 | 0,24 | 1195,43 | 1245,44 |

**Table F.4:** Comparison MNL model with and without non-traders

| | *MNL model* | | *MNL* | *- non-traders* |
|---|---|---|---|---|
| **Parameter** | **Value** | **Rob. t-test** | **Value** | **Rob. t-test** |
| *Alternative Specific Constants* | | | | |
| ASC_e-bike | -0,52 | -0,67* | 0,75 | 0,62* |
| ASC3_car | 0,97 | 1,91 | 2,68 | 3,41 |
| ASC3_pt | 1,38 | 8,52 | 2,73 | 9,80 |
| *Parameters* | | | | |
| COST_E | 0,01 | 0,67* | 0,01 | 0,23* |
| C_PARK | -0,06 | -1,08* | -0,04 | -0,41* |
| DELAY | -0,02 | -3,00 | -0,03 | -2,20 |
| FAC | 0,06 | 0,83* | -0,01 | -0,11* |
| T_PARK | -0,01 | -0,32* | -0,01 | -0,35* |
| *Context Parameter* | | | | |
| WEATHER_e-bike | 0,25 | 1,92 | -0,21 | -0,83* |
| WEATHER_car | -1,56 | -7,27 | -3,20 | -8,49 |
| WEATHER_pt | -1,67 | -9,09 | -3,06 | -9,58 |

* Not significant for 95%

### F.1.4. Car and PT model comparison without non-traders

**Table F.5:** Model fit comparison car and pt model with and without non-traders

| Model | Parameters | Sample size | LL | $\rho^2$ | AIC | BIC |
|---|---|---|---|---|---|---|
| Car and pt | 11 | 657 | -509,04 | 0,30 | 1040,07 | 1089,44 |
| MNL minus non-traders | 11 | 504 | -336,07 | 0,34 | 754,15 | 800,59 |

**Table F.6:** Comparison car/pt model with and without non-traders

| | *Car/PT model* | | *Car/PT - non-traders* | |
|---|---|---|---|---|
| **Parameter** | **Value** | **Rob. t-test** | **Value** | **Rob. t-test** |
| *Alternative Specific Constants* | | | | |
| ASC_e-bike | 2,18 | 1,58* | 2,94 | 1,85* |
| ASC_car | 3,81 | 5,07 | 4,40 | 4,58 |
| ASC_pt | 3,76 | 9,93 | 4,25 | 9,45 |
| *Parameters* | | | | |
| COST_E | -0,01 | -0,45* | -0,02 | -0,56* |
| C_PARK | -0,06 | -0,73* | -0,09 | -0,87* |
| DELAY | -0,03 | -2,27 | -0,05 | -2,81 |
| FAC | 0,03 | 0,31* | -0,05 | -0,36* |
| T_PARK | -0,02 | -0,55* | -0,03 | -0,74* |
| *Context Parameter* | | | | |
| WEATHER_e-bike | -0,25 | -5,88 | -0,60 | -1,39* |
| WEATHER_car | -2,14 | -0,69* | -3,44 | -6,89 |
| WEATHER_pt | -2,50 | -5,86 | -3,50 | -7,02 |

* Not significant for 95%

## F.2. Utilities and Probabilities

The utilities for the alternatives are calculated for both blocks separately. However, the choice probabilities for each alternative are calculated based on the average of both blocks combined. The results are split into two groups, based on the difference between respondents who were shown the car alternative and those who were shown the public transport alternative. The highest probabilities per alternative are highlighted in green. These all show the same patterns for all models, where e-bike always has the highest portability of being chosen in case the car was shown and public transport when that was shown.

**Table F.7:** Utilities MNL model - block 1 and 2

| CS | City bike | E-bike | Car | PT |
|---|---|---|---|---|
| 1 | 0.00 | -0.07 | 0.59 | 1.38 |
| 2 | 0.12 | 0.35 | -1.16 | -0.29 |
| 3 | 0.12 | 0.05 | 0.49 | 1.18 |
| 4 | 0.00 | 0.28 | -1.51 | -0.69 |
| 5 | 0.06 | 0.09 | 0.15 | 1.18 |
| 6 | 0.12 | 0.40 | -1.49 | -0.69 |
| 7 | 0.00 | -0.02 | 0.32 | 1.18 |
| 8 | 0.06 | 0.29 | -1.32 | -0.69 |
| 9 | 0.06 | -0.01 | 0.57 | 1.38 |

| CS | City bike | E-bike | Car | PT |
|---|---|---|---|---|
| 1 | 0.00 | 0.18 | -0.97 | -0.29 |
| 2 | 0.12 | 0.10 | 0.40 | 1.38 |
| 3 | 0.12 | 0.30 | -1.07 | -0.49 |
| 4 | 0.00 | 0.03 | 0.05 | 0.98 |
| 5 | 0.06 | 0.34 | -1.41 | -0.49 |
| 6 | 0.12 | 0.15 | 0.07 | 0.98 |
| 7 | 0.00 | 0.23 | -1.24 | -0.49 |
| 8 | 0.06 | 0.04 | 0.24 | 0.98 |
| 9 | 0.06 | 0.24 | -0.99 | -0.29 |

