MSc thesis in Civil Engineering

Modelling First- and Last-Mile Mode Choice at Green Mobility Hubs: A Case Study of Schiphol Airport

Tabia Binta Farazi

August 24, 2025

A thesis submitted to the Delft University of Technology in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering

The work in this thesis was carried out at:

Dep. Sustainable Urban Mobility & Safety
TNO, The Hague

Supervisors:	Dr. Maaike Snelder
	Dr. Alexandra Gavriilidou
Company-supervisor:	Ir. Aswin Menon Nandakumar

Executive Summary

This thesis investigates how green mobility hubs—integrating bicycles, shared micromobility, shared cars, and zero-emission buses—can reshape commuter behaviour, cut congestion, and improve air quality in high-demand transport regions. The central objective is to understand how mobility hubs—offering green alternatives—affect commuters' first- and last-mile decisions when private vehicle access is restricted at destinations like airports, industrial zones and city centres. The study further explores how these behavioural changes translate into network-wide traffic and air quality impacts, using a combination of discrete choice modelling and advanced Digital Twin simulation.

The research builds on an extensive body of literature that positions mobility hubs as enablers of multimodal and sustainable transport systems. Yet, three key gaps remain. First, most studies focus on public transport users. Secondly, studies look into hubs that offer one single type of services (just e-hubs or shared mobility hubs) or use assumed splits rather than analysing the integrated realistic effects of multiple green modes in a hub setting. Thirdly, very few attempt to link individual-level behaviour with system-level performance indicators such as vehicle kilometres travelled or pollutant concentrations. This study addresses both gaps by combining behavioural insights from a stated preference survey with network-level simulations for Schiphol Airport, one of Europe's busiest transport hubs and an area heavily affected by congestion and air quality concerns.

The methodology followed two main phases. In the first phase, a stated preference survey is conducted to capture how individuals would respond to different combinations of travel time, cost, bus waiting time, and weather conditions. Respondents also provided socio-demographic information including age, gender, education, employment, and digital comfort. A total of 131 valid responses are collected. These data are analysed using discrete choice models: a base Multinomial Logit (MNL), a final MNL and a Panel Mixed Logit (PML). Although the PML model provided a better statistical fit, it was less stable and showed lower prediction ability in simulation, so the MNL model was ultimately chosen for further analysis. Its specification, which included both mode attributes and socio-demographic interactions, achieved good explanatory power (Rho-square bar of 0.309) and produced interpretable parameters for use in policy-oriented applications.

The modelling results revealed clear behavioural patterns. Travel time and cost were the most influential determinants, with students particularly sensitive to cost and younger or digitally skilled individuals highly sensitive to time. Employment status mattered as well: students and full-time workers demonstrated the strongest aversion to time loss, reflecting their more rigid schedules. Weather significantly altered preferences: under rainy conditions, travellers placed less weight on cost and more on comfort, favouring protected modes such as buses or shared cars, while active and exposed modes lost appeal. Sensitivity analyses showed that demand for active modes declined steeply beyond two to three kilometres, while bus usage dropped sharply when waiting times exceeded fourteen minutes. Importantly, even respondents with limited digital comfort expressed willingness to use shared

modes in the hub setting, highlighting the potential for inclusive design to broaden adoption.

In the second phase, the estimated choice model was integrated into TNO's Digital Twin simulation platform to assess system-level impacts for the Schiphol region. Two scenarios were tested: a baseline scenario without hubs and an intervention scenario in which two strategically located hubs restricted car access and offered green alternatives. The simulations showed that hubs produced a measurable reduction in vehicle kilometres travelled and concentrations of NO_2 and particulate matter on peripheral municipalities such as Haarlemmermeer and Haarlem, which experienced declines in through-traffic. At the same time, some central zones like Amsterdam and Amstelveen recorded modest increases in traffic and emission due to redistribution effects and rerouting around car-free zones. Despite these localised shifts, the overall balance showed net reductions in traffic volumes. On the environmental side, the simulations confirmed decreases in regional concentrations of NO_2 and particulate matter, particularly along major corridors such as the A4 and A10. Localised increases occurred around hub access points, but the net result was a substantial improvement in air quality.

These findings contribute both empirically and methodologically. Empirically, the study provides new evidence on how multiple green modes interact within a hub setting and how sensitivities vary across socio-demographic groups and weather conditions. Methodologically, unlike most hub studies, this thesis explicitly links individual-level behavioural sensitivities with system-wide traffic and emissions via a Digital Twin, providing a novel, scalable evaluation framework. The case study at Schiphol illustrates that mobility hubs can simultaneously reduce congestion, and improve environmental outcomes, when they are strategically located and integrated into existing transport networks.

From a policy perspective, the results suggest that the effectiveness of hubs depends on several conditions. High-frequency, weather-resilient services such as zero-emission buses are essential to maintain reliability. Shared micromobility must be protected from weather through covered docking and supported by pricing incentives that make these modes financially attractive. Inclusivity requires providing access both digitally and through alternative channels for those less comfortable with apps. Strategic placement of hubs along ring roads or park-and-ride facilities is critical to intercept car traffic before it enters congested centres. Partnerships with major employers can further support uptake by subsidising passes or memberships for staff, and broader regulatory frameworks such as low car zones or zero-emission zones can be reinforced by hub provision, ensuring that restrictions are paired with attractive alternatives.

This thesis is the first to combine empirically estimated mode choice behaviour of private vehicle users in a mandatory hub setting with a digital twin traffic-environment model, providing both behavioural realism and system-level policy insights. Overall, this study demonstrates that mobility hubs are more than physical infrastructures: they are systemic interventions capable of reshaping both individual behaviour and regional mobility patterns. The integration of behavioural modelling with simulation provides a replicable framework for evaluating such interventions. The findings show that when designed to balance cost, time, weather resilience, and digital inclusivity, hubs can deliver both behavioural and environmental benefits. By confirming their potential in a complex and high-demand setting like Schiphol, this thesis demonstrates not only feasibility but also transferability of hub-based interventions. These insights provide a concrete evidence base for future policy pilots, particularly zero-emission zones at European airports and other high-demand transport hubs.

Acknowledgements

Completing this thesis has been both challenging and rewarding, and it would not have been possible without the support of many people.

First, I would like to thank my supervisors—Maaike, Alexandra, and Aswin—for their invaluable guidance, patience, and constructive feedback throughout this process. Their expertise and encouragement kept me focused and motivated, especially during the difficult phases of the research.

I am grateful to my colleagues at TNO for their support, particularly for their help with the digital twin simulations, interesting talks about their projects and all the fun moments that made the work more enjoyable.

My deepest thanks go to my family for their constant support. Your belief in me gave me the strength to keep going when things were tough.

Finally, I want to thank my friends here and back in Bangladesh for being there for me — for believing that I can do a lot more but I just do not know it yet, for standing up for me and for the much-needed distractions along the way. I have probably had the best time of my life here, even though I was too proud to acknowledge that in those moments. Because the truth is-you never know you are in the good old times, when you are in them. I am not a very nostalgic person, I always believed that looking back even at the good times causes you pain. But I still want to hold on to the beautiful journey I had in Delft.

This thesis would not have been possible without all of you.

Tabia
August 2025

Contents

List of Figures

List of Tables

Acronyms

List of Acronyms

AIC	Akaike Information Criterion
ASC	Alternative Specific Constant
BIC	Bayesian Information Criterion
DCM	Discrete Choice Modelling
IIA	Independence of Irrelevant Alternatives
LCCM	Latent Class Choice Model
LL	Log Likelihood
MNL	Multinomial Logit
NL	Nested Logit
PML	Panel Mixed Logit
PT	Public Transport
RUM	Random Utility Maximisation
SP	Stated Preference
RP	Revealed Preference
TNO	Nederlandse Organisatie voor Toegepast Natuurwetenschappelijk Onderzoek
VKT	Vehicle Kilometers Traveled
ZE	Zero-Emission
IMB	Inter Model Broker
DT	Digital Twin

1. Introduction

As cities worldwide transition toward more sustainable and efficient mobility, green mobility hubs have emerged as promising interventions to promote low-carbon travel behaviour. These hubs are strategically located nodes that integrate multiple sustainable transport modes to support multimodal connectivity [Aono, 2019]. In addition to reducing air pollution and traffic congestion [Becker and Rudolf, 2018; Kondor et al., 2019; Tikoudis et al., 2021], mobility hubs enhance accessibility and transport equity, particularly for peripheral or underserved areas [Guo et al., 2020; Jiao and Wang, 2021].

Functionally, mobility hubs serve as critical access and transition points within multimodal transport networks [Hochmair, 2015], enabling smooth modal transfers and accommodating diverse trip purposes [Henry and Marsh, 2008]. Prior research has shown that green transport services—such as bicycle-sharing [Wu et al., 2019; Ma et al., 2020], e-scooter sharing [Baek et al., 2021], and car-sharing schemes [Correia and Antunes, 2012; Jorge and Correia, 2013]—can improve door-to-door travel experiences and foster environmentally sustainable mobility choices [Scheltes and Correia, 2017].

Despite growing academic and policy interest, a key gap remains in understanding mode choice behaviour within the context of mobility hubs, particularly when travellers switch from private vehicles to green first- and last-mile alternatives. While mode choice behaviour has been extensively studied across general contexts [Ohnemus and Perl, 2016; Shaheen and Chan, 2016; Yap et al., 2016], limited research addresses the unique behavioural dynamics within these hubs. Realizing the full traffic and environmental potential of mobility hubs requires deeper insights into the user-specific and contextual factors—such as travel time, cost, weather, and digital comfort—that shape these choices [Jahanshahi et al., 2020]. Such insights are vital for guiding effective investment in first- and last-mile infrastructure.

This thesis investigates mobility hubs that connect high-demand fixed destinations—such as airports, city centers, or business parks—under a stricter policy context where private vehicle access to the destination is prohibited and travellers must transfer to green first- and last-mile mode options offered at the hubs. The typical trip chain is conceptualized as:

$$\textbf{Origin} \rightarrow \textit{Any Mode} \rightarrow \textbf{Hub} \rightarrow \textit{Green Modes} \rightarrow \textbf{Destination}$$

This structure also accounts for return trips, where the last-mile of the inbound journey becomes the first-mile of the outbound leg, assuming symmetric modal availability. Modelling both directions provides a more realistic representation of travel preferences and hub performance.

The objective of this study is to evaluate how implementing green mobility hubs—designed to replace private vehicle access to fixed destinations—affects travel behaviour, traffic conditions, and emissions. By estimating modal preferences and simulating their impact on system-level indicators—such as vehicle kilometers travelled (VKT), intensity–capacity ratios, and amount of NO_x and particulate matter (PM)—this research bridges micro-level travel preferences with macro-level system outcomes. The resulting insights provide practical guidance for designing green mobility hubs that are behaviourally realistic and operationally effective.

Scientifically, this thesis contributes in three key ways: (1) it empirically models mode choice behaviour within multimodal green hub contexts, focusing on private vehicle users; (2) it integrates behaviourally estimated models into a simulation-based evaluation of system-wide impacts; and (3) it links individual travel preferences with macro-level policy outcomes, advancing the behavioural realism of sustainable transport planning.

1.1. Problem Statement and Knowledge Gap

Numerous studies have investigated individual mode preferences across various transport systems, with particular emphasis on access and egress mode choice for public transport. For instance, Van Kuijk et al. [2024] and Oeschger et al. [2023] explored how users select first- and last-mile options when using public transport, highlighting the rising use of shared bikes, e-bikes, and e-scooters. Similarly, Sanders [2015] identified travel time and cost as key determinants in selecting access-egress modes for public transport users. Studies by Horjus et al. [2024] and Torabi et al. [2023] conceptualized public transport stops as hubs and concluded that cost is the most influential factor in first- and last-mile mode choices. While these works provide valuable insights into multimodal travel behaviour, they predominantly focus on public transport users—overlooking other segments such as car or private vehicle users. This group is particularly important when designing low-car or zero-emission zones for high-demand destinations like airports, industrial areas, and city centers due to their impacts on traffic and environmental conditions.

More recent studies have shifted attention toward mobility hubs that integrate a specific type of sustainable transport mode. For example, Liao et al. [2023] and Hosseini et al. [2024] examined electric mobility hubs (e-hubs) and found that public transport users are generally more receptive to hub-based electric modes than car users. Similarly, Xanthopoulos et al. [2024] and Garritsen et al. [2024] investigated shared-mobility hubs and suggested that deploying more hubs with fewer vehicles may enhance operational efficiency. However, these studies often rely on hypothetical modal splits or simplified assumptions, lacking empirical modelling of traveller preferences—especially in the context of green mobility hubs. These studies also focus on hubs offering one particular type of mode instead of focusing on the most feasible and preferred transport modes, which undermines the benefits that are possible to achieve from a green mobility hub.

A more behaviourally focused perspective is provided by Zhou et al. [2023], who concluded that introducing hubs alone does not significantly reduce car use. Zuurbier [2023] similarly observed that frequent car users often maintain their reliance on private vehicles, even when sustainable alternatives are made available. While Hachette et al. [2024] quantified potential emission reductions from hub implementations, the underlying behavioural mechanisms driving such outcomes remain unexplored. In addition, Xanthopoulos et al. [2024] reported only marginal travel time and emission reductions from shared modes in the Amsterdam region, though this analysis was based on assumed rather than observed mode choice behaviour. However, these studies examine contexts where using a hub is only an option and private vehicle users can still access destinations directly. The stricter context of prohibiting private vehicles from high-demand destinations and requiring transfer at a hub has not yet been examined.

Overall, the behavioural dimension of green mobility hubs—particularly for private vehicle users required to switch to sustainable first- and last-mile options—remains underexplored. This thesis addresses that gap by empirically modelling how car users trade off between multiple sustainable modes under mandatory hub-transfer conditions, and embedding these behavioural insights into a simulation of traffic and environmental impacts.

1.2. Research Goal and Scope

The goal of this research is to assess how the introduction of green mobility hubs influences travel behaviour and, in turn, affects traffic performance and environmental indicators. Specifically, the study examines how travellers who currently rely on private vehicles adapt their first- and last-mile choices when they are required to transfer at a hub and select among sustainable alternatives such as shared bikes, e-scooters, or zero-emission buses.

To achieve this, the research investigates how mode choices are shaped by contextual factors—including weather, travel cost, and digital accessibility—using empirically collected choice data. The analysis focuses on adults aged 18 and older living in the Netherlands.

Research Questions

Main Research Question:

What are the traffic and environmental impacts of introducing multimodal green mobility hubs for first- and last-mile travel?

This question aims to assess the broader impact of implementing multimodal green mobility hubs on the sustainability and performance of the Dutch transport system. It serves as the central focus of the research, linking individual choices to aggregated traffic and environmental outcomes.

Sub-questions

The following sub-questions are derived to answer the main research question:

1. *Which traffic and environmental indicators are suitable for assessing the impacts of a mobility hub, and why, according to existing literature?*
   This sub-question explores relevant academic literature to identify measurable indicators—such as vehicle kilometers travelled (VKT), intensity-capacity ratios, and quantity of emissions—that reflect changes in transport system performance and sustainability following the introduction of a mobility hub.
2. *What mode attributes and individual characteristics influence first- and last-mile mode choices at green mobility hubs?*
   This sub-question investigates mode attributes (e.g., travel time, cost, and weather) and user characteristics (e.g., age, digital literacy)—that shape decision-making in the context of mobility hubs.

3. *Which modelling framework best captures individual mode choice behaviour in the context of a mobility hub?*
   This sub-question identifies the modelling framework (e.g., Multinomial Logit, Nested Logit) suitable for representing mode choice behaviour. It addresses how utility functions are structured, whether to include interaction effects or dummy variable terms, and how to decide which model yields the best result in the context of this study.

4. *To what extent do the identified mode attributes and individual characteristics influence mode choice behaviour?*
   This sub-question quantifies the statistical strength and significance of various influencing factors, forming the basis for empirical choice modelling and behavioural parameter estimation.

5. *How is demand redistributed among available modes when the mobility hub is introduced?*
   This sub-question evaluates how the availability of multiple green alternatives at a mobility hub reallocates travel demand across modes. It enables the calculation of associated traffic and emission impacts.

Figure 1.1 illustrates how the sub-questions were derived via the method of unraveling key concepts.