**Table F.8:** Probabilities MNL model

| CS | City bike | E-bike | Car |
|---|---|---|---|
| 1 | 0.33 | 0.36 | 0.31 |
| 2 | 0.35 | 0.40 | 0.26 |
| 3 | 0.35 | 0.38 | 0.27 |
| 4 | 0.36 | 0.43 | 0.21 |
| 5 | 0.36 | 0.42 | 0.22 |
| 6 | 0.37 | 0.44 | 0.20 |
| 7 | 0.35 | 0.39 | 0.26 |
| 8 | 0.36 | 0.40 | 0.24 |
| 9 | 0.34 | 0.36 | 0.30 |
| **Average** | 0,35 | 0,40 | 0,25 |

| CS | City bike | E-bike | PT |
|---|---|---|---|
| 1 | 0.25 | 0.28 | 0.46 |
| 2 | 0.26 | 0.30 | 0.43 |
| 3 | 0.29 | 0.32 | 0.40 |
| 4 | 0.28 | 0.34 | 0.37 |
| 5 | 0.27 | 0.33 | 0.40 |
| 6 | 0.29 | 0.36 | 0.35 |
| 7 | 0.27 | 0.31 | 0.42 |
| 8 | 0.29 | 0.34 | 0.37 |
| 9 | 0.26 | 0.29 | 0.45 |
| **Average** | 0,28 | 0,32 | 0,41 |

# F.3. Interaction effects

Several interaction where tested in the model to gain more insight into the specific attributes and their possible relations. However not all interactions are used as not all increased model fit or proved to be statistically significant. This is a list of interaction between attributes which where tested but not taken into account in the final model:

- Facilities and purchase cost an the e-bike
- Weather and walking and parking time
- Parking cost and walking and parking time
- Parking cost and the cost for an e-bike.
- Parking cost and weather

Aside from the interaction between attributes where also interaction tested between attributes and attitudes. The following two interactions proved not the increase the model fit and where not statistically significant.

- The purchase cost of an e-bike and the "Activity" statement
- The weather and the "Sustainability" statement

Interaction between attributes an sociodemographic characteristics where also tested. The relationship below did lead to an increased model dit or statistical significant results:

- The purchase cost of an e-bike and the the knowledge a respondent had about the bike plan (BP)
- The cost for parking and the shift a respondent works
- The purchase cost of an e-bike and the current mode of a respondent
-

# G

# Python code

## G.1. MNL model

The Python code used for the estimation of models 4 through 6 is identical to that of the Total MNL model. The only difference lies in the input, as a different CSV file is used for each model. The code itself remains unchanged. The same applies to model 3, which focuses solely on the two bicycle alternatives. However, additionally are the utility functions and related code for the car and public transport alternatives excluded.

**Listing G.1:** Python syntax MNL

```
import biogeme
from biogeme import models
from biogeme.expressions import Beta, Variable, log, exp
import biogeme.database as db
import biogeme.biogeme as bio
from biogeme.nests import OneNestForNestedLogit, NestsForNestedLogit

# General python packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pathlib import Path

pd.set_option('display.max_columns', None)

# Path to  CSV file
file_path = 'Total.csv'
df = pd.read_csv(file_path, delimiter=';')

biodata = db.Database('Total MNL', df)

# Variabels
FAC = Variable('FAC')
COST_E = Variable('COST_E')
T_PARK = Variable('T_PARK')
C_PARK = Variable('C_PARK')
DELAY = Variable('DELAY')
WEATHER = Variable('WEATHER')
CHOICE = Variable('CHOICE1')
AVAIL_CAR = Variable('AVAIL_CAR')
AVAIL_OV = Variable('AVAIL_OV')

# Parameters
B_FAC = Beta('B_FAC', 0, None, None, 0)
B_COST_E = Beta('B_COST_E', 0, None, None, 0)
B_T_PARK = Beta('B_T_PARK', 0, None, None, 0)
B_C_PARK = Beta('B_C_PARK', 0, None, None, 0)
B_DELAY = Beta('B_DELAY', 0, None, None, 0)
ASC2 = Beta('ASC2', 0, None, None, 0)
ASC3_CAR = Beta('ASC3_CAR', 0, None, None, 0)
```

```
ASC3_OV = Beta('ASC3_OV', 0, None, None, 0)
B_WEATHER2 = Beta('B_WEATHER2', 0, None, None, 0)
B_WEATHERcar = Beta('B_WEATHERcar', 0, None, None, 0)
B_WEATHERpt = Beta('B_WEATHERpt', 0, None, None, 0)

# Utility functies
V1 =  B_FAC * FAC
V2 = ASC2 + B_FAC * FAC + B_COST_E * COST_E + B_WEATHER2 * WEATHER

# Alternatief 3 afhankelijk van availability
V3_CAR = ASC3_CAR + B_T_PARK * T_PARK + B_C_PARK * C_PARK + B_DELAY * DELAY + B_WEATHERcar *
    WEATHER
V3_OV = ASC3_OV + B_DELAY * DELAY + B_WEATHERpt * WEATHER
V3 = AVAIL_CAR * V3_CAR + AVAIL_OV * V3_OV

# Utilities with availability based on alternative 3
V = {1: V1, 2: V2, 3: V3}
av = {1: 1, 2: 1, 3: AVAIL_CAR + AVAIL_OV}

def estimate_combined_mnl(V1, V2, V3, CHOICE, AVAIL_CAR, AVAIL_OV, database, model_name):
    import biogeme.biogeme as bio
    import biogeme.models as models
    from biogeme.expressions import log

    # Define utility functions
    V = {1: V1, 2: V2, 3: V3}

    # Conditional availability for alternative 3
    av = {1: 1, 2: 1, 3: AVAIL_CAR + AVAIL_OV}

    # Log-likelihood function
    prob = models.logit(V, av, CHOICE)
    logprob = log(prob)

    # Setup the Biogeme model
    biogeme = bio.BIOGEME(database, logprob)
    biogeme.modelName = model_name

    # Avoid saving files
    biogeme.generate_pickle = False
    biogeme.generate_html = False
    biogeme.save_iterations = False

    # Calculate null log-likelihood for model diagnostics
    biogeme.calculate_null_loglikelihood(av)

    # Estimate the model
    results = biogeme.estimate()

    return results

results = estimate_combined_mnl(V1, V2, V3, CHOICE, AVAIL_CAR, AVAIL_OV, biodata, "Total MNL
    ")

# Print results
print(results.short_summary())
print(results.get_estimated_parameters())
```

## G.2. NL model

**Listing G.2:** Python syntax NL

```
import biogeme
from biogeme import models
from biogeme.expressions import Beta, Variable, log, exp
import biogeme.database as db
import biogeme.biogeme as bio
from biogeme.nests import OneNestForNestedLogit, NestsForNestedLogit

# General python packages
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pathlib import Path

# Pandas setting to show all columns when displaying a pandas dataframe
pd.set_option('display.max_columns', None)

# Path to your CSV file (make sure the path is correct if not in the same directory)
file_path = 'Total.csv'

# Load the CSV file using the correct delimiter (semicolon)
df = pd.read_csv(file_path, delimiter=';')

biodata = db.Database('Total nested', df)

# Define variables
FAC = Variable('FAC')
COST_E = Variable('COST_E')
T_PARK = Variable('T_PARK')
C_PARK = Variable('C_PARK')
DELAY = Variable('DELAY')
WEATHER = Variable('WEATHER')
CHOICE = Variable('CHOICE1')
AVAIL_CAR = Variable('AVAIL_CAR')
AVAIL_OV = Variable('AVAIL_OV')

# Parameters
B_FAC = Beta('B_FAC', 0, None, None, 0)
B_COST_E = Beta('B_COST_E', 0, None, None, 0)
B_T_PARK = Beta('B_T_PARK', 0, None, None, 0)
B_C_PARK = Beta('B_C_PARK', 0, None, None, 0)
B_DELAY = Beta('B_DELAY', 0, None, None, 0)

# Only ASC2 and ASC3 are estimated - alt 1 is reference
ASC2 = Beta('ASC2', 0, None, None, 0)
ASC3_CAR = Beta('ASC3_CAR', 0, None, None, 0)
ASC3_OV = Beta('ASC3_OV', 0, None, None, 0)

B_WEATHER2 = Beta('B_WEATHER2', 0, None, None, 0)
B_WEATHERcar = Beta('B_WEATHERcar', 0, None, None, 0)
B_WEATHERpt = Beta('B_WEATHERpt', 0, None, None, 0)

# Nesting parameters
MU_BIKE = Beta('MU_BIKE', 1.5, 1.0, 10.0, 0)  # Estimated
MU_MOTORIZED = 1.0  # Fixed for identification

# Define utility functions
V1 =  B_FAC * FAC
V2 = ASC2 + B_FAC * FAC + B_COST_E * COST_E + B_WEATHER2 * WEATHER

# Third alternative based on availability
V3_CAR = ASC3_CAR + B_T_PARK * T_PARK + B_C_PARK * C_PARK + B_DELAY * DELAY + B_WEATHERcar *
    WEATHER
V3_OV = ASC3_OV + B_DELAY * DELAY + B_WEATHERpt * WEATHER
V3 = AVAIL_CAR * V3_CAR + AVAIL_OV * V3_OV

# Utility and availability
V = {1: V1, 2: V2, 3: V3}
av = {1: 1, 2: 1, 3: AVAIL_CAR + AVAIL_OV}

# Nest definitions
bike_nest = OneNestForNestedLogit(MU_BIKE, list_of_alternatives=[1, 2])
motorized_nest = OneNestForNestedLogit(MU_MOTORIZED, list_of_alternatives=[3])
nests = NestsForNestedLogit(choice_set=[1, 2, 3], tuple_of_nests=(bike_nest, motorized_nest))

# Define the model and log likelihood
prob = models.nested(V, av, nests, CHOICE)
logprob = log(prob)

# Estimate model using BIOGEME
```

```
biogeme = bio.BIOGEME(biodata, logprob)
biogeme.modelName = "Total nested"

# Disable output file generation
biogeme.generate_pickle = False
biogeme.generate_html = False
biogeme.save_iterations = False

# Calculate null log-likelihood for diagnostics
biogeme.calculate_null_loglikelihood(av)

# Estimate and print results
results = biogeme.estimate()
print(results.short_summary())
print(results.get_estimated_parameters())
```