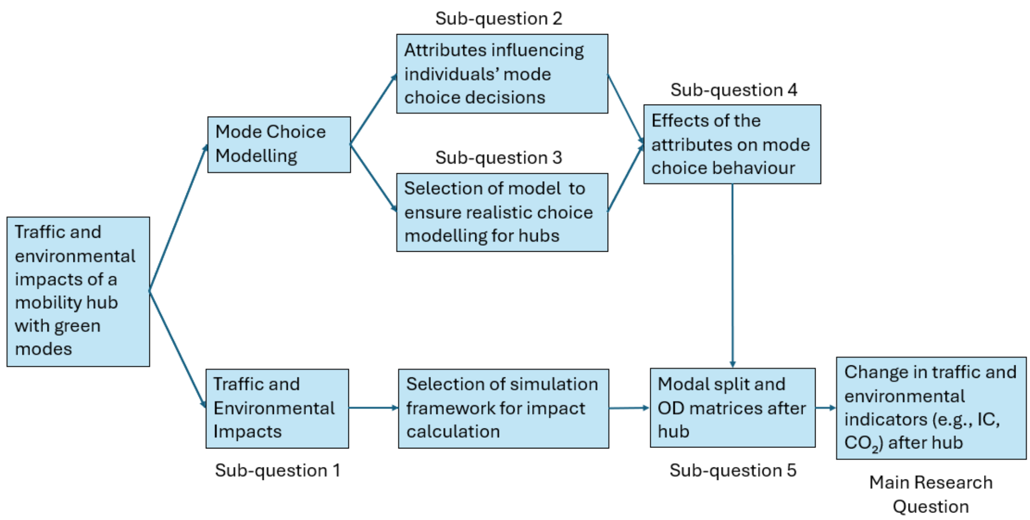


Figure 1.1.: Using method of unraveling key concepts to derive research questions

1.3. Research Relevance

Empirical insights into how travellers choose green first- and last-mile alternatives in mobility hub contexts are still limited. This study addresses that gap through an integrated approach combining empirical choice modelling and simulation. This is particularly relevant for creating low-car zone or zero-emission zones around high demand areas like city centers, industrial areas or airports.

For municipalities and transport planners, the findings help identify which mode combinations and design features—such as frequency, cost, and distance—make green hubs most effective. Insights from the simulation can support infrastructure investment decisions, optimize hub placement, and inform environmental policy development.

For policymakers, the research strengthens the case for mobility hubs as measures to meet climate targets and reduce congestion—especially around key destinations. The case study application in this study demonstrates the practical feasibility and policy relevance of the proposed modelling approach.

Scientifically, the research advances transport modelling by analysing mode choice behaviour in multimodal, hub-based settings. It contributes methodological value through its integration of behavioural estimation with simulation—addressing the relatively underexplored domain of first- and last-mile substitutions.

For the general public, green mobility hubs improve accessibility, especially in underserved areas, with car-sharing playing a major role [Frank et al., 2021]. By reducing travel costs and emissions while improving system efficiency, these hubs contribute to healthier, more inclusive urban environments.

1.4. Thesis Outline

This thesis is structured to systematically address the research questions. The Introduction in Chapter 1 outlines the background, motivation, research gap, and objectives. The Literature Review in Chapter 2 examines key topics such as green mode alternatives at mobility hubs, mode choice, relevant traffic and environmental indicators, and relevant modelling approaches.

Chapter 3 describes the methodology of the thesis: data collection process using a stated preference survey and the modelling tools employed. Chapter 4 presents the results from the survey, including sample characteristics, descriptive statistics, and the discrete choice model estimations.

In Chapter 5, the developed mode choice model is applied to different scenarios, including Dutch adults and Schiphol commuters. The modal splits and sensitivity analyses under varying conditions, such as distance and weather, are explored in detail. Chapter 6 explores the results from the Digital Twin simulation. Chapter 7 provides a discussion of the findings, reflecting on their practical relevance, limitations, and the interpretation of the final model coefficients. Chapter 8 summarizes the answers to the research questions, provides conclusions and recommendations for both practice and future research.

2. Literature Review

This chapter provides a structured review of the academic literature relevant to mode choice preferences and the impact evaluation of green mobility hubs. The review serves two main purposes: (i) to define the research problem by identifying relevant first- and last-mile transport modes (2.1), the factors influencing mode choice (2.2), and key environmental and traffic indicators (2.4) likely to be affected by the introduction of mobility hubs; and (ii) to inform the selection of an appropriate methodological approach (2.3).

The review focuses particularly on access and egress behaviour in the context of mobility hubs or hub-like environments (e.g., public transport stations), which closely approximate the functional characteristics of green mobility hubs. To support this, three primary search terms were used: "mobility hubs", "mode choice" and "mobility hubs", and "impact" in relation to mobility hubs. These terms were applied in ScienceDirect and Google Scholar to retrieve a broad set of academic sources. All identified documents were screened for relevance based on their title, abstract, and full text. A smaller subset was selected for in-depth review. Additional literature was identified through backward and forward citation tracking (i.e., snowballing).

2.1. Green Mode Alternatives as First and Last Mile Transportation Options

According to Bertolini [2008], a hub comprises two elements: a network node facilitating intermodal transfers and a place providing amenities and services for passengers. By integrating complementary travel modes, such hubs aim to enhance travel efficiency and reduce the environmental and spatial burdens of car dependence [Pitsiava-Latinopoulou and Iordanopoulos, 2012].

A substantial body of research has investigated access and egress mode choices at transport nodes such as railway stations and metro stops. Recent studies increasingly examine the incorporation of shared and low-emission modes within the mobility hub framework. For instance, Abe [2021] analyzed access modes at Tokyo's railway stations, accounting for options like bicycles, private cars, motorcycles, and autonomous vehicles. Similarly, Baek et al. [2021] examined subway access in Seoul, including town buses, shared bicycles, and e-scooters.

In Europe, the access mode landscape has also evolved. Dutch studies, including Van Kuijk et al. [2024] and Tona et al. [2024], analyzed access to rail stations using a wide range of modes: shared bikes, e-bikes, e-scooters, e-mopeds, on-demand rides, and taxis. Other Dutch research by Van Mil et al. [2020] and Stam et al. [2021] considered walking, cycling, and car access to stations, reflecting typical first- and last-mile patterns. In Spain, Aguilera-García et al. [2020] examined shared vehicle access at railway stations, while Chan and

Farber [2020] and Wu et al. [2019] studied shared micromobility use (e.g., e-scooters and bicycles) in metro and transit settings.

The integration of active and shared modes at these hubs is widely recognized as a strategy to improve travel experience and reduce car reliance, especially for short-distance trips. Zhou et al. [2023] emphasized the importance of design features that prioritize active mobility, and Alpkokin [2012] highlighted cycling as a viable alternative to cars in small cities and for shorter journeys.

More recent literature also explores fully electric hubs (E-hubs) offering only electric vehicles as access options. Although e-bikes have reduced conventional bicycle use in the Netherlands, their ability to substitute car travel remains limited [Kroesen, 2017; de Haas et al., 2021; Sun et al., 2020]. These findings largely pertain to privately owned vehicles; however, shared electric modes often exhibit different adoption patterns [Wang et al., 2020].

Van Kuijk et al. [2024] found that shared bikes and e-scooters were the most preferred modes at hubs offering only shared options—especially among younger users and those traveling to suburban destinations. Similarly, Torabi et al. [2023] confirmed the continued popularity of shared bicycles. E-mopeds consistently rank among the least preferred shared electric modes [Van Kuijk et al., 2024].

Table 2.1 provides an overview of selected studies in different countries, showing the range of first- and last-mile options that have been analysed.

Table 2.1.: Selected studies on access-egress options in hub-like contexts

Study	**Country**	**Context**	**Modes reviewed**
Molin and Timmermans (2010)	Netherlands	Railway stations	Public transport, taxi, bike, shared bike, Shared e-cars
Ryley et al. (2014)	United Kingdom	Rail stations	Bus, cycling, demand-responsive transport, car, walking
Yap et al. (2016)	Netherlands	Rail stations	Bicycle, AV car-sharing, private car
Halldórsdóttir et al. (2017)	Denmark	Rail stations	Bus, BRT, walking, cycling
Shelat et al. (2018)	Netherlands	Rail stations	Walking, cycling, private car, car passenger
Wu et al. (2019)	Taiwan	Metro stations	Shared bicycles
Aguilera-García et al. (2020)	Spain	Rail stations	Shared e-cars, private mopeds, motorcycles, walking, PT, bike-sharing, scooter-sharing, taxis, ride-sourcing
Abe (2021)	Japan	Railway stations	Bicycle, private car, motorcycle, walking, autonomous vehicles
Baek et al. (2021)	South Korea	Subway	Town bus, shared bicycles, shared e–scooters, walking
Zhou et al. (2023)	Netherlands	Mobility hubs	Walking, cycling, shared bicycles
Van Kuijk et al. (2024)	Netherlands	Rail stations	Shared bikes, e-bikes, e–scooters, e–mopeds, on-demand rides, taxis

Five green modes consistently emerge as the most widely preferred access–egress options across the literature: walking, cycling, shared bicycles, shared e-scooters, and shared electric cars. These alternatives are well suited for integration into the mobility hub concept and form the foundation for this study's mode choice analysis.

2.2. Attributes Influencing Mode Choice in Multimodal Transportation

Mode and user characteristics, particularly sociodemographic attributes, play a crucial role in determining modal split within the context of this research. Numerous studies have explored how different mode and personal attributes influence mode choice for first- and last-mile transportation across various contexts. Age, gender, education level, employment status, primary mode of transportation and trip purpose consistently emerge as significant factors. For research involving shared and digital transport services, factors such as digital literacy and prior experience with shared mobility are also critical. Regarding mode-specific characteristics, travel cost, distance, and waiting time are recurrent variables identified in the literature.

Travel Costs

Financial considerations significantly influence mode choice decisions. Chen et al. [2020] notes that travel cost is a major determinant of behavioural shifts. Torabi et al. [2023] found travel cost to be the most important factor influencing mode choice. Similarly, Sanders [2015] demonstrated that travel time and cost are key determinants when travellers decide modes for medium- to long-distance journeys. Affordability remains consistently important across traveller segments.

Distance

Trip distance plays a significant role in the adoption of green modes. Liao et al. [2023] identified trip length as a key factor in determining willingness to switch modes. Ma et al. [2020] found that short- to medium-distance trips are particularly conducive to bike-sharing system adoption. Similarly, Jahanshahi et al. [2020] confirmed that travel distance influences user acceptance of shared bikes.

Public Transport Frequency

Several studies have demonstrated the importance of public transport frequency in shaping mode preferences. Scheltes and Correia [2017] showed that improved PT headways significantly enhanced integration with shared vehicles and feeder modes. Shaheen et al. [2017] emphasized that increased frequency not only improves system efficiency but also equity and accessibility, particularly when combined with shared mobility options. The less time spent waiting, the more appealing the mode becomes [Dubey et al., 2024]. Increased transfer time reduces the utility of choosing park and ride modes [Habib et al., 2012].

Weather

Weather conditions are critical in shaping decisions- especially for active modes. Tona et al. [2024] and Torabi et al. [2023] include weather as a contextual variable, while Wu et al. [2019] observed that rain or extreme cold reduces bike-share usage, leading travellers to opt for more sheltered or motorized alternatives.

Age

Age is a consistently influential factor in mode choice. Hensher et al. [2024] observed that younger, tech-savvy, and environmentally conscious individuals tend to prefer micromobility and active transport for short distances and as first/last-mile options. This is corroborated by Shelat et al. [2018], who found that individuals aged 17–27 are most likely to combine cycling with public transport. Conversely, older adults are generally less inclined to use shared bicycles [Böcker et al., 2020]. Van Kuijk et al. [2024] further highlights age as a key determinant in preferences for shared mobility. Additionally, Jorritsma et al. [2021] found that over half of Dutch car-sharing users are between 31 and 50 years old, while slightly less than one-third are under 30.

Gender

Gender-based differences in mobility patterns are well documented in recent studies. Men generally cycle more than women [Meng et al., 2016; Park et al., 2014], while women show a preference for private over shared bicycles when accessing railway stations [Ji et al., 2017]. Men are also more inclined to use scooters for last mile travel, whereas women are more likely to opt for buses [Halldórsdóttir et al., 2017; Tran et al., 2014]. These differences underscore gender as a critical factor in first and last-mile transport preferences.

Employment Status

Employment status significantly impacts modal preference. Jorritsma et al. [2021] found that individuals with higher incomes—typically linked to full-time employment—are more likely to use shared cars, while those with lower incomes tend to prefer shared bikes due to their affordability. Similarly, Aguilera-García et al. [2020] found that middle- and high-income individuals are more inclined to adopt scooter-sharing services in Spanish cities.

Education Level

Education level also influences green mode uptake. Shelat et al. [2018] and Jonkeren et al. [2021] found that highly educated individuals are more likely to integrate cycling into multimodal trips. Shaheen et al. [2017] suggests that individuals with higher educational attainment are generally more open to adopting shared and emerging transport technologies.

Travel Purpose

The purpose of a trip has a notable impact on mode choice. Jiao and Bai [2020] showed that commuters and those traveling for errands or leisure display different adoption rates for shared e-scooters, with commuters showing a stronger preference due to time and convenience. Tona et al. [2024] also emphasized the significance of trip purpose in shaping first/last-mile decisions, especially in the context of shared and hub-based services.

Primary mode of transportation

Primary mode of transportation strongly influences first- and last-mile travel behaviour. Studies consistently find that car ownership reduces the attractiveness of walking and cycling alternatives [Halldórsdóttir et al., 2017]. Puello and Geurs [2015] noted that motorcycle ownership reduces the likelihood of walking. Kroesen [2017] found that car users are more willing to adopt e-bikes compared to conventional bicycles or public transport, especially when e-bikes offer convenience and speed advantages. However, receptiveness to mobility hubs differs between user groups: Liao et al. [2023] observed that public transport users are more open to hub-based shared modes. Nonetheless, under favourable conditions—such as free parking at the hub, good weather, and short distances—car users become more likely to switch to shared or active modes facilitated by mobility hubs [Zhou et al., 2023; Rongen et al., 2024].

Digital Skills

Digital literacy is a growing concern in equitable mobility access. Garritsen et al. [2024] found that lower digital skills are associated with reduced use of shared modes. Vulnerable groups—including older adults and lower-income individuals—face more barriers to adopting digital mobility solutions, raising concerns around transport equity. Non et al. [2023], drawing on data from OECD [2013], revealed that individuals with lower digital proficiency—often older, less educated, and more frequently female—are less likely to adopt shared services.

Shared Mode Experience

Prior experience with shared mobility services strongly influences an individual's likelihood of future adoption. For instance, Habib et al. [2012] found that individuals with prior experience using car-sharing services showed significantly higher willingness to adopt them again. Studies also show that familiarity with one shared mode often facilitates adoption of others. Shaheen and Chan [2016] observed that early adopters of one shared service (e.g., bike-share) are more open to trying additional shared options (e.g., e-scooters or ride-hailing), suggesting a cumulative learning effect. These findings underscore the importance of habit formation and ease-of-use in promoting sustained shared mobility use.

A wide range of sociodemographic and contextual factors influence first- and last-mile mode choice. These insights inform both the specification of utility functions in discrete choice models and the design of policy interventions aimed at supporting equitable and efficient mobility hub implementation.

2.3. Models for Mode Choice

There are multiple frameworks to model and explain travel behaviour, each operating under a distinct set of assumptions and methodologies, contributing to the understanding of travel choices [Kroesen, 2023]. These frameworks aim to predict and explain travel behaviour based on their underlying assumptions. This thesis specifically focuses on evaluating mode choice preferences for a mobility hub, and the econometric modelling paradigm is considered the most suitable for this analysis [Kroesen, 2023]. This paradigm assumes that travellers make decisions that maximize their utility. A key mathematical framework within this paradigm is the Random Utility Model (RUM), a well-established tool for explaining mode choice.

Discrete Choice Modelling (DCM) has become a widely adopted technique for analysing travel behaviour and understanding how individuals make choices among different alternatives [Ben-Akiva and Bierlaire, 2003]. Within DCM, models belonging to the logit family are particularly common [Train, 2002]. As outlined by Ben-Akiva and Bierlaire [2003], four types of logit-based models are extensively used: the Multinomial Logit Model (MNL), the Nested Logit Model (NL), the Panel Mixed Logit Model (Panel ML), and the Latent Class Choice Model (LCCM).

- The MNL model remains popular due to its simplicity and computational efficiency. However, one of its key drawbacks is the assumption of independence from irrelevant alternatives (IIA). This implies that the odds of selecting between two alternatives are not influenced by the presence of additional choices, which may not always reflect real-world decision-making.

- The NL model helps overcome IIA by accounting for correlations between similar alternatives. This makes it a better fit for scenarios where choices can be naturally grouped. By removing the IIA assumption, the NL model becomes a more representative model for grouped alternatives [Train, 2002].

- The Panel ML model can be a more representative model when studying repeated choices by the same individuals. It captures personal variations for each individual and provides a more comprehensive understanding of choice behaviour by incorporating random heterogeneity in preferences [Train, 2002].

- The Latent Class Choice Model (LCCM) concept states that individuals form latent groups based on their differing attitudes, motivations, experiences, and needs. This integrates both the econometric and mobility styles paradigms to capture the impact of these latent groups.

The psychological modelling paradigm is also relevant for understanding travel behaviour decision-making. This framework suggests that people's choices are shaped by psychological factors, such as habits, social norms, and attitudes [Kroesen, 2023].

Given the research objective of modelling access and egress mode choices in green mobility hubs, selecting an appropriate modelling framework is essential. The MNL model offers simplicity and ease of estimation, but its assumption of Independence from Irrelevant Alternatives (IIA) can be problematic. The NL model is more suitable if the alternatives have overlapping characteristics. If panel data or repeated choice observations are available, the Panel Mixed Logit (PML) model is advantageous for capturing individual-level heterogeneity in preferences. Likewise, if the aim is to segment travellers based on unobserved behavioural traits—such as environmental concern or digital proficiency—the Latent Class Choice Model (LCCM) is well suited. Each of these models offers distinct strengths, and their appropriateness depends on the data structure, behavioural assumptions, and the desired level of analytical depth.

2.4. Environmental and Traffic Impacts of Mobility Hubs

Mobility hubs can play a pivotal role in mitigating the environmental burden of urban passenger transport. In the Netherlands, passenger cars cover 122.5 billion kilometers countrywide annually [Statistics Netherlands, nd]. In 2019, 49% of all trips were made by private cars [Statistics Netherlands, nd], underscoring the urgency of shifting toward more sustainable modes. Common traffic indicators—such as traffic flow volumes, intensity-capacity (IC) ratios, and vehicle kilometers travelled (VKT)—are frequently used in previous studies to assess the impact of transport interventions [Stam et al., 2021; Xanthopoulos et al., 2024].

A growing body of evidence supports the environmental benefits of integrating shared mobility services—such as shared bikes, e-cars, and public transport—within multimodal mobility hubs. Meijkamp [2000] found that car-sharing users reduce their car kilometers by two-thirds, resulting in a 40% lower environmental impact per household.

Mobility hubs also help reducing local pollutants like NO_2 and PM, which are prominent in short car trips. Shared e-bikes and public transport modes produce drastically lower emissions per passenger-kilometer—in NO_2, and PM compared to conventional cars [Chen et al., 2020; Hosseini et al., 2024].

The guideline followed in this study for environmental quality is European Commission [nd] standards. According to EU standards, the annual average limit for NO_2 is 40 µg/m³, PM_{10} is 40 µg/m³ and $PM_{2.5}$ is 25 µg/m³. These environmental indicators form the basis for empirical evaluation in this study.

Furthermore, research by Stam et al. [2021] and Xanthopoulos et al. [2024] confirms that hubs reduce traffic congestion and parking demand by promoting seamless transitions between modes. By combining infrastructure upgrades (e.g., e-bike lanes) with shared mobility, Hosseini et al. [2024] show that cities can achieve measurable environmental benefits, especially when such services attract users with high environmental awareness [Sytsma and Stulen, 2018; Zijlstra et al., 2020].

In sum, mobility hubs—when integrated with green modes—offer a compelling and empirically supported pathway to reduce NO_2, PM, and intensity-capacity ratios, while supporting the behavioural shift needed for sustainable urban mobility.

2.5. Conclusion on Literature Review

This literature review has provided a comprehensive overview of the factors influencing mode choice behaviour at mobility hubs, as well as the potential traffic and environmental impacts of introducing green, multimodal transport options. Prior studies consistently highlight the role of user-specific attributes—such as age, gender, education level, employment status, digital literacy, and prior shared mode experience—in shaping travel decisions. Mode-specific attributes, particularly travel cost, distance, weather conditions, and public transport frequency, also emerge as critical determinants in multimodal contexts.

Although green transport options such as shared bikes, e-scooters, and shared electric cars have been studied individually, there is limited research that evaluates these modes collectively within the framework of a mobility hub serving a fixed destination, such as an airport.

From a modelling perspective, the Multinomial Logit (MNL) model is widely used for its simplicity and interpretability. The Panel Mixed Logit (PML) model is better suited when repeated choice data are available, as it can account for unobserved individual heterogeneity. The Nested Logit (NL) model becomes appropriate when multiple alternatives share similar attributes. The Latent Class Choice Model (LCCM), on the other hand, is useful for segmenting users based on unobserved behavioural traits.

To link individual-level behavioural shifts with broader traffic and environmental outcomes, this study draws upon established indicators identified in the literature—such as traffic volumes, intensity-capacity (IC) ratios, and emissions of NO_2, and PM.

This research builds on existing literature by addressing the gap in understanding how green mobility hubs influence mode choice and traffic and environmental performance when multiple sustainable transport options are made available. The parameters derived from the literature, in combination with choice modelling and traffic-environmental simulation, provide a robust framework to investigate this complex and emerging topic.

3. Methodology

This chapter outlines the methodological framework used to evaluate the influence of green mobility hubs on travel behaviour, traffic dynamics, and environmental outcomes. The study adopts a hybrid approach that combines a stated preference survey, discrete choice modelling, and simulation-based impact analysis.

Figure 3.1 illustrates the methodological sequence followed in this research, linking each stage to specific sub-research questions. It presents the operational flow—from behavioural data collection to the simulation of traffic and environmental indicators—clarifying how the various components of the analysis are interconnected.

The chapter is organised into four main sections. Section 3.1 describes the design and distribution of the stated preference survey. Section 3.2 outlines the data preparation steps undertaken prior to model estimation. Section 3.3 presents the discrete choice modelling framework, including model selection, utility specification, and estimation strategies. Finally, Section 3.4 explains how the estimated model outputs are integrated into a simulation environment to assess the network-level impacts of mobility hub interventions under different scenarios.

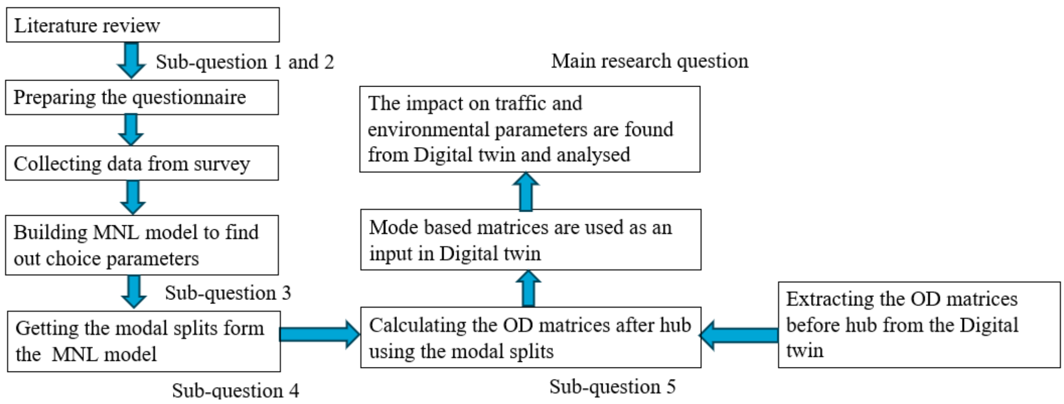


Figure 3.1.: Methodology

3.1. Stated Preference Survey

As the literature lacks empirical data or detailed studies on modal split at green mobility hubs, a primary data collection effort is required. In travel behaviour research, two main approaches are commonly used for data collection: revealed preferences (RP) and stated preferences (SP) [Kroesen, 2023]. RP methods are based on observing actual travel decisions made by individuals in real-world settings. In contrast, SP methods involve presenting respondents with hypothetical yet realistic travel scenarios to elicit their preferences.

Collecting large-scale, high-quality RP data for mobility hub users would require extensive fieldwork, partnerships with transport operators, or access to administrative datasets—resources not feasible within the scope and timeline of this thesis. In contrast, SP surveys offer a cost-effective and efficient method of obtaining mode choice data, particularly when the infrastructure being studied is not yet operational. This approach is widely recognised and validated in transport research for evaluating new or emerging transport services, hypothetical alternatives, and latent preferences [Torabi et al., 2023; Van Kuijk et al., 2024]. Prior studies investigating mode choice, shared mobility adoption, and behavioural responses to contextual variables have successfully employed SP surveys for these purposes [Pham, 2023; van Langevelde van Bergen, 2023].

Since the proposed mobility hub is not yet implemented in practice, a hypothetical scenario was constructed to evaluate user behaviour. This further supports the appropriateness of the SP approach. Including a combination of emerging green alternatives—such as a zero-emission bus—would not have been feasible with RP data. The SP method allows for controlled manipulation of key attributes (e.g., travel costs, waiting times, and environmental conditions) to create realistic yet unobserved combinations that reflect possible future conditions.

Additionally, SP surveys allow respondents to make multiple hypothetical choices, facilitating the observation of personal variation in preferences. This repetition increases model reliability even with a relatively small sample size [Molin, 2023]. However, repeated observations can introduce bias. To address this, a Panel Mixed Logit (PML) model can be used in this study to account for unobserved heterogeneity across repeated choices.

Furthermore, RP data would only capture behaviour from existing users of mobility hubs, excluding the preferences of potential future users—particularly relevant for concepts like green mobility hubs, which are still in early implementation stages.

Despite its advantages, the SP method is not without limitations. A key concern is hypothetical bias—the difference between how individuals say they would behave in a survey and how they would act in reality. This can arise because SP surveys often present idealised or unfamiliar conditions, including perfect information, which respondents do not typically experience in real-world settings. Another source of bias is sample representativeness—if the respondent group differs demographically from the target population, the results may not generalise well [Molin, 2023].

To mitigate the limitations associated with hypothetical bias in SP surveys, several best practices are followed, drawing on recommendations from Heufke Kantelaar et al. [2022] and Ben-Akiva et al. [2019]. First, ensuring that respondents are familiar with the alternatives under evaluation is critical. In this study, the modes and the function of the mobility hub are introduced at the beginning of the survey, accompanied by clear and neutral explanations to minimise framing effects. Second, efforts are made to ensure that the sample was reasonably representative of the broader population in terms of key socio-demographic variables, both during survey design and distribution. Third, attention is paid to the overall quality of the questionnaire. This included a careful selection of mode alternatives, the inclusion of relevant socio-demographic questions, and the integration of context-specific variables such as weather and distance. Fourth, the complexity of the design is deliberately controlled by limiting the number of attributes and alternatives. This helped reduce cognitive fatigue and improved the reliability of responses across multiple choice tasks. Finally, although a formal calibration with RP data is not feasible within the constraints of this study, real-world costs, travel times, and service frequencies are incorporated into the SP scenarios to improve realism and reduce the gap between hypothetical and actual behaviour.

3.1.1. Context Scenario of the Survey

To evaluate individual mode choice behaviour, a hypothetical scenario is developed and presented to respondents as part of the stated preference survey. In this scenario, the mobility hub is defined as a transfer point where travellers are required to switch to alternative green transport modes to reach key destinations such as city centres or airports. Crucially, private vehicles—excluding bicycles—are not permitted beyond the hub. This design reflects the operational principles of restrictive green mobility hubs, which aim to reduce emissions and encourage sustainable travel by limiting private motor vehicle access. Travellers may arrive at the hub by car, bicycle, or other means, but must complete their journey using one of the available green alternatives.

In the case of private bicycles, respondents are assumed to either use their own bike from the origin or pick it up at the hub and park it at the destination. Bicycles are allowed beyond the hub because they align with the environmental objectives of the green mobility hub concept. Shared modes are assumed to be available at the hub. Users operate these vehicles themselves for the final leg of their trip and drop them off at the destination.

Although in practice some travellers may opt to switch to conventional public transport services (e.g., trains or regional buses), if they are required to use the hub, such switches are excluded from this study. This modelling choice ensures a focused analysis of first- and last-mile mode choice behaviour within the operational boundaries of the green mobility hub, rather than broader multimodal travel chains.

All shared modes are assumed to allow one-way usage. That is, users pick up the vehicle at the mobility hub and drop it off at the destination, where dedicated parking or docking facilities are assumed to exist. For the outbound trip, they can also pick up their first mile modes from the destination parking or docking facilities and go to the hub to switch to their original modes. There is no expectation that users must return the vehicle to the hub or keep it for extended durations. This assumption reflects the realistic operational model of available shared mobility systems [Micromobiliteit.nl, 2024].

3.1.2. Mode Alternatives

In the stated preference experiment, respondents are asked to choose between multiple transport mode alternatives available at the proposed mobility hub. These alternatives represent a diverse set of sustainable options designed to serve as first- and last-mile connections. The modes selected for this study are:

- Walk
- Private Bike
- Shared Bike
- Shared E-scooter

- Shared E-car
- Zero-Emission Bus (ZE Bus)

The first five modes are selected based on consistent findings in the literature indicating their prevalence and relevance in the context of mobility hubs (See section 2.1). Walking and private bikes are included as active, emission-free modes that are particularly appropriate for short distances and are widely adopted in the Dutch transport landscape. Shared bikes, e-scooters, and e-cars reflect the increasing role of flexible, user-driven, and low-emission shared mobility options in urban environments.

The Zero-Emission Bus (ZE Bus) is included as an emerging public transport alternative. While not yet commonly integrated into mobility hubs, it aligns with broader sustainability and climate mitigation policies. Its inclusion enables the study to examine user preferences when clean public transport options are offered alongside active and shared mobility solutions, broadening the scope of behavioural insights into future-oriented green transport systems.

3.1.3. Personal And Mode Attributes

Mode Attributes

Each transport alternative in the stated preference experiment is characterised by a set of mode-specific attributes that influence travellers' decision-making. The final list of attributes and attribute levels is derived from a combination of literature review, expert input, and contextual relevance to the Dutch urban transport setting. The selection aims to ensure sufficient realism while maintaining cognitive feasibility for respondents. The attributes used in the mode choice tasks are:

- Distance from Hub: Two levels—2 km and 4 km—represent the travel distance from the mobility hub to the destination. These distances are selected based on literature, where 2–5 km is typically considered the range for first- and last-mile trips [Torabi et al., 2023]. 2 km and 4 km were chosen to strike a balance between a commonly walkable range and a moderate cycling distance. Including both values supports sensitivity analysis of distance effects on mode choice.

- Travel Cost: Two levels—€0 (free) and realistic cost per km per mode—capture respondents' sensitivity to out-of-pocket costs. The non-zero cost levels are based on actual fare structures from Dutch transport providers, including NS, GVB, and Greenwheels [GVB, 2025; NS, 2023a,b; GreenWheels, 2023]. For bus, reference is taken from GVB in Amsterdam (€1.12 base cost and €0.207 per km)[GVB, 2025]. For e-scooter, NS have a start cost of €1 and then €0.33 per minute [NS, 2023a]. NS bike costs €4.55 per day [NS, 2023b] and greenwheels shared e-car costs €3.60 per hour [GreenWheels, 2023]. These reference prices are used to calculate approximate trip costs for each mode based on the 2 km and 4 km distances, as shown in Table 3.1.

- Weather: Included as a contextual variable with two levels — rainy and sunny. This accounts for weather-dependent mode preferences, especially for walking and cycling.

Table 3.1.: Cost Comparison for Different Transport Modes

Mode	Unit Cost	Cost for 2 km (Euro)	Cost for 4 km (Euro)
Shared Bike	Euro 4.55 per day	4.55	4.55
Shared E-Scooter	Euro 1 + 0.33 per minute	2.98	4.96
Shared E-Car	Euro 3.6 per hour	3.60	7.20
Bus	Euro 1.12 fixed + 0.207 per km	1.534	1.948

- Public Transport Frequency: Relevant for the ZE Bus alternative, with two levels — 5 minutes and 10 minutes — representing service frequency. In the Netherlands, especially within the Randstad region, buses typically operate with a headway of 10 to 15 minutes, influenced by factors such as passenger demand, area characteristics, and time of day [GVB, 2025]. In general, passenger waiting time is assumed to be half of the service headway, so people generally wait around 5 to 7.5 minutes. As it is a specialized service, 5 and 10 minutes wait time are considered. A sensitivity analysis is conducted to see the effect of various wait time in mode choice behaviour.

These attributes are assigned only to the relevant modes. For example, frequency applies exclusively to ZE Bus, while walking and private bike alternatives are assumed to have no monetary cost.

Travel time for all the modes derived from realistic average speeds per mode over distances of 2 km and 4 km, are provided in the survey to help respondents better understand the practical implications of choosing each mode.

Mode	Speed (km/h)	Travel Time for 2 km (min)	Travel Time for 4 km (min)
Walking	5	24.0	48.0
Bike	15	8.0	16.0
Shared Bike	15	8.0	16.0
Shared e-Scooter	20	6.0	12.0
Shared e-Car	40	3.0	6.0
Zero Emission Bus	24	5.0	10.0

Table 3.2.: Reference speeds and estimated travel times for 2 km and 4 km distances

Socio-demographic Attributes

To understand how personal characteristics influence mode choice behaviour, a range of sociodemographic variables is included in the survey. These variables allow the estimation of interaction effects between user profiles and transport mode preferences. Incorporating sociodemographics is crucial for identifying heterogeneity in travel behaviour, which can inform more targeted and inclusive transport policies. Eight socio-demographics are selected based on literature. The selected sociodemographic variables are as follows:

- Age: Age is collected in categorical ranges (e.g. 18–24, 25–29 etc.) to assess how preferences vary across different age groups, particularly in relation to the use of shared, active and digital modes.

- Gender: Gender is captured to examine potential differences in comfort, safety perceptions, and mobility preferences across genders.
- Education level: Education is used to understand how education level impacts the mode choice behaviour among the population.
- Employment status: Helps distinguish between the choice of people from different employment status, which may affect time and cost sensitivity and mode selection.
- Trip purpose: Respondents are asked to indicate the purpose of their most common reason to use a mobility hub (e.g., work, leisure, shopping), as this influences travel time tolerance and mode preferences.
- Shared transport experience: Measures prior use of shared transport services. Familiarity with shared systems can reduce perceived barriers and increase adoption likelihood.
- Primary mode of transport: Indicates car dependency and baseline availability of private vehicles.
- Comfort with digital mobility: Captures digital literacy and willingness to engage with app-based booking systems, essential for most shared and green alternatives.