## G.3. Interaction model

**Listing G.3:** Python syntax Attitude interaction

```
# --- ALLE INTERACTIETERMEN SAMENGEVOEGD ---

# Stellingvariabelen
S2 = Variable('S2')
S6 = Variable('S6')
S4 = Variable('S4')
S5 = Variable('S5')
MODE = Variable('MODE')
GEN = Variable('GENDER')


# Interaction sociodemographics
DELAY_MODE0 = DELAY * (MODE == 0)
DELAY_MODE1 = DELAY * (MODE == 1)
DELAY_MODE2 = DELAY * (MODE == 2)
DELAY_MODE3 = DELAY * (MODE == 3)
C_PARK_GEN0 = C_PARK * (GEN == 0)
C_PARK_GEN1 = C_PARK * (GEN == 1)


# Interactievariabelen
DELAY_S6 = DELAY * S6
T_PARK_S2 = T_PARK * S2
C_PARK_S6 = C_PARK * S6
COST_E_S4 = COST_E * S4
DELAY_S5 = DELAY * S5
DELAY_WEATHER = DELAY * WEATHER

# Bijbehorende Beta-parameters
B_DELAY_S6 = Beta('B_DELAY_S6', 0, None, None, 0)
B_T_PARK_S2 = Beta('B_T_PARK_S2', 0, None, None, 0)
B_C_PARK_S6 = Beta('B_C_PARK_S6', 0, None, None, 0)
B_COST_E_S4 = Beta('B_COST_E_S4', 0, None, None, 0)
B_DELAY_S5 = Beta('B_DELAY_S5', 0, None, None, 0)
B_DELAY_WEATHER = Beta('B_DELAY_WEATHER', 0, None, None, 0)

# Parameters voor de interactietermen
B_DELAY_MODE0 = Beta('B_DELAY_MODE0', 0, None, None, 0)
B_DELAY_MODE1 = Beta('B_DELAY_MODE1', 0, None, None, 0)
B_DELAY_MODE2 = Beta('B_DELAY_MODE2', 0, None, None, 0)
B_DELAY_MODE3 = Beta('B_DELAY_MODE3', 0, None, None, 0)
B_C_PARK_GEN1 = Beta('B_C_PARK_GEN1', 0, None, None, 0)
B_C_PARK_GEN0 = Beta('B_C_PARK_GEN0', 0, None, None, 0)




# Utility functies met alle interactietermen
V1_all = B_FAC * FAC  \