These variables are primarily categorised based on CBS [Statistics Netherlands, nd] studies, to align the sample analysis with nationally recognised demographic segmentation, thereby enhancing comparability and generalisability. Following this categorization also helps the application step, where to create a synthetic Dutch and Schiphol commuter population, data from CBS is used (See Section 3.3.4). These variables not only support descriptive analysis of the sample but also allow for deeper insights when integrated into discrete choice models through interaction terms. Including these sociodemographic indicators enhances the explanatory power and realism of the mode choice models used in this study.

3.1.4. Survey Design

The survey is administered online via the Qualtrics platform [Qualtrics, nd] and comprises two core components:

- A series of stated preference (SP) choice tasks, in which respondents select their preferred transport mode from several alternatives under varying hypothetical conditions (e.g., cost, distance, weather).
- A set of socio-demographic questions designed to capture personal characteristics relevant for discrete choice modelling.

To generate the choice sets, Ngene software is used. The syntax is given in Appendix A. Since no previous study has incorporated all six selected green alternatives together in the context of mobility hubs, prior parameter estimates are not available. Consequently, an orthogonal fractional factorial design is adopted, as recommended in the literature for cases with no priors [Molin, 2024]. This design ensures that all attribute levels appear an equal number of times across tasks, while having reduced number of choice sets to maintain manageable cognitive load for respondents.

Because the alternatives are labelled (e.g., e-scooter, ZE bus), a labelled design is implemented using simultaneous generation of choice sets. Ngene generated a design with eight unique choice tasks, which vary cost and frequency attributes across alternatives, as shown in Table 3.3.

Choice Tasks	Shared Bike (€)	E-Car (€)	E-Scooter (€)	ZE Bus (€)	ZE Bus Frequency (Mins)
1	4.55	3.60	0.00	1.54	5
2	0.00	0.00	0.00	0.00	10
3	4.55	0.00	0.00	1.54	5
4	0.00	3.60	0.00	1.54	10
5	0.00	3.60	2.98	0.00	5
6	4.55	0.00	2.98	0.00	10
7	0.00	0.00	2.98	1.54	5
8	4.55	3.60	2.98	1.54	10

Table 3.3.: Choice task attributes with realistic costs and ZE bus frequency for 2 km trips

For 4 Km scenarios, the costs are changed based on table 3.1. To test the effect of context on mode choice, each choice task was presented under four different scenarios:

- 2 km, Rainy
- 2 km, Sunny
- 4 km, Rainy
- 4 km, Sunny

This results in 8 tasks in 4 contexts, meaning 32 total choice tasks. Additionally, to explore the bias related to private bike usage—the sample is split. Half the respondents received scenarios including the private bike alternative, while the other half received scenarios excluding it. This approach is supported by previous studies. This adjustment increased the number of total unique choice tasks to 64 (32 with bike + 32 without bike).

To manage cognitive load and avoid respondent fatigue, a blocking design was implemented. The 64 tasks were divided into four blocks of 16 tasks. Each participant was randomly assigned to one block and exposed to only four choice tasks per context—either tasks 1–4 or 5–8—ensuring full coverage of all four contexts with only 16 tasks per respondent. Changing context every four questions also serves as a cognitive reset, helping to reduce fatigue and maintain participant engagement throughout the survey.

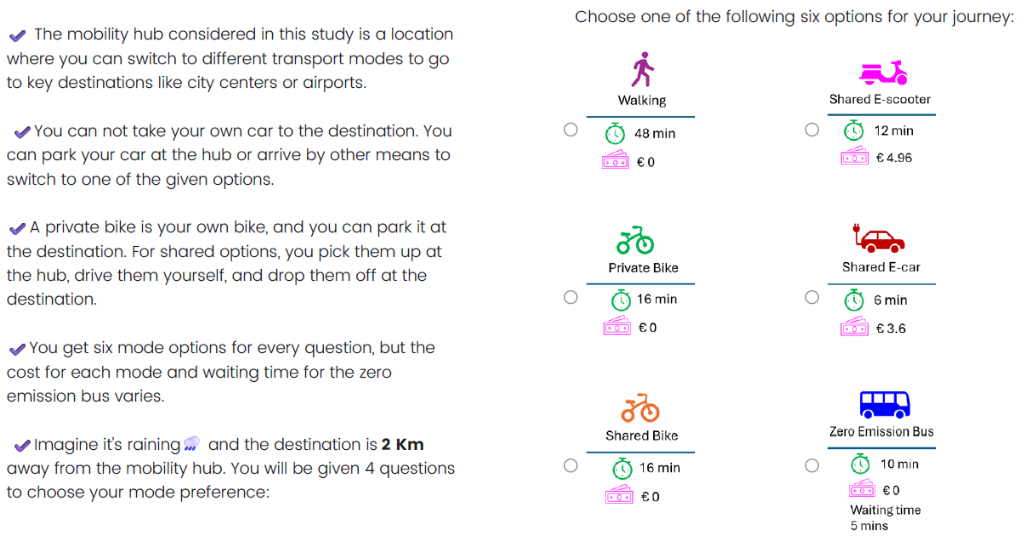
One block of the survey is provided in Appendix B. An example of how context and SP choice tasks are presented to the respondents is shown in Figure 3.2.

3.1.5. Necessary Number of Responses

Reliable estimation of parameters in stated preference (SP) models depends on having a sufficiently large and well-distributed sample. To estimate the minimum required responses, this study follows the heuristic by Orme [2010], presented in Equation 3.1:

$$\frac{n \cdot t \cdot a}{c} \geq 500 \tag{3.1}$$

Where:



(a) Survey context (b) Example SP choice task

Figure 3.2.: Context and choice tasks from the stated-preference survey.

- n = number of respondents,
- t = number of choice tasks per respondent,
- a = number of alternatives per task,
- c = largest number of attribute levels for any single attribute.

For this study:

- $c = 2$ (maximum number of levels for cost, distance and frequency),
- $t = 16$ (choice tasks per respondent),
- $a = 6$ (when private bike is included), or $a = 5$ (when excluded).

With Private Bike:

$$n \geq \frac{500 \cdot 2}{16 \cdot 6} = 10.41 \approx 11 \tag{3.2}$$

Without Private Bike:

$$n \geq \frac{500 \cdot 2}{16 \cdot 5} = 12.5 \approx 13 \tag{3.3}$$

Thus, the minimum sample size required to estimate main effects for two blocks each of both designs (with and without private bike) is: $11 \times 2 + 13 \times 2 = \mathbf{48}$ **respondents**

However, this threshold only ensures aggregate-level estimation. One of the core goals of this study is to investigate interaction effects across socio-demographic segments. Among the selected variables, age contains the largest number of subgroups—up to 8 categorical bins (e.g., 18–24, 25–29, etc.)—while others (e.g., education, employment, digital comfort) typically have fewer (3–5) categories. To ensure sufficient statistical power for subgroup analysis, literature suggests a minimum of 30 respondents per subgroup [Pham, 2023]. Therefore, to robustly estimate interactions across the age variable:

$$8 \text{ subgroups} \times 30 = \textbf{240 respondents}$$

Although fewer respondents may suffice for other socio-demographic variables, age segmentation imposes the most stringent requirement. Accordingly, a target sample size of at least 240 respondents is adopted to ensure reliable estimation of both main effects and subgroup interactions in the discrete choice models.

3.1.6. Survey Distribution

To ensure adequate response volume and diversity in the sample, a multi-pronged strategy is employed for survey distribution:

- Posters and flyers are placed in common areas at TU Delft, targeting students and staff.
- The survey is shared online via the researcher's professional and academic network, using social media and emails to expand outreach beyond the university.
- Employees working at Schiphol Airport and TNO are approached via email, with permission from relevant contact points and stakeholders.
- Additional outreach targets professionals involved in mobility-related projects at Schiphol to ensure contextual relevance among respondents.

All survey procedures are reviewed and approved by the TU Delft Human Research Ethics Committee. The study adheres to the General Data Protection Regulation (GDPR) framework throughout its design and deployment. Participation is voluntary, and informed consent is obtained at the beginning of the survey. Respondents are clearly informed about the purpose of the study, the anonymous nature of their responses, how their data will be used, and their right to withdraw at any stage.

No personally identifiable information (PII) is collected. All data are stored securely using GDPR-compliant infrastructure via the Qualtrics platform [Qualtrics, nd]. These measures ensure that the research is conducted ethically, transparently, and in full compliance with data protection standards.

3.2. Data Preparation

The data preparation phase ensures that the dataset is clean, consistent, and ready for discrete choice modelling. Raw data collected from Qualtrics [Qualtrics, nd] is first filtered to retain only fully completed surveys. Incomplete responses are excluded to avoid introducing missing values or response bias. A minimum survey completion time of three minutes is used as a quality threshold, based on the estimated time required to read and understand all survey information. Responses submitted faster than this threshold are discarded, as they may indicate disengagement or inattentiveness.

Each respondent receives either the version of the survey that includes the private bike option or the version without it. For those in the latter group, private bike availability is set to zero in the dataset. The contextual variables—distance (2 km or 4 km) and weather (sunny or rainy)—are assigned to each choice task based on the respondent's experimental block.

The raw choice data is then transformed into a panel structure suitable for use in Biogeme. This includes re-indexing all mode alternatives with numeric identifiers, encoding the respondent's actual choices into a choice variable, and stacking all tasks from the same respondent to allow for panel estimation. Mode attributes—such as cost, frequency, and travel time—are mapped to each alternative for each task based on the experimental design.

Socio-demographic variables are also processed for model inclusion. Categorical variables (e.g., age group, education level, employment status) are converted into binary dummy variables. These variables are used both directly in the model and for interaction terms to capture preference heterogeneity. For example, age or comfort with digital platforms can be interacted with cost or travel time to study conditional sensitivities. Responses marked as "Prefer not to say" for any socio-demographic question are excluded from that specific subgroup analysis to avoid bias. In cases where a subgroup contains fewer than 30 respondents, categories are either removed or merged with similar ones, following the recommendation of Gavriilidou [2024], although exceptions can be made for minor categories with irreplaceable characteristics.

3.2.1. Statistical Testing

To assess whether the characteristics of the collected sample differ significantly from those of the target population, and to examine the influence of socio-demographic variables on mode preferences, a Chi-square (χ^2) test is conducted. This non-parametric statistical test evaluates the association between categorical variables by comparing observed and expected frequencies across different categories. The Chi-square statistic is calculated using the following formula:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{3.2}$$

Where:

- O_i is the observed frequency for category i,

- E_i is the expected frequency for the same category, based on population-level statistics (e.g., CBS data).

Expected frequencies are derived from official demographic distributions to ensure representativeness [Statistics Netherlands, nd]. The test is applied to socio-demographic variables such as age, gender, education level, and employment status, enabling the identification of sample-population disparities.

In addition, Chi-square tests are employed to determine whether mode preferences differ significantly across socio-demographic subgroups. This allows the study to identify which user characteristics may significantly influence mode choice behaviour, supporting the inclusion of sociodemographic terms in the model.

Each test result is interpreted using the p-value at a 95% confidence level. A p-value below 0.05 indicates a statistically significant difference between observed and expected values, and suggests that the corresponding variable may influence mode choice. Conversely, a p-value above 0.05 indicates no statistically significant difference and implies limited or no impact on mode choice. These findings help selecting significant socio-demographic variables in the modelling process.

3.3. Discrete Choice Modelling

To analyze the stated preference (SP) data, this study employs discrete choice models to examine the influence of various mode and user characteristics on mobility hubs. Two model structures are applied: the Multinomial Logit (MNL) and the Panel Mixed Logit (PML). The Multinomial Logit (MNL) model is chosen due to its simplicity, computational efficiency, and suitability for capturing general mode choice behaviour. The Panel Mixed Logit (PML) model is employed to account for repeated observations from the same individuals, thereby capturing panel effect and improving model robustness. Other model types, such as the Nested Logit (NL), are not suitable for this study, as the alternatives considered do not exhibit hierarchical similarity or shared unobserved components. Likewise, the Latent Class Choice Model (LCCM) is not applied, since the objective of this research is to understand the average effect of mobility hubs on the general population rather than segmenting it into latent user classes. Both MNL and PML models are grounded in the Random Utility Maximization (RUM) framework.

Under the RUM framework, an individual n is assumed to choose the alternative i that offers the highest utility U_{ni}. The utility is composed of an observable deterministic part V_{ni} and an unobserved random component ε_{ni}:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{3.3}$$

The deterministic component is modelled as:

$$V_{ni} = \sum_{k=1}^{K} \beta_k X_{nik} \tag{3.4}$$

Where:

- X_{nik}: value of attribute k for individual n and alternative i,
- β_k: parameter to be estimated, representing the marginal utility of attribute k,
- K: total number of attributes included in the model.

Despite the simplicity and intuitive interpretation offered by the MNL model, it has several known limitations. Specifically, it assumes homogeneous preferences across individuals, does not capture correlation in unobserved factors across repeated choices, and imposes the Independence of Irrelevant Alternatives (IIA) property. These assumptions limit its ability to account for realistic substitution patterns or taste variation. In the context of this study—where each respondent completes multiple choice tasks—ignoring panel effects could bias the results. To address these issues, a more flexible modelling framework is required. Therefore, a Panel Mixed Logit (PML) model is also employed, which relaxes these assumptions by allowing for random parameters and accommodating repeated observations per individual [Train, 2002].

3.3.1. Model Specification

Base MNL Model: The first model estimates choices based solely on alternative-specific constants (ASCs), that captures the effect on the utility of an alternative that is not explained by the attributes, and transport attributes such as cost, travel time, and frequency (for ZE Bus). Utility for reference alternative (ZE bus for this study) does not include ASC. For example, utility function of shared bike for base model is:

$$U_{\text{Shared Bike}} = \text{ASC}_{\text{Shared Bike}} + \beta_{\text{Cost}} \cdot \text{Cost} + \beta_{\text{Travel Time}} \cdot \text{Travel Time} \tag{3.5}$$

Where:

- $\text{ASC}_{\text{Shared Bike}}$: Captures the alternative-specific constant for Shared Bike, reflecting unobserved preferences not explained by observed attributes.
- β_{Cost}: Represents the marginal utility associated with an increase in travel cost.
- $\beta_{\text{Travel Time}}$: Represents the marginal utility associated with an increase in travel time.
- Cost and Travel Time: These are the actual values of cost and travel time for the Shared Bike alternative in a given choice scenario.

Sociodemographic Models: To add personal characteristics to the model, two methods are used, (i) socio-demographic characteristics are added as binary dummies and (ii) interaction terms are added between socio-demographic characteristics (e.g., age, education, employment status) and travel attributes (e.g., cost, time) [Gavriilidou, 2024]. Binary dummies are created for all categorical variables. For example utility function of shared bike, where gender is included as binary dummy (female is the reference category) is given below:

$$U_{\text{Shared Bike}} = \text{ASC}_{\text{Shared Bike}} + \beta_{\text{Cost}} \cdot \text{Cost} + \beta_{\text{Travel Time}} \cdot \text{Travel Time} + \beta_{\text{Male}} \cdot \text{Male} \tag{3.6}$$

Where:

- β_{Male} captures the difference in utility for male respondents compared to the female reference group.
- Male is a dummy variable. Male =1 for males and 0 for females.

Sociodemographics as interaction terms are tested in three different ways. For example, to add gender as interaction terms three sociodemographic models are tested, (i) gender-cost interaction (ii) gender-travel time interaction, and (iii) gender as interaction terms with both cost and travel time. Utility of shared bike when gender is included as interaction term with both cost and travel time:

$$\begin{aligned} U_{\text{Shared Bike}} = \text{ASC}_{\text{Shared Bike}} &+ \beta_{\text{Cost, Male}} \cdot \text{Male} \cdot \text{Cost} + \beta_{\text{Cost, Female}} \cdot \text{Female} \cdot \text{Cost} \\ &+ \beta_{\text{TT, Male}} \cdot \text{Male} \cdot \text{Travel Time} + \beta_{\text{TT, Female}} \cdot \text{Female} \cdot \text{Travel Time} \end{aligned} \tag{3.7}$$

Here:

- $\beta_{\text{Cost, Male}}$ is the marginal utility of cost for male respondents. It reflects how sensitive male respondents are to changes in cost.
- $\beta_{\text{Cost, Female}}$ is the marginal utility of cost for female respondents. It reflects cost sensitivity among female participants.
- $\beta_{\text{Time, Male}}$ and $\beta_{\text{Time, Female}}$ represent the marginal utilities of travel time for males and females, respectively, indicating how much utility decreases with increasing travel time for each gender.

Final MNL model: The best-performing interaction terms and dummy variable terms (based on sociodemographic models) are iteratively added to the base model using forward stepwise method until no further improvement in model fit is observed (Section 3.3.2). This approach balances model complexity with explanatory power. All variables with p-values greater than 0.05 are excluded in each step as they are not significant, thus parsimony is improved. By excluding attributes that do not significantly improve the model, the forward stepwise approach helps prevent overfitting, enhancing the model's generalisability to new data. The final MNL model includes all significant attributes and interaction terms. Each coefficient is interpreted based on sign and magnitude.

Panel Mixed Logit (PML) Model: To account for the repeated nature of choice observations per individual and to relax the restrictive assumptions of the Multinomial Logit (MNL) model, a Panel Mixed Logit (PML) model is estimated. The PML framework allows parameters to vary randomly across individuals. Each individual is assumed to have their own preference structure, represented by random coefficients. A panel-specific random effect is introduced in the final MNL model utility functions of all non-reference alternatives to allow for correlation across repeated choices made by the same respondent. The panel-specific coefficient for respondent n is modelled as:

$$\beta'_n = \beta_0 + \sigma_{\text{panel}} \cdot \nu_n \tag{3.8}$$

where β_0 is the mean of the distribution and is fixed to zero for identification purposes. The term σ_{panel} denotes the standard deviation, capturing the extent of unobserved heterogeneity, and ν_n is a random draw from a standard normal distribution, i.e., $\nu_n \sim \mathcal{N}(0,1)$. This formulation ensures that each individual n has a unique realization of the utility coefficient β'_n, reflecting individual-specific preferences.

To ensure robustness in parameter estimation, the model employs Maximum Simulated Likelihood using Monte Carlo simulation with 1000 Halton draws, which provide better coverage of the integration space compared to purely random draws.

All models are estimated using Biogeme [bio, 2024], an open-source package that uses Maximum Likelihood Estimation (MLE) to estimate choice probabilities. MLE is chosen for its robustness and widespread use in discrete choice analysis [Ben-Akiva and Bierlaire, 2003].

3.3.2. Goodness of Fit and Evaluation

To evaluate and compare the performance of estimated models, this study adopts a structured approach centered around three primary goodness-of-fit metrics: Adjusted Rho-square ($\bar{\rho}^2$), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC).

Adjusted Rho-square is the principal measure used to assess model fit throughout the forward stepwise selection process and in final model selection. It extends the traditional Rho-square by incorporating a penalty for the number of estimated parameters, thereby discouraging overfitting. A higher $\bar{\rho}^2$ value indicates a better trade-off between explanatory power and model complexity. In this study, it serves as the primary decision criterion for including or excluding interaction terms in successive model iterations.

As a secondary selection metric, AIC is consulted when multiple models exhibit similar $\bar{\rho}^2$ values. AIC supports parsimony by balancing fit and complexity. BIC, imposes a stricter penalty for model complexity, particularly with large sample sizes, and therefore serves as a conservative cross-validation tool. When AIC and BIC jointly favor a particular model (i.e., has lower values) among those with similar adjusted Rho-square values, it strengthens confidence in the model's generalizability.

Log-likelihood values and Rho-square (ρ^2) are also reported for completeness and transparency. However, they are not used as the main criteria for final model selection. Instead, they help provide context for how much explanatory power is gained relative to a null model.

In addition to fit indices, model convergence diagnostics are closely monitored to ensure numerical reliability. Specifically, the final gradient norm is examined as an indicator of convergence quality. A low gradient norm—typically below 10^{-3}—suggests that the estimation process has reached a stable local maximum of the log-likelihood function. This metric helps confirm that parameter estimates are robust and the optimization process has adequately converged.

By prioritizing $\bar{\rho}^2$ while supplementing with AIC, BIC, and convergence checks, this evaluation strategy ensures that the selected models are both statistically valid and behaviourally interpretable. While fit metrics inform the statistical quality of the model, validation ensures its predictive strength.

3.3.3. Validation and Predictive Accuracy

To ensure the robustness and predictive accuracy of the estimated discrete choice models, a structured validation procedure is implemented. Validation is crucial for demonstrating that model results are not driven by overfitting for sample-specific characteristics, but are generalizable to similar real-world contexts.

Following best practices in discrete choice modelling [Gavriilidou, 2024], the full stated preference dataset is decided to be randomly partitioned into two subsets: 80% for training and 20% for testing. The training set is used to estimate the model parameters, while the test set serves to evaluate the model's predictive performance on unseen data.

However, as recommended by Ben-Akiva and Bierlaire [2003], when the total sample size or specific subgroup sizes fall below threshold (e.g., fewer than 30 observations per subgroup), data splitting can compromise estimation stability and test power. In such cases, the full dataset is used for both estimation and evaluation. This ensures reliable parameter estimation while still allowing meaningful inference.

For each respondent, the probability of selecting each available alternative is computed based on the utility functions and the estimated model parameters, following the probability of individual n choosing alternative i under the Multinomial Logit (MNL) model:

$$P(i) = \frac{e^{V_i}}{\sum_j e^{V_j}} \tag{3.9}$$

Where:

- $P(i)$ is the probability that alternative i is chosen,
- V_i is the deterministic utility component of alternative i,
- The denominator sums over all alternatives j in the choice set, ensuring that the probabilities across all options sum to 1.

To compute aggregate mode shares, the predicted probabilities were summed across all individuals, as in Equation 3.10. For interpretability, this total was normalized by the number of individuals N and expressed as a percentage. This yields the estimated modal split across the population. This is operationalized through the following formula:

$$\hat{C}_j = \frac{1}{N} \sum_{i=1}^{N} P_{ij} \times 100 \tag{3.10}$$

Where:

- $\hat{C}_j$ is the aggregated probability of alternative j being chosen for the whole target population,
- P_{ij} is the probability that individual i selects alternative j,
- N is the total number of respondents.

These are then compared to the actual observed frequencies from the data. To quantify the model's aggregate predictive accuracy, the Normalized Absolute Error (NAE) is calculated:

$$\text{NAE} = \frac{\sum_{j=1}^{J} |\hat{C}_j - C_j|}{\sum_{j=1}^{J} C_j} \tag{3.11}$$

Where:

- C_j is the observed frequency of alternative j,
- $\hat{C}_j$ is the predicted frequency of alternative j,
- J is the total number of alternatives.

The NAE provides a direct, interpretable measure of how closely the model replicates observed aggregate behaviour. A lower NAE reflects stronger predictive power and supports the model's generalizability.

In contrast to the MNL validation, the Panel Mixed Logit (PML) model validation accounts for repeated choices made by the same respondent by treating their observations as a panel. Instead of assuming independent observations, the validation uses Panel Likelihood Trajectory in Biogeme to preserve within-individual correlation. Additionally, it incorporates random taste heterogeneity by simulating individual-specific coefficients through 1000 Halton draws. These draws are used to integrate over the distribution of random parameters during simulation, allowing each respondent to reflect unique preference variations. Predicted choice probabilities are computed for each task, then aggregated across individuals to estimate modal shares (Equation 3.9 and 3.10). This approach ensures that both panel structure and heterogeneity are retained in validation, making the prediction more behaviourally consistent with the PML assumptions.

In this study, both model fit and predictive accuracy are used as complementary criteria for final model selection. Model fit indicates how well the model explains the choices observed in the training data. However, high goodness of fit does not guarantee that the model will generalize well to new or unseen data. Therefore, predictive accuracy is equally important. It assesses the model's external validity and guards against overfitting by measuring how well the estimated parameters perform when applied beyond the estimation sample. This dual approach ensures that the final model is not only statistically robust but also practically reliable for forecasting future behaviour. It aligns with best practices in discrete choice modelling, where the goal is to balance explanatory power with predictive utility.

3.3.4. Model Application

To evaluate how the estimated discrete choice models translate into population-level behaviour, a stochastic simulation framework is used. The model is applied to a synthetic population of Dutch residents and Schiphol commuters, enabling the computation of predicted mode shares. The modal split of the Dutch population is first computed to establish a national benchmark. This is then compared to that of the Schiphol commuter group to assess the realism and specificity of the simulated predictions for the target population. But the modal split for Schiphol commuter population is used in the case study simulation to see traffic and environmental effects. All simulations are implemented in Python using Biogeme's simulation framework, enabling full reproducibility and scalability to different target populations.

A synthetic population of 100,000 individuals is generated using demographic and behavioural distributions derived from Dutch national statistics [Statistics Netherlands, nd] and [Royal Schiphol Group, 2023]. Since the SP survey sample is not representative of the entire commuting population in Schiphol Airport, relying solely on the raw responses would bias modal split estimates. The synthetic population ensures that the mode choice model is applied across a demographically realistic sample, enabling the estimation of aggregate modal shares that are grounded in observed behavioural heterogeneity. Each synthetic respondent is assigned attributes—such as age group, employment status, trip purpose, and primary travel mode—based on empirically grounded probabilities. For instance, the distribution of age groups (11% aged 18–24, 8% aged 25–29, etc.) and employment types (e.g., 56% full-time employed) are designed to match observed proportions in the targeted population. These characteristics influence mode choice utilities through interaction terms in the model. Trips simulated in this setup are fictive trips, 50% of 2 Km and 50% of 4 Km. For each synthetic individual, weather conditions are also randomly assigned according to realistic probabilities of rain in the Netherlands (e.g., 40% rainy, 60% sunny) [Statista Research Department, 2023], which influence utility components via weather interaction terms. All these assumptions are made to get one aggregate modal share that imitates real life conditions and will be used for simulation in the next step.

Key travel attributes such as cost, travel time, and wait time were fixed based on the levels presented in the SP survey. This ensured internal validity of the application and avoided introducing inconsistencies that could arise from extrapolating beyond the original experimental design. Although these trips are hypothetical, the use of realistic distributions and empirically grounded parameters allows for meaningful behavioural inference.

The predictive mode shares are computed using individual-level choice probabilities, which are obtained by applying the estimated utility functions to each respondent's profile. The final predicted share for each mode is calculated using Equation 3.9 and 3.10.

To complement the main simulation results, sensitivity analyses are conducted to assess the robustness of mode choice predictions under varying conditions. Specifically, key attributes such as travel costs and travel distances are systematically adjusted (e.g., increased or decreased by fixed percentages), while keeping other parameters fixed, to examine their effect on predicted mode shares. This analysis provides insights into how sensitive the population's mode choices are to marginal changes in attributes. These insights help identify the most effective policy levers—such as adjusting pricing or improving travel times. Furthermore, the resulting mode share estimates can serve as inputs for traffic and environmental scenario analyses in future applications to see the effect of different contexts.

3.4. Traffic and Environmental Evaluation using the Digital Twin

To evaluate the system-wide impacts of green mobility hubs, this study integrates behavioural outputs from discrete choice modelling into a simulation framework. This enables the translation of individual-level mode preferences into network-level outcomes, allowing estimation of key indicators such as vehicle kilometers travelled (VKT), intensity–capacity (I/C) ratios, and emissions of NO_x, and particulate matter (PM).

3.4.1. Rationale for Using the Digital Twin Framework

The TNO in-house Digital Twin [Lohman, 2023] is selected for its technical capacity to simulate multimodal travel behaviour and assess macroscopic traffic and environmental impacts. Digital Twin operates on the Inter Model Broker (IMB) framework, which is designed for real-time scenario testing, distributed data management, and parallel computing [Lohman, 2023]. This technological foundation enables rapid simulation of "what-if" scenarios, making it possible to assess the potential impacts of policy interventions, such as the implementation of green mobility hubs, under varying demand, weather, and infrastructure conditions. This is particularly valuable for evaluating dynamic system-level indicators such as network flow, intensity–capacity (I/C) ratios, and emission concentrations.

Moreover, the DT is calibrated using real-world OD data and network data from Venom model [Vervoerregio Amsterdam, 2024] (Base year for this data is 2019 and forecasted year is 2030). This ensures credible baseline alignment to calculate the change of the indicators.

While the DT framework offers substantial analytical advantages, it also presents several limitations. The model relies on static assumptions for key variables such as mode availability, and hub accessibility, which may not fully capture real-world fluctuations or disruptions—such as vehicle shortages, infrastructure failures, or weather-induced delays. In this study, Volume Averaging (VA) assignment is used for car, shared electric car, and zero-emission bus. VA approximates more realistic flow dispersion than All-or-Nothing (AON) but can obscure localised bottlenecks and may overestimate network resilience. On the other hand, All-or-Nothing (AON) assignment is used for bike, shared bike, shared e-scooter, and walking modes, where users are more likely to follow a single, shortest-path route due to network constraints or habitual behaviour. However, AON concentrates all demand on the least-cost path, ignoring route diversity and user equilibrium, which may lead to underestimation of congestion and overloading on specific links. The combination of these two assignment methods introduces limitations in calculating precise link-level outcomes under peak or disrupted conditions.

3.4.2. Simulation Design and OD Reallocation

In this study, the Digital Twin takes car-based commuter flows as input and redistributes them based on the fixed modal shares derived from the final discrete choice model application on a synthetic Schiphol commuter population. All traffic simulations are based on the morning peak period. Morning peak traffic represents the most critical load on urban transport infrastructure, especially for work-related commuter flows, which are typically more directional and concentrated. Modelling this period captures the system under its highest stress, thus yielding more policy-relevant insights.

Car-based commuter flows are calculated from scaling the baseline car OD matrix, by using a national average commuter share of 55% [PBL Netherlands Environmental Assessment Agency, nd]. Trips undertaken entirely (from the origin) by private bike are not modelled, as this remains unchanged and does not influence traffic or emissions. Passengers who switch to and from bikes at hubs are modelled. Other private modes (except car and bike) are excluded due to data unavailability.

Commuter trips are selected as they account for a significant share of car travel to Schiphol, and shifting this group to green modes is expected to yield significant traffic and environmental benefits.

The generated OD flows were divided into six mode-specific OD matrices at the two main hubs, based on the modal shares predicted by the MNL model. Each matrix was assigned to the corresponding mode's network. Passengers are assumed to leave their green mode at the destination after use. For modelling simplicity, this process was represented using four destination hubs. The same predicted modal split was applied across these hubs, assuming that travellers drop off their shared mode at the destination and may continue their onward journey with another shared mode. While this assumption may oversimplify actual behaviour, it enables tractable and reproducible DT integration.

Two scenarios are simulated: the baseline (car-only access to Schiphol) and the intervention (two strategically placed mobility hubs). Figure 3.3 shows the location of the two hubs for the intervention scenario. The hubs are strategically placed on the northern and southern edges of the Schiphol Airport zone. The northern hub, located near the A4/A9 junction, enables efficient access to and from Amsterdam and Amstelveen, key residential and employment centers. The southern hub, situated near Rozenburg and Hoofddorp, serves the growing suburban corridor of Haarlemmermeer and connects directly to regional roadways such as the A4, N201, and N520. The DT assigns traffic flows using Static Traffic Assignment (STA), which distributes trip volumes along shortest paths based on travel time and distance, calculated using the Bureau of Public Roads (BPR) function. Dijkstra's algorithm is applied with a generalized cost function, and the "all-or-nothing" method (for bike, walk, shared bike, and shared e-scooter) and "volume averaging" (for car, e-car, and ZE bus) assign flows until convergence. This method, while simplifying congestion dynamics, is appropriate for average peak-period analyses [Ortúzar and Willumsen, 2011]. Both outbound and inbound trips between all of the Netherlands and Schiphol Airport are included.

To integrate the mobility hubs, new green modes are implemented in the DT by creating network structures for all the modes. After generating the new network structures for the modes, they are populated with relevant link-level data such as travel time, cost, and allowed turns. As illustrated in Figure 3.4, the base car network feeds into the mobility hub, where flows are redistributed to six mode-specific networks—walking, cycling, shared bike, shared e-scooter, shared e-car, and ZE bus—each represented as its own layer with mode-specific link attributes.