```

```
V2_all = ASC2 + B_FAC * FAC + B_COST_E * COST_E + B_WEATHER2 * WEATHER + B_COST_E_S4 * COST_E_S4 \

V3_CAR_all = ASC3_CAR + B_T_PARK * T_PARK + B_C_PARK * C_PARK + B_DELAY * DELAY + B_WEATHERcar * WEATHER + \
             B_DELAY_S6 * DELAY_S6 + B_T_PARK_S2 * T_PARK_S2 + B_C_PARK_S6 * C_PARK_S6 + B_DELAY_S5 * DELAY_S5 + B_DELAY_WEATHER * DELAY_WEATHER \
            + B_DELAY_MODE0 * DELAY_MODE0 + B_DELAY_MODE1 * DELAY_MODE1 + B_DELAY_MODE2 * DELAY_MODE2 + B_DELAY_MODE3 * DELAY_MODE3 \
           + B_C_PARK_GEN0 * C_PARK_GEN0 + B_C_PARK_GEN1 * C_PARK_GEN1

V3_OV_all = ASC3_OV + B_DELAY * DELAY + B_WEATHERpt * WEATHER + \
            B_DELAY_S6 * DELAY_S6 + B_DELAY_WEATHER * DELAY_WEATHER \
 + B_DELAY_MODE0 * DELAY_MODE0 + B_DELAY_MODE1 * DELAY_MODE1 + B_DELAY_MODE2 * DELAY_MODE2 + B_DELAY_MODE3 * DELAY_MODE3

V3_all = AVAIL_CAR * V3_CAR_all + AVAIL_OV * V3_OV_all

# Modeldefinitie
V_all = {1: V1_all, 2: V2_all, 3: V3_all}
av_all = {1: 1, 2: 1, 3: AVAIL_CAR + AVAIL_OV}

prob_all = models.logit(V_all, av_all, CHOICE)
logprob_all = log(prob_all)

# Model bouwen en schatten
biogeme_all = bio.BIOGEME(biodata, logprob_all)
biogeme_all.modelName = "DCE_Alle_Interacties_Corrected"

# Voeg deze regel toe om null log-likelihood te laten berekenen
biogeme_all.calculate_null_loglikelihood(av_all)

# Model schatten
results_all = biogeme_all.estimate()

# Resultaten tonen
print(results_all.short_summary())
print(results_all.get_estimated_parameters())
```

## G.4. LCCM

### G.4.1. Class estimation

**Listing G.4:** Python syntax LCCM

```
# Load and clean data
df = pd.read_csv('Total.csv', delimiter=';')

# Convert necessary columns to numeric
for col in ['EXP', 'MODE', 'BIKE_PLAN', 'TIME', 'FUNC', 'SHIFT', 'S4', 'S6']:
    df[col] = pd.to_numeric(df[col], errors='coerce')

# Temporarily convert MODE and BIKE_PLAN to categorical to set custom reference levels
df['MODE'] = pd.Categorical(df['MODE'], categories=[5, 0, 1, 2, 3, 4], ordered=False)
df['BIKE_PLAN'] = pd.Categorical(df['BIKE_PLAN'], categories=[1, 0, 2, 3, 4], ordered=False)

# Create dummy variables (reference: mode_5 and bikeplan_1 will be dropped)
mode_dummies = pd.get_dummies(df['MODE'], prefix='mode', drop_first=True)
bikeplan_dummies = pd.get_dummies(df['BIKE_PLAN'], prefix='bikeplan', drop_first=True)

# Drop the original categorical columns and add dummy variables
df = df.drop(columns=['MODE', 'BIKE_PLAN'])
df = pd.concat([df, mode_dummies, bikeplan_dummies], axis=1)

# Ensure all data is numeric
df = df.astype({col: 'int32' for col in df.select_dtypes(include='bool').columns})

# Biogeme database
biodata = db.Database('LCCM_data', df)
available_columns = df.columns