The Mobility Hub setup in DT ensures that all trips arriving at or departing from Schiphol are routed through one of the two hubs. An example of how the car trips are reallocated at the hub is shown in Figure 3.5. The diagram illustrates a fictional scenario where in the intervention scenario, within Schiphol Airport zone 50% trips are allowed to go via car and 50% trips have to switch to bike at the hub. In the baseline scenario, all 20 trips from the origin to Schiphol Airport are made directly by car. After the hub is introduced in the intervention scenario, 50% of these trips—10 out of 20—are assumed to switch to bike through the hub. This results in a two-leg journey for these 10 trips: car from origin to the hub, and bike from the hub to the airport. The remaining 10 trips still continue directly to Schiphol Airport by car. For this study, modal switches at the hubs are implemented using fixed modal shares from the MNL model applied to a synthetic population. These ratios are

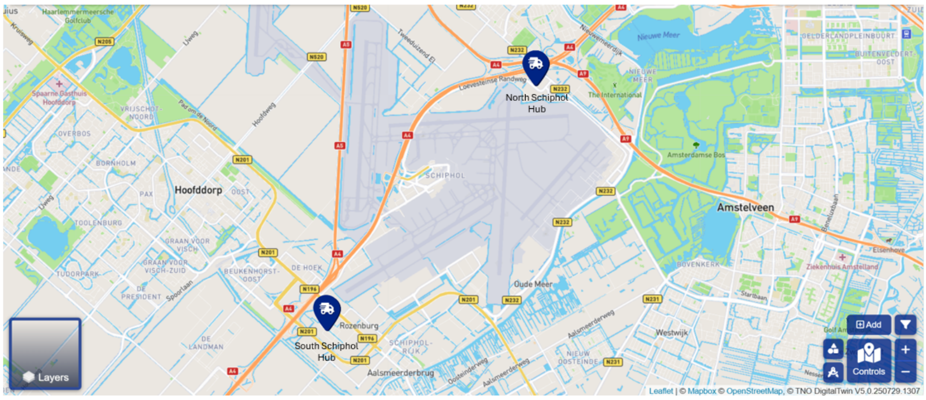


Figure 3.3.: Location of the two hubs for intervention scenario

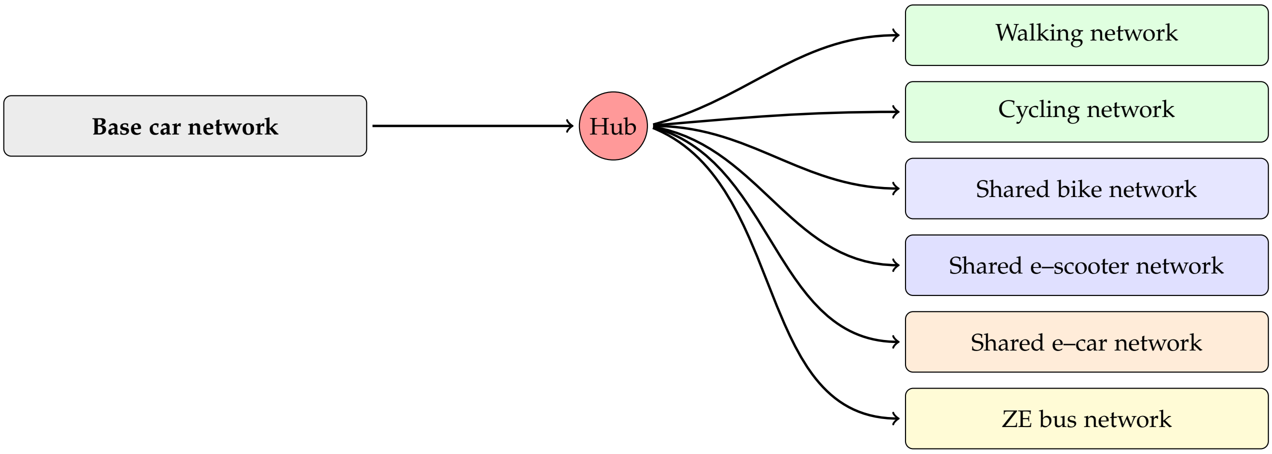


Figure 3.4.: Flow from the base car network through a mobility hub to six mode-specific networks.

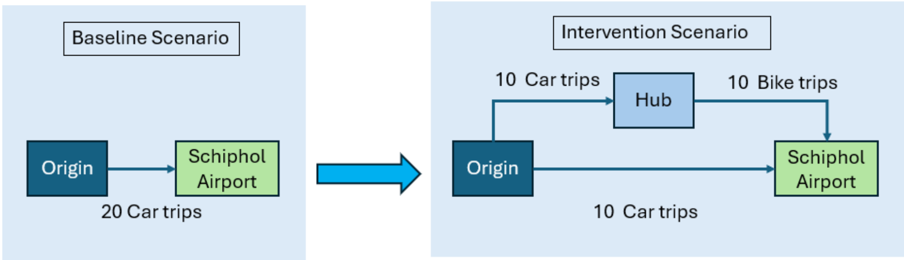


Figure 3.5.: Reallocation of trips at hub location

used to assign the second leg of inbound trips and first leg of outbound trips across green modes.

This approach offers multiple advantages: it integrates behaviourally grounded mode shares into a macroscopic traffic simulation, models green mode usage inside Schiphol Airport, and enables estimation of system-level indicators.

However, limitations remain. By applying fixed, weighted-average modal splits, the model cannot capture stochastic variation or context-specific switching (e.g., based on exact weather, trip length, or socio-demographics). While this approach avoids overfitting and remains reproducible, it overlooks individual-level heterogeneity. Moreover, universal mode availability is assumed—shared services are always accessible and unconstrained by capacity. This necessary simplification, due to the macroscopic resolution, may underestimate real-world disruptions or shortages. Additionally, hub-to-destination network links do not dynamically adjust utilities based on real-time conditions; travel times and costs are statically configured. While simplifying integration, this omits dynamic feedback between network states and behavioural choices. Future work could enhance realism with stochastic availability, agent-based integration, or capacity-constrained service modeling.

3.4.3. Traffic Indicators and Emission Estimation

Following the traffic assignment using Static Traffic Assignment (STA), the resulting network flows are used to compute key system-level indicators: Vehicle Kilometers Travelled (VKT), intensity–capacity (I/C) ratios, and amount of NO_x, and particulate matter (PM). These indicators form the basis for assessing the impact of the mobility hub intervention.

In DT, air emissions are calculated using the standardized Dutch SRM1 [Smit et al., 2006] and SRM2 [Smit et al., 2007; Wesseling and Zandveld, 2006] models, which estimate pollutant concentrations based on road type, traffic volume, vehicle type, speed, and congestion levels. However, a key limitation is that these models assume average meteorological and background conditions for a given year, which may overlook short-term variations in weather, traffic dynamics, or localized sources of pollution, potentially leading to under- or overestimation of actual exposure levels. Emission outputs and VKT are evaluated both spatially and numerically. First, results are visualized on all the districts to identify geographic patterns in traffic and environmental impact. This spatial approach helps uncover localised improvements or deteriorations in traffic conditions and pollutant concentrations.

Second, changes in emissions and VKT are analysed in aggregated formats for each of the districts, breaking down changes at the district level to identify areas with the most significant shifts. Then a net-change calculation is conducted to evaluate the impact across the entire study area. These outputs enable both system-wide and place-specific insights into the effects of hub implementation.

In addition, total emissions and I/C ratios after intervention are compared against established benchmarks. For emissions, EU air quality thresholds are used as reference values to assess whether pollution levels remain within acceptable environmental limits [European Commission, nd]. For traffic efficiency, I/C ratios are evaluated relative to the critical threshold value of 1.0, which signifies full capacity utilization. This allows for a nuanced interpretation: even if certain links experience increased flows or emissions post-intervention, they may still fall within acceptable operational or environmental boundaries.

Microscopic dynamics such as agent-level transitions, intra-hub crowding, or intermodal competition are not captured in this simulation. The Digital Twin also requires significant computational resources and domain-specific calibration, which may limit its replicability in other urban contexts without extensive data access and technical expertise. Lastly, while the platform enables modular scenario testing, the interpretation of results still depends on the quality and representativeness of input data and assumptions, which introduces a degree of uncertainty into impact projections.

The Digital Twin offers a scalable, behaviourally informed platform for evaluating large-scale sustainable mobility interventions. Its Inter Model Broker (IMB) architecture ensures modularity, reproducibility, and computational transparency. The integration of empirically estimated modal splits from the MNL model into a macroscopic traffic environment provides a methodologically robust and policy-relevant framework for understanding the systemic impacts of green mobility hubs.

4. Results

A total of 213 responses are initially collected from the survey. The dataset is then cleaned by filtering out entries with missing values and inconsistencies. Of the valid responses, 138 participants progressed 100% of the survey, but only 130 of them answered all questions. To maximize the usable sample size, respondents who completed all 16 choice tasks but had missing sociodemographic information are also included. This brings the final analytical sample to 131 respondents. The remaining 82 respondents have less than 50% progress and 40 of them have spent less than 3 minutes on the survey.

The survey was built with detailed categories to understand a wide range of personal attributes, enabling a nuanced analysis of demographic and behavioural patterns. This level of specificity was intended to identify whether certain groups showed distinct preferences that might be overlooked using broader classifications.

However, during the analysis, it is found that some categories had very low response counts (fewer than 30), which could undermine statistical power. To address this, similar categories are combined—for example, age groups 40–49 and 50–59 are merged, as are employment types such as part-time and unemployed. These adjustments ensure adequate sample sizes for meaningful analysis.

Responses marked as “Prefer not to say” and those from participants who indicated they would never use a mobility hub are excluded from the socio-demographic-based analyses. In addition, categories such as “Other” gender or education levels like “High School” and “MBO” are excluded due to insufficient responses.

Nevertheless, certain small groups—such as respondents aged 40-59 and 60+, people who work part-time or unemployed, those whose primary mode of transport is walking or categorized as “Other,” and those selecting “Other” and shopping for trip purpose—are retained in the analysis. These groups are considered essential for understanding diverse mobility needs and choice behaviours, as their perspectives may significantly differ from those of the general population and are not represented by other categories.

With these adjustments, all retained categories include more than 30 respondents, except for the few mentioned above, which are preserved due to their critical analytical value.

4.1. Sample characteristics

The sample characteristics from the dataset are presented in Table 4.1 with the count and percentage of each aggregated category. The survey dataset is then compared to the CBS Data for the Dutch population. Digital mobility skill (DMS) percentages are taken from Garritsen et al. [2023]. As it is not possible to collect all this Data specifically for Schiphol commuters, Dutch population is considered as it is a good representation of Schiphol commuters.

Table 4.1.: Sociodemographic Distribution: Survey Sample vs CBS Population (NL)

Variable	**Category**	**Count**	**Sample (%)**	**CBS (%)**
Gender	Male	83	63.8	49.6
	Female	43	33.1	50.4
	Other	2	1.5	–
	Prefer not to say	2	1.5	–
Age Group	18–24	34	26.2	11.0
	25–29	37	28.5	8.0
	30–39	35	26.9	16.0
	40–59	20	15.4	31.0
	60+	4	3.1	34.0
	Prefer not to say	0	0.0	–
Education	High School	2	1.5	–
	MBO	1	0.8	–
	Bachelor	48	36.9	–
	Master+	79	60.8	–
	None / Not answer	0	0.0	–
Employment	Full-time	69	53.1	56.3
	Part-time / Unemployed	12	9.2	29.6
	Student	48	36.9	20.01
	Retired	0	0.0	–
	Prefer not to say	1	0.8	–
Trip Purpose	Work	96	40.0	20.0
	Leisure	70	29.2	33.0
	Shopping	19	7.9	22.0
	Education	33	13.8	9.0
	Other	5	2.1	16.0
	Will never use a hub	3	1.3	-
Comfort with Digital modes	High	49	37.7	37.0
	Medium	56	43.1	47.0
	Low	25	19.2	16.0
Shared Mode Usage Frequency	Never	45	34.6	-
	1–3 times/week	36	27.7	-
	More than 3/week	49	37.7	-
Primary Mode	Car	16	12.3	40.0
	Public Transport	45	34.6	2.0
	Bike	64	49.2	35.0
	Walk/ Other	5	3.8	23.0

Gender

The gender distribution among respondents is relatively balanced, with males comprising approximately 63% of the sample and females around 33% . A small portion either identified as non-binary or preferred not to disclose their gender. Compared to national figures reported by the Centraal Bureau voor de Statistiek [Statistics Netherlands, nd], where the distribution is roughly 50.4% of women and 49.6% of men, the sample over-represents males. This over-representation may reflect higher male engagement in transport and mobility-related studies, or a sampling bias through academic or technical channels.

Age

Respondents are categorized into six age brackets: 18–24, 25–29, 30–39, 40–59, 60+ and ”Prefer not to say”. The largest group consists of individuals aged 25–39, accounting for more than half the sample. In contrast, respondents aged 60+ make up less than 5%, and no respondents are under 18, which aligns with the legal adult threshold and survey design.

The dominance of the 25–39 age group reflects a highly relevant demographic for mobility innovation. This group is more likely to adopt app-based solutions and alternative transport modes such as shared bikes and e-scooters [Van Kuijk et al., 2024]. However, it should be noted that older adults, who are critical for universal mobility planning, are underrepresented compared to national CBS [Statistics Netherlands, nd] age statistics. For context, over 34% of the Dutch population is aged 60 and above. This skew should be considered when generalizing results to the national level.

Education Level

The sample is notably highly educated. Almost all of the respondents hold a bachelor's or master's degree. In contrast, high school and MBO has just 2 and 1 responses. So these responses are removed from the analysis. According to CBS classifications, 34% of the working-age population in the Netherlands holds a higher education degree (HBO/WO), which means the survey sample over-represents individuals with advanced education.

This over-representation likely stems from the online distribution of the survey through academic and professional networks, which tends to attract more educated respondents. Nonetheless, this demographic is likely to be early adopters of smart mobility systems, making their preferences relevant for forward-looking infrastructure planning. However, the over-representation should be considered while drawing any conclusion from the results.

Employment Status

In terms of employment, most respondents are either employed full-time (over 50%) or currently studying (around 35%). A small portion reported being unemployed or part-time workers. This distribution reflects an economically active and mobile population segment. Given that students and working professionals often form the majority of daily commuters, their travel behaviour is central to understanding peak hour loads and preferences for multimodal connectivity.

Table 4.2.: Chi-square test results for sociodemographic groups

Variable	Chi-square	DF	Critical Value	P value
Age group	2426.489	4	9.488	0.00000
Gender	213.557	1	3.841	2.30×10^{-48}
Purpose	1800.656	4	9.488	0.00000
Primary Mode	2304.855	5	11.070	0.00000
Digital Comfort	796.034	2	5.991	1.39×10^{-173}

Trip Purpose

When asked about the primary reason they will use mobility hubs, a majority of respondents cited commuting to work or school, followed by leisure and shopping. Only a small percentage selected "will never use a hub," indicating a strong relevance of the mobility hub context for functional as well as discretionary trips. This balance confirms that mobility hubs must serve both routine and occasional travel needs effectively.

Primary Mode of Transport

Nearly half of the respondents (49.2%) reported using the bicycle as their primary mode of transport, followed by public transport users at 34.6%. In contrast, only 12.3% of respondents primarily relied on cars, despite cars typically being dominant in broader travel patterns. A small minority (3.8%) indicated walking or other modes as their primary means of travel. Compared to CBS, bike and PT is overrepresented and other modes are dramatically underrepresented. This skew toward active and public transport modes suggests that the sample is relatively sustainability-oriented, which could influence overall willingness to adopt green mobility hub services. It may also partially reflect the recruitment method or urban context of the sample.

Experience with Shared Mobility

Respondents are also asked about their use of shared mobility options. A significant share reported using shared mobility at least once per month. This finding confirms a familiarity and comfort with shared modes, especially among younger and more digitally confident users. It also indicates readiness for further integration of shared services within mobility hubs.

Comfort with Digital Transport Apps

Digital comfort — the self-assessed ease with using digital devices and apps — is high among the sample. Over 80% of respondents rated themselves as having medium to high comfort.

All Chi-square statistics presented in Table 4.2 exceed their respective critical values by a large margin, and all associated p-values are far below the 0.05 significance threshold. This indicates that the sociodemographic composition of the survey sample is statistically different from the reference population for every variable tested. These differences suggest that the sample may be skewed towards younger, highly educated individuals, which could limit the generalizability of the findings—particularly to older or less digitally engaged populations. This skew is likely due to the survey's distribution primarily within university settings and among young professionals in the Randstad region.

While this discrepancy raises concerns about representativeness, it may not necessarily undermine the study's value. It closely reflects the target users of emerging urban mobility systems—young, digitally engaged individuals. This makes it well-suited for analysing future trends and behaviour within early-adopting segments. Therefore, although the dataset may not reflect the current population structure, it remains relevant for exploring emerging trends. Nonetheless, the potential for bias in model predictions when applied to the general population should not be overlooked. These demographic differences must be taken into account when interpreting the results to ensure accurate and contextually appropriate conclusions.

4.2. Mode Choice of the Sample Across Demographics and Contexts

Understanding how different socio-demographic groups choose their travel modes provides crucial insights into mobility behaviour. Table 4.3 shows the percentage of each mode getting selected by each respondent groups. For overall shares, ZE bus and private bikes are the most chosen options. Shared e-car has the third most responses showcasing growing preference for shared motorized modes, while walk and shared e-scooter are the least popular options. Effect of these socio-demographics on mode choice is discussed below. Some combination effects are also examined. These combinations are selected based on their pronounced behavioural contrasts, policy relevance, and alignment with existing gender and equity concerns in sustainable transport. These trends not only stand out in the data but also highlight user vulnerabilities and service design needs (e.g., weather, safety), especially for female or older commuters.

Gender

Female respondents show greater use of zero emission buses (43%) and private bikes (25%), than men whereas males show higher reliance on shared e-cars (22%) than women and a slightly more diversified modal profile overall. This could be attributed to perceived safety, physical convenience, or broader social norms.

Age

Modal preferences show distinct variations across age categories. Younger age groups (18–29) exhibit a higher preference for shared and digitally enabled modes such as e-scooters and shared bikes, while older groups tend to rely more on zero emission Buses. Private bike usage remains relatively consistent across all groups, while walking sees a rise among those aged 40 and above. These shifts likely reflect broader lifestyle transitions and comfort with newer mobility options, especially those requiring digital interaction.

Table 4.3.: Combined Modal Split by Socio-Demographic Groups, Behavioural Factors, Overall Share, Weather and Distance Effects (%)

Group/Condition	Walk(%)	Private Bike(%)	Shared Bike(%)	Shared E-scooter(%)	Shared E-car(%)	ZE Bus(%)
Overall Share and Effects						
Overall Share	5	21	11	5	19	38
Sunny Weather	8	31	18	9	12	22
Rainy Weather	3	11	5	2	25	55
Short Trip (2 km)	9	24	11	6	15	34
Long Trip (4 km)	1	18	11	5	22	43
Gender						
Male	5	19	11	6	22	36
Female	5	25	11	4	12	43
Age Group						
Age 18–24	3	25	13	6	24	29
Age 25–29	5	18	13	8	16	41
Age 30–39	4	17	10	4	23	43
Age 40–59	11	27	9	1	11	41
Age 60+	11	25	6	5	9	44
Education						
Bachelor	4	21	12	7	21	36
Master+	7	20	11	5	16	40
Employment Status						
Full-time Employed	6	20	11	5	17	41
Student	3	23	12	6	22	34
Part-time/Unemployed	11	19	14	4	16	36
Digital Comfort						
High	3	19	10	5	19	43
Medium	6	24	12	5	20	32
Low	8	18	11	6	15	42
Trip Purpose						
Work	6	24	9	5	17	39
Leisure	6	25	11	6	19	33
Shopping	4	22	9	5	21	39
Education	3	24	12	4	20	36
Other	14	21	20	4	22	19
Primary Mode						
Biking	5	26	15	6	17	31
Public Transport	6	17	8	4	20	45
Car (Driver + Passenger)	7	20	3	4	19	45
Walk/Other	1	14	12	4	22	49
Shared Mobility Frequency						
Never	4	20	12	6	18	39
1–3 times	5	17	11	5	20	42
More than 3 times	6	24	11	5	18	35

Education

Both Bachelor's and Master's+ degree holders display a fairly even spread in modal share, with ZE bus dominating for both groups (36–40%). The share for other modes for both groups remain quite similar.

Employment Status

Employment status is also a strong differentiator. Students select private bike and shared e-car more than other groups and part-time/unemployed group show higher usage of shared bikes and walking, likely reflecting cost-consciousness or less rigid schedules. Full-time workers show a higher preference for ZE bus. These patterns suggest practical constraints and lifestyle rhythms influence mode choice substantially.

Comfort with Digital Modes

Users with higher digital comfort are more inclined to choose shared e-modes like shared cars than others. But people who are less comfortable with digital modes also show almost similar interests in shared bike and e-scooter. These patterns prove even people who are not fully comfortable with digital mode are also interested in using shared digital modes at the hubs.

Trip Purpose

Trip purpose significantly shapes modal choice. Commuting to work is associated with higher private bike (24%) and ZE bus (39%) usage, while leisure trips also favor active modes such as private bikes (25%). Shopping trips see moderate use of shared e-cars (21%) and buses (39%), reflecting practical transport needs. Education-related trips favor buses (36%) and private bikes (24%), underscoring the importance of affordable, sustainable options for students. Notably, 'other' trips show a lower reliance on ZE buses (19%) and higher shared e-car use (22%), suggesting a degree of flexibility and mode substitution depending on the nature of the trip.

For commuting to work, users may prioritize reliability and directness, which makes private bikes attractive for short distances and ZE buses for longer or more structured routes. Leisure trips, being more flexible in schedule and distance, can tolerate active modes like walking or biking, particularly among health- or cost-conscious users. Shopping trips often involve carrying goods, making shared e-cars and buses more practical than active modes. Similarly, education-related trips tend to follow routine schedules and are cost-sensitive—explaining higher bus usage among students, and some bike reliance where distances are manageable.

The "other" category likely includes more irregular or spontaneous travel, which may involve longer distances or a need for convenience (e.g., family visits, medical appointments). This could explain higher e-car use (for comfort and flexibility) and lower ZE bus use, as users in this category may be less tied to fixed transit schedules or routes.

Primary Mode of Transport

The stated choice data reveals mixed pattern between participants' primary travel modes and the modes they selected during the survey. Individuals who primarily bike maintained consistency, with 26% choosing the private bike and 15% opting for the shared bike. Car users (driver or passenger), by contrast, shifted their preferences significantly: with a substantial 45% selected the Zero-Emission (ZE) bus. This indicates openness to public transport options when presented with structured choices. Similarly, individuals whose main mode is public transport also gravitated toward the ZE bus (45%) in the stated preference tasks, reaffirming mode familiarity. Interestingly, respondents who indicated "Walk/Other" as their primary mode showed the highest share for ZE bus (49%) and relatively low selection of shared modes. This likely reflects accessibility constraints or lack of private vehicle ownership. Overall, the data suggest that while many participants exhibit inertia toward familiar modes, the ZE bus—attracted significant interest across user groups.

Shared Transport Frequency

Unsurprisingly, shared transport familiarity shaped preferences for specific services. Respondents who reported using shared modes more than three times per week leaned more toward private bike (24%), but interestingly, even this group maintained a strong preference for ZE bus (35%). Infrequent or non-users of shared transport modes still exhibited substantial interest in bus services (up to 39%).

Among respondents who reported using shared mobility more than three times per week, a notable 35% still chose mostly ZE bus and private bikes in the stated choice tasks. This reflects that even frequent shared mode users may favor reliable, protected, or cost-effective options like ZE bus when presented with multiple alternatives under controlled trade-offs. Factors such as perceived comfort, weather sensitivity, and cost-effectiveness during hypothetical scenarios could drive this shift. Rather than implying avoidance, the result suggests that stated preference experiments successfully elicit respondents' latent preferences when all options are equally available and attributes are explicitly stated—conditions that are often not guaranteed in real-world situations.

Weather

Weather conditions demonstrated a notable influence on modal preferences. During rainy conditions, use of ZE buses surged to 55%, displacing modes such as shared bikes and e-scooters, which rely heavily on good weather. In contrast, on sunny days, private bikes (31%) and shared bikes (18%) gained significant modal share. This weather-dependent modal shift reflects the sensitivity of open and active transport modes to environmental conditions. The consistent decrease in e-scooter, and walk shares under rain indicates that weather-resilient infrastructure and vehicle access (e.g., covered bike lanes or e-car promotion) can play a decisive role in maintaining mobility during adverse conditions.

Distance

The most immediate trend observed is the significant increase in walking share for short trips—from just 1% at 4 km to 9% at 2 km. This suggests that walking becomes a viable and appealing option only when the distance is minimal. Similarly, private bike usage increases from 18% to 24% for shorter trips, reinforcing that active travel modes thrive in proximity-based contexts.

Interestingly, shared bikes maintain a consistent share (11%) across both distances. This consistency implies that shared bikes are perceived as equally suitable for both short and long distances, potentially due to their ease of access and mechanical support which lowers physical effort compared to private bikes.

In contrast, shared e-cars and ZE buses exhibit a marked increase in modal share for longer trips. Shared e-cars rise from 15% (short) to 22% (long), while the use of ZE Buses increases from 34% to 43%, making it the dominant mode for 4 km trips. These shifts signal that as distance increases, comfort and convenience outweigh cost or environmental considerations, nudging users toward motorized, enclosed modes.

The low but slightly rising use of shared e-scooters (from 5% to 6%) suggests niche appeal, potentially for users seeking a balance between convenience and speed over moderate distances.

Table 4.4.: Chi-square Test Results for Association Between Socio-demographic Factors and Mode Choice

Factor	Chi-square Statistic	p-value
Gender	76.11	$<$0.001
Age Group	124.80	$<$0.001
Education	76.65	$<$0.001
Employment Status	94.33	$<$0.001
Trip Purpose	174.43	$<$0.001
Shared Mobility Frequency	17.58	0.0624
Primary Mode	135.82	$<$0.001
Digital Comfort	36.26	$<$0.001

The results of the Chi-square tests, summarised in Table 4.4, provide statistical evidence regarding the association between socio-demographic and mode choice. Most factors, including gender, age, education, employment status, trip purpose, primary mode of transport, and digital comfort, demonstrate statistically significant associations with mode choice, as indicated by p-values below 0.05. This suggests that transport preferences vary meaningfully across different population groups, highlighting the importance of accounting for socio-demographic heterogeneity in the discrete choice modelling process.

Interestingly, shared mobility frequency did not show a statistically significant association with mode choice at the 95% confidence level. This implies that prior experience with shared mobility services does not strongly predict stated transport preferences within this sample. These findings support the inclusion of interaction terms between socio-demographics and mode attributes to capture behavioural variability in mode choice decisions, particularly in the context of designing mobility hubs.

Gender-Based Weather Effects

As shown in Figure 4.1, under sunny conditions both male and female participants displayed a stronger inclination toward active and shared micromobility modes. However, when the weather shifts to rainy conditions, both genders significantly reduce their reliance on exposed or active modes. ZE bus usage becomes dominant, particularly for females, with a striking 61% modal share compared to 51% for males. This indicates that females are more sensitive to adverse weather and tend to prefer enclosed, reliable options. shared e-cars also gain traction in rainy conditions, capturing 30% of male and 17% of female trips, likely due to their perceived protection and comfort.

Interestingly, micromobility modes like shared e-scooters and shared bikes see a sharp decline across both genders under rain. This demonstrates the importance of weather resilience in shared mobility offerings, such as sheltered waiting areas or incentivized mode switching.

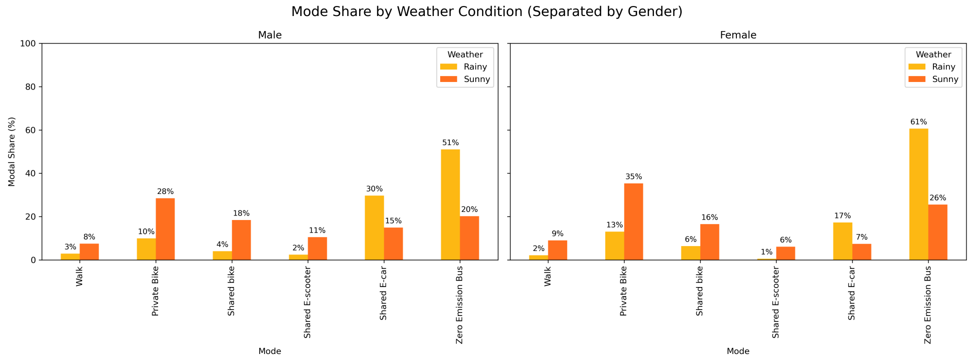


Figure 4.1.: Weather effect on modal choice by gender.

Age-Based Differences in Travel Time

Mode choice varies by age group for short (2 km) and long (4 km) trips (Figure 4.2). For short trips, the most popular mode across all age groups is the ZE bus, ranging from 29% (18–24) to 41% (25–29), suggesting that public transport remains a preferred choice for short commutes. Private bike use is also significant, particularly among the 25–29 and 30–39 age groups (both around 20%), reflecting a younger demographic's preference for active, flexible modes. For long trips (right chart), there is a clear shift toward greater ZE bus use, particularly among older age groups, peaking at 53% for those aged 60+, reflecting a reliance on affordable, accessible transport for longer distances. Private bike use declines for longer trips, particularly among older groups, consistent with the physical limitations or comfort preferences of older individuals. Shared e-car use remains substantial across all age groups (14% to 25%), suggesting that shared car services are a viable alternative for longer distances, especially among younger adults (18–39). Walking is virtually negligible for long trips, while shared bike and e-scooter use declines as trip distance increases.

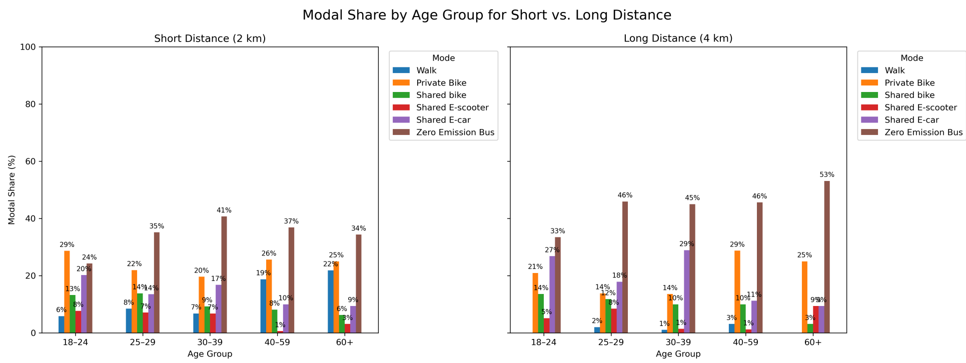


Figure 4.2.: Modal choice by age group under short vs. long travel time.

4.3. Model Building

To build the multinomial logit (MNL) and panel-based models, Biogeme is selected for its efficiency in working with utility functions and its compatibility with survey data structured as repeated choices.

4.3.1. Base MNL Model

The base model employed in this analysis is a multinomial logit (MNL) model. It serves as the foundational model in this study, providing a benchmark for evaluating the impact of additional sociodemographic and contextual interaction terms included in extended models. The base model's utility function for each mode includes the alternative specific constants and mode attributes. ZE bus is considered as reference alternative. So the utility functions for base model are:

$$
\begin{aligned}
V_{\text{walk}} &= \text{ASC}_{\text{walk}} + \beta_{\text{travel\_time}} \cdot TT_0 \\
V_{\text{bike}} &= \text{ASC}_{\text{bike}} + \beta_{\text{travel\_time}} \cdot TT_1 \\
V_{\text{shared\_bike}} &= \text{ASC}_{\text{shared\_bike}} + \beta_{\text{travel\_time}} \cdot TT_2 + \beta_{\text{cost}} \cdot TC_2 \\
V_{\text{shared\_escooter}} &= \text{ASC}_{\text{shared\_escooter}} + \beta_{\text{travel\_time}} \cdot TT_3 + \beta_{\text{cost}} \cdot TC_3 \\
V_{\text{shared\_ecar}} &= \text{ASC}_{\text{shared\_ecar}} + \beta_{\text{travel\_time}} \cdot TT_4 + \beta_{\text{cost}} \cdot TC_4 \\
V_{\text{ze\_bus}} &= \beta_{\text{travel\_time}} \cdot TT_5 + \beta_{\text{cost}} \cdot TC_5 + \beta_{\text{wait\_time\_bus}} \cdot WT_5
\end{aligned}
$$

Where,

TT_0, TT_1, TT_2, TT_3, TT_4, TT_5 = Travel time for walk, private bike, shared bike, shared e-scooter, shared e-car, and zero-emission bus

TC_2, TC_3, TC_4, TC_5 = Travel cost for shared bike, shared e-scooter, shared e-car, and zero-emission bus

Table 4.5.: Estimation Results for the Base Model

Parameter	Value	Rob. Std Err	Rob. t-test	Rob. p-value
ASC_bike	-0.077	0.172	-0.451	0.652
ASC_shared_bike	-1.016	0.175	-5.795	6.83×10^{-9}
ASC_shared_ecar	-1.538	0.167	-9.205	< 0.0001
ASC_shared_escooter	-2.278	0.177	-12.848	< 0.0001
ASC_walk	-0.117	0.355	-0.329	0.742
β_{cost}	-0.480	0.025	-19.337	< 0.0001
$\beta_{\text{travel time}}$	-0.119	0.015	-8.214	2.22×10^{-16}
$\beta_{\text{wait time (bus)}}$	-0.091	0.019	-4.676	2.93×10^{-6}

The code for base model is give in Appendix C. The model includes 8 estimated parameters. It achieved a final log-likelihood of -2613.762, with a Rho-square of 0.266 and a Rho-square-bar of 0.264, indicating low explanatory power. The likelihood ratio test yielded a value of 1892.634, confirming the model's overall significance.

Table 4.6.: Model Fit Statistics for the Base Model

Statistic	Value
Number of estimated parameters	8
Sample size	131
Initial log-likelihood	-3560.079
Final log-likelihood	-2613.762
Log-likelihood ratio	1892.634
Rho-square	0.266
Rho-square-bar	0.264
Akaike Information Criterion	5243.524
Bayesian Information Criterion	5288.707
Final gradient norm	0.060

Among the alternative-specific constants (ASCs), all modes except walking and biking are statistically significant and negative, implying a lower intrinsic preference for shared modes compared to the base alternative ZE bus. Specifically, shared e-scooter and shared e-car alternatives have the most negative constants, suggesting these modes require higher utility from other attributes to be chosen.

The estimated coefficients for key travel attributes are all negative and statistically significant, aligning with theoretical expectations. The travel cost coefficient (β_{cost} =-0.480) has the largest magnitude, suggesting that cost is the most influential deterrent similar to the existing literature [Torabi et al., 2023]. Travel time also has a significant effect ($\beta_{\text{travel time}}$ =-0.119), reinforcing the sensitivity of users to time-based burdens. The waiting time for buses is also negatively valued ($\beta_{\text{wait time bus}}$ =-0.091), with a smaller magnitude. In the base model, all of the model parameters without the ASCs for bike and walk, have a p-value lower than 5%, meaning that their effect observed in the dataset is statistically significant.

Overall, the base model confirms that minimizing cost and time-related burdens significantly increases the likelihood of selecting shared mobility options. The results highlight the importance of improving operational efficiency and affordability to promote mode shift.

4.3.2. Socio-demographic Models

Building on the base model introduced earlier, the modelling effort is expanded by incorporating sociodemographic interactions to assess their explanatory value. To capture heterogeneity across user groups, additional models are estimated by introducing sociodemographic variables and their interactions with mode attributes.