```

```
# === VARIABLES ===
CHOICE = Variable('CHOICE1')
FAC = Variable('FAC')
COST_E = Variable('COST_E')
T_PARK = Variable('T_PARK')
C_PARK = Variable('C_PARK')
DELAY = Variable('DELAY')
WEATHER = Variable('WEATHER')
AVAIL_CAR = Variable('AVAIL_CAR')
AVAIL_OV = Variable('AVAIL_OV')
Distance = Variable('EXP')
S4 = Variable('S4')

# === PARAMETERS CLASS 1 ===
B_FAC_1 = Beta('B_FAC_1', 0, None, None, 0)
B_COST_E_1 = Beta('B_COST_E_1', 0, None, None, 0)
B_T_PARK_1 = Beta('B_T_PARK_1', 0, None, None, 0)
B_C_PARK_1 = Beta('B_C_PARK_1', 0, None, None, 0)
B_DELAY_1 = Beta('B_DELAY_1', 0, None, None, 0)
B_WEATHERebike_1 = Beta('B_WEATHERebike_1', 0, None, None, 0)
B_WEATHERcar_1 = Beta('B_WEATHERcar_1', 0, None, None, 0)
B_WEATHERpt_1 = Beta('B_WEATHERpt_1', 0, None, None, 0)
ASC2_1 = Beta('ASC2_1', 0, None, None, 0)
ASC3_CAR_1 = Beta('ASC3_CAR_1', 0, None, None, 0)
ASC3_OV_1 = Beta('ASC3_OV_1', 0, None, None, 0)

# === PARAMETERS CLASS 2 ===
B_FAC_2 = Beta('B_FAC_2', 0, None, None, 0)
B_COST_E_2 = Beta('B_COST_E_2', 0, None, None, 0)
B_T_PARK_2 = Beta('B_T_PARK_2', 0, None, None, 0)
B_C_PARK_2 = Beta('B_C_PARK_2', 0, None, None, 0)
B_DELAY_2 = Beta('B_DELAY_2', 0, None, None, 0)
B_WEATHERebike_2 = Beta('B_WEATHERebike_2', 0, None, None, 0)
B_WEATHERcar_2 = Beta('B_WEATHERcar_2', 0, None, None, 0)
B_WEATHERpt_2 = Beta('B_WEATHERpt_2', 0, None, None, 0)
ASC2_2 = Beta('ASC2_2', 0, None, None, 0)
ASC3_CAR_2 = Beta('ASC3_CAR_2', 0, None, None, 0)
ASC3_OV_2 = Beta('ASC3_OV_2', 0, None, None, 0)

# === PARAMETERS FOR CLASS 3 ===
B_FAC_3 = Beta('B_FAC_3', 0, None, None, 0)
B_COST_E_3 = Beta('B_COST_E_3', 0, None, None, 0)
B_T_PARK_3 = Beta('B_T_PARK_3', 0, None, None, 0)
B_C_PARK_3 = Beta('B_C_PARK_3', 0, None, None, 0)
B_DELAY_3 = Beta('B_DELAY_3', 0, None, None, 0)
B_WEATHERebike_3 = Beta('B_WEATHERebike_3', 0, None, None, 0)
B_WEATHERcar_3 = Beta('B_WEATHERcar_3', 0, None, None, 0)
B_WEATHERpt_3 = Beta('B_WEATHERpt_3', 0, None, None, 0)
ASC2_3 = Beta('ASC2_3', 0, None, None, 0)
ASC3_CAR_3 = Beta('ASC3_CAR_3', 0, None, None, 0)
ASC3_OV_3 = Beta('ASC3_OV_3', 0, None, None, 0)

# === CLASS MEMBERSHIP FUNCTION ===
CLASS_1_INTERCEPT = Beta('CLASS_1_INTERCEPT', 0, None, None, 0)
CLASS_1_DIST = Beta('CLASS_1_DIST', 0, None, None, 0)
CLASS_1_S4 = Beta('CLASS_1_S4', 0, None, None, 0)

classMembership1 = CLASS_1_INTERCEPT + CLASS_1_DIST * Distance + CLASS_1_S4 * S4

for i in [0, 1, 2, 3, 4]:
    varname = f'mode_{i}'
    if varname in available_columns:
        exec(f"{varname} = Variable('{varname}')")
        exec(f"B_MODE_{i} = Beta('B_MODE_{i}', 0, None, None, 0)")
        classMembership1 += eval(f"B_MODE_{i} * {varname}")

for i in [0, 2, 3, 4]:
    varname = f'bikeplan_{i}'
    if varname in available_columns:
        exec(f"{varname} = Variable('{varname}')")
        exec(f"B_BP_{i} = Beta('B_BP_{i}', 0, None, None, 0)")
```

```
        classMembership1 += eval(f"B_BP_{i} * {varname}")

# CLASS 2 MEMBERSHIP
CLASS_2_INTERCEPT = Beta('CLASS_2_INTERCEPT', 0, None, None, 0)
CLASS_2_DIST = Beta('CLASS_2_DIST', 0, None, None, 0)
CLASS_2_S4 = Beta('CLASS_2_S4', 0, None, None, 0)

classMembership2 = CLASS_2_INTERCEPT + CLASS_2_DIST * Distance + CLASS_2_S4 * S4

for i in [0, 1, 2, 3, 4]:
    varname = f'mode_{i}'
    if varname in available_columns:
        exec(f"B2_MODE_{i} = Beta('B2_MODE_{i}', 0, None, None, 0)")
        classMembership2 += eval(f"B2_MODE_{i} * {varname}")

for i in [0, 2, 3, 4]:
    varname = f'bikeplan_{i}'
    if varname in available_columns:
        exec(f"B2_BP_{i} = Beta('B2_BP_{i}', 0, None, None, 0)")
        classMembership2 += eval(f"B2_BP_{i} * {varname}")

# CLASS PROBABILITIES
denom = 1 + exp(classMembership1) + exp(classMembership2)
probClass1 = exp(classMembership1) / denom
probClass2 = exp(classMembership2) / denom
probClass3 = 1 - probClass1 - probClass2

# === UTILITIES ===
V1_1 = B_FAC_1 * FAC
V2_1 = ASC2_1 + B_FAC_1 * FAC + B_COST_E_1 * COST_E + B_WEATHERebike_1 * WEATHER
V3_CAR_1 = ASC3_CAR_1 + B_T_PARK_1 * T_PARK + B_C_PARK_1 * C_PARK + B_DELAY_1 * DELAY +
    B_WEATHERcar_1 * WEATHER
V3_OV_1 = ASC3_OV_1 + B_DELAY_1 * DELAY + B_WEATHERpt_1 * WEATHER
V3_1 = AVAIL_CAR * V3_CAR_1 + AVAIL_OV * V3_OV_1
V_1 = {1: V1_1, 2: V2_1, 3: V3_1}

V1_2 = B_FAC_2 * FAC
V2_2 = ASC2_2 + B_FAC_2 * FAC + B_COST_E_2 * COST_E + B_WEATHERebike_2 * WEATHER
V3_CAR_2 = ASC3_CAR_2 + B_T_PARK_2 * T_PARK + B_C_PARK_2 * C_PARK + B_DELAY_2 * DELAY +
    B_WEATHERcar_2 * WEATHER
V3_OV_2 = ASC3_OV_2 + B_DELAY_2 * DELAY + B_WEATHERpt_2 * WEATHER
V3_2 = AVAIL_CAR * V3_CAR_2 + AVAIL_OV * V3_OV_2
V_2 = {1: V1_2, 2: V2_2, 3: V3_2}

V1_3 = B_FAC_3 * FAC
V2_3 = ASC2_3 + B_FAC_3 * FAC + B_COST_E_3 * COST_E + B_WEATHERebike_3 * WEATHER
V3_CAR_3 = ASC3_CAR_3 + B_T_PARK_3 * T_PARK + B_C_PARK_3 * C_PARK + B_DELAY_3 * DELAY +
    B_WEATHERcar_3 * WEATHER
V3_OV_3 = ASC3_OV_3 + B_DELAY_3 * DELAY + B_WEATHERpt_3 * WEATHER
V3_3 = AVAIL_CAR * V3_CAR_3 + AVAIL_OV * V3_OV_3
V_3 = {1: V1_3, 2: V2_3, 3: V3_3}

# AVAILABILITY
av = {1: 1, 2: 1, 3: AVAIL_CAR + AVAIL_OV}

# === LOG-LIKELIHOOD ===
loglikelihood_class1 = log(models.logit(V_1, av, CHOICE))
loglikelihood_class2 = log(models.logit(V_2, av, CHOICE))
loglikelihood_class3 = log(models.logit(V_3, av, CHOICE))

logprob = log(
    probClass1 * exp(loglikelihood_class1) +
    probClass2 * exp(loglikelihood_class2) +
    probClass3 * exp(loglikelihood_class3)
)

# === ESTIMATE MODEL ===
biogeme = bio.BIOGEME(biodata, logprob)
biogeme.modelName = 'LCCM_3class'
results = biogeme.estimate()
```

```
print(results.short_summary())
print(results.get_estimated_parameters())

# === SIMULATE CLASS MEMBERSHIP PROBABILITIES ===
simulate = {
    'Prob_Class_1': probClass1,
    'Prob_Class_2': probClass2,
    'Prob_Class_3': probClass3
}
biogeme_sim = bio.BIOGEME(biodata, simulate)
biogeme_sim.modelName = 'simulate_class_probs_3class'
beta_values = results.get_beta_values()
sim_results = biogeme_sim.simulate(beta_values)

# === ASSIGN CLASS AND COUNT ===
sim_results['Assigned_Class'] = sim_results[['Prob_Class_1', 'Prob_Class_2', 'Prob_Class_3
    ']].idxmax(axis=1).str[-1].astype(int)

class_counts = sim_results['Assigned_Class'].value_counts().sort_index()
print("\nNumber of individuals per class:")
print(class_counts)

print("\nPercentage of individuals per class:")
print((class_counts / class_counts.sum() * 100).round(2))
```

### G.4.2. Additional calculations

```
    # Make sure CHOICE1 is used directly and correctly
# Your dataset must already use:
# 1 = City bike, 2 = E-bike, 3 = Car/PT
CHOICE = Variable('CHOICE1')

# Re-create Biogeme database using your cleaned dataframe (if needed)
biodata = db.Database('LCCM_data', df)

# === Simulation dictionary ===
simulate_bike_choice = {
    # Class 1
    'Prob_Choose_CityBike_Class1': probClass1 * models.logit(V_1, av, 1),
    'Prob_Choose_Ebike_Class1': probClass1 * models.logit(V_1, av, 2),

    # Class 2
    'Prob_Choose_CityBike_Class2': probClass2 * models.logit(V_2, av, 1),
    'Prob_Choose_Ebike_Class2': probClass2 * models.logit(V_2, av, 2),

    # Class 3
    'Prob_Choose_CityBike_Class3': probClass3 * models.logit(V_3, av, 1),
    'Prob_Choose_Ebike_Class3': probClass3 * models.logit(V_3, av, 2),

    # Overall expected probability of choosing any bike mode
    'Prob_Choose_AnyBike':
        probClass1 * (models.logit(V_1, av, 1) + models.logit(V_1, av, 2)) +
        probClass2 * (models.logit(V_2, av, 1) + models.logit(V_2, av, 2)) +
        probClass3 * (models.logit(V_3, av, 1) + models.logit(V_3, av, 2))
}

# === Run simulation ===
biogeme_bike_sim = bio.BIOGEME(biodata, simulate_bike_choice)
biogeme_bike_sim.modelName = 'bike_choice_simulation'

# Use estimated beta values from your LCCM results
beta_values = results.get_beta_values()
bike_probs = biogeme_bike_sim.simulate(beta_values)

# === Print results ===
print("\n=== Average Class-Conditional Bike Choice Probabilities ===")
print(bike_probs[[
    'Prob_Choose_CityBike_Class1',
    'Prob_Choose_Ebike_Class1',
    'Prob_Choose_CityBike_Class2',
```

```
    'Prob_Choose_Ebike_Class2',
    'Prob_Choose_CityBike_Class3',
    'Prob_Choose_Ebike_Class3',
]].mean().round(4))

print("\n=== Overall Expected Bike Mode Share ===")
print(f"{bike_probs['Prob_Choose_AnyBike'].mean() * 100:.2f}% of the population is likely to
    choose a bike (city or e-bike)")

# === CAR users only ===
car_users_df = df[df['CURRENT_MODE'] == 2].copy()
car_users_biodata = db.Database("car_users", car_users_df)

biogeme_car = bio.BIOGEME(car_users_biodata, simulate_bike_choice)
car_probs = biogeme_car.simulate(beta_values)

print("\n=== Bike Choice Probabilities for CURRENT Car Users ===")
print(car_probs[['Prob_Choose_CityBike', 'Prob_Choose_Ebike', 'Prob_Choose_AnyBike']].mean().
    round(4))

# === PT users only ===
pt_users_df = df[df['CURRENT_MODE'] == 3].copy()
pt_users_biodata = db.Database("pt_users", pt_users_df)

biogeme_pt = bio.BIOGEME(pt_users_biodata, simulate_bike_choice)
pt_probs = biogeme_pt.simulate(beta_values)

print("\n=== Bike Choice Probabilities for CURRENT PT Users ===")
print(pt_probs[['Prob_Choose_CityBike', 'Prob_Choose_Ebike', 'Prob_Choose_AnyBike']].mean().
    round(4))

# === City bike users only ===
city_users_df = df[df['CURRENT_MODE'] == 0].copy()
city_users_biodata = db.Database("cityb_users", city_users_df)

biogeme_city = bio.BIOGEME(city_users_biodata, simulate_bike_choice)
city_probs = biogeme_city.simulate(beta_values)

print("\n=== Bike Choice Probabilities for CURRENT City Users ===")
print(city_probs[['Prob_Choose_CityBike', 'Prob_Choose_Ebike', 'Prob_Choose_AnyBike']].mean()
    .round(4))

# === E-bike users only ===
e_users_df = df[df['CURRENT_MODE'] == 1].copy()
e_users_biodata = db.Database("e_users", e_users_df)

biogeme_e = bio.BIOGEME(e_users_biodata, simulate_bike_choice)
e_probs = biogeme_e.simulate(beta_values)

print("\n=== Bike Choice Probabilities for CURRENT E Users ===")
print(e_probs[['Prob_Choose_CityBike', 'Prob_Choose_Ebike', 'Prob_Choose_AnyBike']].mean().
    round(4))
```

# H

# Acknowledged AI Assistance

In the preparation of this research proposal, I utilized OpenAI's ChatGPT and Gemini as a tool to support various aspects of the research and writing process. Specifically, these tools were used to:

- Generate an image for the title page.
- Review and suggest improvements to spelling and grammar.
- Summarize texts and documents.
- Provide ideas and insights into the implementation of methods.

  *Example question: What are closely related factors to bicycle commuting?*
- Offer explanations to deepen my understanding of subjects.

  *Example question: How are DCE and EFA related to one another?*
- Help with solving issues related to Python coding.

The use of ChatGPT and Gemini was intended to enhance the efficiency and quality of the thesis, while all critical analysis, interpretations, and conclusions remain my own. Furthermore is all the information given by ChatGTP and Gemini checked for errors or nonsense information.