Each model is evaluated using the adjusted Rho-square bar statistic, due to its power to explain model fit and complexity. Table 4.7 presents all the model specification for each sociodemographic or contextual factor.

Weather model has the highest Rho square bar value, indicating that weather-related effects have a strong impact on travel behaviour. Other notable improvements over the base model came from interactions with age, employment status and digital comfort.

Table 4.7.: Socio-demographic Models Ranked by Rho-square bar

Model	**Specification**	**Rho-square-bar**
Weather	Both time and cost interactions	0.3009
Weather	Travel time interactions	0.2997
Age	Both time and cost interactions	0.2761
Weather	Travel cost interactions	0.2757
Employment	Both time and cost interactions	0.2725
Comfort with Digital modes	Both time and cost interactions	0.2711
Comfort with Digital modes	Travel time interactions	0.2708
PrimaryMode	Travel time interactions	0.2707
PrimaryMode	Both time and cost interactions	0.2703
Frequency	Travel time interactions	0.2695
Base_model	Only ASC and mode attributes	0.2694
Comfort with Digital modes	Travel cost interactions	0.2693
Frequency	Both time and cost interactions	0.2692
Weather	As dummy variable	0.2691
PrimaryMode	Travel cost interactions	0.2691
Frequency	Travel cost interactions	0.2690
Frequency	As dummy variable	0.2689
Comfort with Digital modes	As dummy variable	0.2689
PrimaryMode	As dummy variable	0.2686
Purpose	As dummy variable	0.2684
Age	As dummy variable	0.2683
Education	Both time and cost interactions	0.2665
Gender	Both time and cost interactions	0.2662
Education	Travel time interactions	0.2659
Gender	Travel cost interactions	0.2657
Gender	Travel time interactions	0.2656
Gender	As dummy variable	0.2652
Education	Travel cost interactions	0.2651
Employment	Travel cost interactions	0.2628
Purpose	Travel cost interactions	0.2626
Purpose	Travel time interactions	0.2584
Purpose	Both time and cost interactions	0.2538
Age	Travel time interactions	0.2153
Employment	Travel time interactions	0.2106
Age	Travel cost interactions	0.1991
Education	As dummy variable	0.1323
Employment	As dummy variable	0.1227

4.3.3. Final MNL Model

The final model is constructed by combining the most influential variables from the above analysis one by one and testing for improvement. Only the combinations that improved the previous models are kept. The best possible combination based on Rho square bar includes:

- Age
- Weather scenario
- Comfort with Digital modes
- Employment status

Let V_i, TT_i, TC_i be the utility, travel time and travel cost of mode i, where: $i = 0, 1, 2, 3, 4, 5$: is Walk, Private bike, Shared bike, Shared e-scooter, Shared e-car and Zero-emission bus

The utility functions are defined as:

$$
\begin{aligned}
V_0 &= \text{WeatherBlock}(TT_0, TC_0) + \text{AgeBlock}(TT_0, TC_0) + \text{EmploymentBlock}(TT_0, TC_0) \\
&\quad + \text{ComfortBlock}(TT_0, TC_0) \\
V_1 &= \text{WeatherBlock}(TT_1, TC_1) + \text{AgeBlock}(TT_1, TC_1) + \text{EmploymentBlock}(TT_1, TC_1) \\
&\quad + \text{ComfortBlock}(TT_1, TC_1) \\
V_2 &= \text{ASC}_{\text{shared\_bike}} + \text{WeatherBlock}(TT_2, TC_2) + \text{AgeBlock}(TT_2, TC_2) + \text{EmploymentBlock}(TT_2, TC_2) \\
&\quad + \text{ComfortBlock}(TT_2, TC_2) \\
V_3 &= \text{ASC}_{\text{shared\_escooter}} + \text{WeatherBlock}(TT_3, TC_3) + \text{AgeBlock}(TT_3, TC_3) + \text{EmploymentBlock}(TT_3, TC_3) \\
&\quad + \text{ComfortBlock}(TT_3, TC_3) \\
V_4 &= \text{ASC}_{\text{shared\_ecar}} + \text{WeatherBlock}(TT_4, TC_4) + \text{AgeBlock}(TT_4, TC_4) + \text{EmploymentBlock}(TT_4, TC_4) \\
&\quad + \text{ComfortBlock}(TT_4, TC_4) \\
V_5 &= \text{WeatherBlock}(TT_5, TC_5) + \text{AgeBlock}(TT_5, TC_5) + \text{EmploymentBlock}(TT_5, TC_5) \\
&\quad + \beta_{\text{wait\_bus}} \cdot WT_5 + \text{ComfortBlock}(TT_5, TC_5)
\end{aligned}
$$

Weather Block(TT, TC)**:** Captures travel time and cost sensitivities under different weather scenarios:

$$
\text{WeatherBlock}(TT, TC) = \beta_{\text{tt, rainy}} \cdot TT \cdot \text{rainy} + \beta_{\text{cost, rainy}} \cdot TC \cdot \text{rainy} + \beta_{\text{cost, sunny}} \cdot TC \cdot \text{sunny} \tag{4.1}
$$

Age Block(TT, TC)**:** Represents interaction of travel time and cost with age groups.

$$\text{AgeBlock}(TT, TC) = \beta_{\text{tt, age18-24}} \cdot TT \cdot \text{Age}_{\text{18-24}} + \beta_{\text{tt, age25-29}} \cdot TT \cdot \text{Age}_{\text{25-29}} + \beta_{\text{tt, age30-39}} \cdot TT \cdot \text{Age}_{\text{30-39}} \tag{4.2}$$

Comfort Block(TT, TC)**:** Interaction of travel time and cost with digital comfort level.

$$\text{ComfortBlock}(TT, TC) = \beta_{\text{tt, comfort-high}} \cdot TT \cdot \text{Comfort}_{\text{High}} + \beta_{\text{tt, comfort-mid}} \cdot TT \cdot \text{Comfort}_{\text{Mid}} \tag{4.3}$$

Employment Block(TT, TC)**:** Captures the effect of employment status on travel time and cost sensitivity.

$$\begin{aligned} \text{EmploymentBlock}(TT, TC) = {} & \beta_{\text{tt, emp-fulltime}} \cdot TT \cdot \text{Emp}_{\text{FullTime}} \\ & + \beta_{\text{tt, emp-student}} \cdot TT \cdot \text{Emp}_{\text{Student}} \\ & + \beta_{\text{cost, emp-student}} \cdot TC \cdot \text{Emp}_{\text{Student}} \end{aligned} \tag{4.4}$$

The code for final MNL model is given in Appendix D. The final MNL model includes 15 parameters based on a cleaned dataset of 126 respondents. The estimation yielded the value of parameters given in 4.8.

Table 4.8.: Final MNL Model Estimation Results

Parameter	Value	Rob. Std. Err.	Rob. t-test	Rob. p-value
ASC_shared_bike	-1.02	0.09	-11.73	$< 10^{-10}$
ASC_shared_ecar	-1.99	0.14	-14.26	$< 10^{-10}$
ASC_shared_escooter	-2.36	0.12	-20.07	$< 10^{-10}$
beta_cost_emp_student	-0.22	0.06	-3.74	1.88×10^{-4}
beta_cost_weather_rainy	-0.37	0.03	-11.34	$< 10^{-10}$
beta_cost_weather_sunny	-0.54	0.05	-9.99	$< 10^{-10}$
beta_travel_time_age_18_24	-0.05	0.01	-3.75	1.78×10^{-4}
beta_travel_time_age_25_29	-0.04	0.01	-3.72	1.97×10^{-4}
beta_travel_time_age_30_39	-0.08	0.01	-5.74	9.72×10^{-9}
beta_tt_digital_comfort_high	-0.04	0.01	-4.89	9.93×10^{-7}
beta_tt_digital_comfort_mid	-0.02	0.01	-2.32	2.04×10^{-2}
beta_tt_emp_fulltime	-0.04	0.01	-5.50	3.83×10^{-8}
beta_tt_emp_student	-0.06	0.01	-4.36	1.31×10^{-5}
beta_tt_weather_rainy	-0.15	0.02	-6.28	3.38×10^{-10}
beta_wait_time_bus	-0.12	0.01	-10.31	$< 10^{-10}$

Table 4.9.: Final MNL Model Fit Statistics

Statistic	**Value**
Number of estimated parameters	15
Sample size	126
Excluded observations	0
Initial log likelihood	-3425.49
Final log likelihood	-2351.594
Likelihood ratio test (vs. init model)	2147.791
Rho-square (init model)	0.314
Adjusted Rho-square	0.309
Akaike Information Criterion (AIC)	4733.189
Bayesian Information Criterion (BIC)	4817.322
Final gradient norm	2.1948×10^{-3}

The values in Table 4.9 reflect a substantial improvement over the base model, confirming the added explanatory value of incorporating individual-level and contextual interactions. It achieved a final log-likelihood of –2351.59, which marks a substantial improvement over the initial log-likelihood of –3425.49. This difference is confirmed by a highly significant likelihood ratio test value of 2147.79, validating that the extended specification adds significant explanatory power over the base model.

The Rho-square value of 0.314 and the adjusted Rho-square-bar of 0.309 indicate a good model fit and improvement over the base model (Rho-square-bar of 0.264). These metrics demonstrate that the model successfully captures meaningful variation in mode choice behaviour [Pham, 2023; Torabi et al., 2023]. Moreover, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values of 4733.19 and 4817.32, respectively, reflect a better balance between model complexity and explanatory power compared to simpler alternatives.

The Alternative Specific Constants (ASCs) indicate baseline preferences for different modes relative to a reference alternative (ZE bus). The ASCs for shared modes such as e-cars, shared bikes and e-scooters remain significantly negative, reaffirming lower intrinsic preferences for these modes unless compensated by strong attribute performance (e.g., shorter travel time or lower cost). Shared e-scooter has the most negative value, indicating lowest intrinsic preference towards this mode.

Students exhibit strong cost aversion, as expected due to lower disposable income. They have constrained budgets and are thus more sensitive to monetary costs associated with travel. This effect is critical in the context of shared mobility and zero-emission modes, where pricing policies can significantly influence uptake.

Weather-related parameters show expected and statistically significant effects. The coefficient for travel cost in sunny weather ($\beta_{\text{cost,weather.sunny}}$) is -0.537, which is more negative than ($\beta_{\text{cost,weather.rainy}}$), indicating that travel cost sensitivity increases during sunny conditions. More negative value indicates that an increase in travel cost leads to more reduction in the utility of transport modes when it is sunny. This indicates that during unfavorable rainy conditions, individuals place more emphasis on other attributes such as comfort, protection, or convenience, and become less cost-conscious. Individuals are more price-sensitive under favorable weather conditions, their willingness to pay increases during rainy weather, likely reflecting a higher priority given to comfort or protection from adverse conditions over cost considerations.

Age-based travel time sensitivities also reveal interesting patterns. Younger travelers (18–39) have negative travel time coefficients, suggesting they are more time-sensitive. Notably, individuals aged 30–39 exhibit the highest sensitivity, likely due to increased time constraints from employment and family obligations.

Individuals with higher digital comfort are more time-sensitive. Higher digital comfort enhances individuals' ability to access, navigate, and utilize shared mobility services, apps, and real-time information. So with easier access to more options, they exhibit increased travel time sensitivity. They are more likely to actively seek faster, optimized travel options, often leveraging digital tools for decision-making.

Employment status also presents important insights. The travel time sensitivity of students and fully employed individuals, is significant compared to other groups. This highlights the constraints imposed by structured schedules or fixed commitments. Students and employees often operate under rigid timeframes, making punctuality critical, while retirees may prioritize convenience to maintain independence and routine. In contrast, part-time workers and unemployed individuals may have greater schedule flexibility, resulting in lower urgency and reduced travel time sensitivity.

The model results indicate disutility associated with travel time during rainy conditions, as captured by the parameter $\beta_{\text{tt, weather rainy}} = -0.149$. This negative coefficient implies that individuals are significantly more averse to longer travel times when it is raining. Rain likely amplifies discomfort and inconvenience during travel, particularly for active or partially exposed modes such as walking or cycling. As a result, rainy conditions could trigger a behavioural shift towards faster, more protected options like shared electric cars or public transport. From a policy perspective, this highlights the value of adaptive mobility services that can respond to real-time weather changes—for example, by offering dynamic pricing, upgraded comfort, or alternative mode suggestions during adverse conditions.

Finally, the coefficient for bus wait time ($\beta_{\text{wait.time.bus}} = -0.12$) is large in magnitude, negative, and significant, confirming the well-established aversion to waiting times in public transport choices.

The Value of Time (VoT) represents the monetary value travellers assign to saving time, often expressed in euros per minute or hour. In this study, VoT is calculated using the negative ratio of the weighted average travel time coefficient to the weighted average cost coefficient from the final Multinomial Logit model:

$$\text{VoT} = -\left(\frac{\beta_{\text{time (weighted avg)}}}{\beta_{\text{cost (weighted avg)}}}\right) = -\left(\frac{-0.0596}{-0.4067}\right) \approx 0.146 \text{ €/min}$$

This corresponds to approximately €8.8/hour, which is remarkably close to the Dutch national benchmark of €9/hour for car users [Kouwenhoven et al., 2014]. This proximity suggests that the model accurately captures realistic travel behaviour in terms of time–money trade-offs. The alignment between estimated and benchmark VoT values adds external validity to the stated preference data and supports the credibility of cost and time coefficients used in scenario simulations. Consequently, policy evaluations and pricing strategies derived from this model are likely to yield behaviourally plausible and economically grounded outcomes.

4.3.4. Panel Mixed Logit Model

To account for the repeated choice behaviour of individual respondents and capture unobserved heterogeneity across decision-makers, a Panel Mixed Logit (PML) model is estimated. This model builds on the Multinomial Logit (MNL) foundation by incorporating a random parameter—specifically, a normally distributed random coefficient. The panel model aim to relax the independence from irrelevant alternatives (IIA) assumption, which is a limitation of the standard Multinomial Logit (MNL) framework.

This model is tested using 1000 of Monte Carlo draws to approximate the simulated likelihood function. Halton sequences are used. The estimation process converged successfully after a reasonable number of iterations. The model fit statistics are summarized in Table 4.10 and the estimation results are presented in Table 4.11.

The model specification includes 13 estimated parameters and was estimated on a dataset comprising 2,016 observations from 126 individuals. The model demonstrates strong statistical fit. The initial log-likelihood was -3422.762, which improved substantially to a final log-likelihood of -2312.186. This improvement yields a likelihood ratio test statistic of 2221.153, indicating that the model provides a significantly better fit than a null model. The ρ^2 value is 0.324, while the adjusted $\bar{\rho}^2$ is 0.321, both indicating an acceptable level of explanatory power for behavioural modeling purposes. The convergence quality is demonstrated by a final gradient norm of 0.4437, and the relative gradient reached 1.20×10^{-4}, which met the specified convergence threshold.

Table 4.10.: Model Fit Statistics for Panel Mixed Logit Model (1000 Draws)

Statistic	**Value**
Number of estimated parameters	13
Sample size	126
Initial log likelihood	-3422.762
Final log likelihood	-2312.186
Likelihood ratio test	2221.153
Rho-square	0.324
Adjusted Rho-square	0.321
Akaike Information Criterion (AIC)	4650.371
Bayesian Information Criterion (BIC)	4687.243
Final gradient norm	0.4437
Number of draws	1000
Relative gradient	0.00012017693253012157

Among the alternative specific constants (ASCs), shared mobility modes continue to show negative coefficients, indicating lower baseline preference compared to the reference alternative (Zero Emission Bus). ($\sigma_{\text{panel}} = 2.05$) is also significant. This indicates that the cost parameter varies across individuals, reflecting heterogeneity in sensitivity within the sample. The significance of this parameter supports the inclusion of random coefficients to

Table 4.11.: Estimation Results for PML Model

Parameter	Value	Rob. Std. Err.	Rob. t-test	Rob. p-value
ASC_shared_bike	-0.97	0.17	-5.85	4.84×10^{-9}
ASC_shared_ecar	-2.23	0.25	-8.92	$< 10^{-10}$
ASC_shared_escooter	-2.42	0.21	-11.70	$< 10^{-10}$
Sigma_panel	2.05	0.22	9.15	$< 10^{-10}$
beta_cost_emp_student	-0.23	0.09	-2.48	0.01
beta_cost_weather_rainy	-0.38	0.04	-8.97	$< 10^{-10}$
beta_cost_weather_sunny	-0.55	0.08	-6.64	3.06×10^{-11}
beta_travel_time_age_25_29	-0.04	0.02	-1.87	0.06
beta_travel_time_age_30_39	-0.09	0.03	-2.84	0.00
beta_tt_emp_fulltime	-0.10	0.02	-5.47	4.49×10^{-8}
beta_tt_emp_student	-0.14	0.02	-7.53	5.06×10^{-14}
beta_tt_weather_rainy	-0.17	0.04	-4.39	1.13×10^{-5}
beta_wait_time_bus	-0.13	0.02	-6.62	3.71×10^{-11}

capture unobserved taste variation, whereas the use of a panel specification is justified by the repeated choices provided by each respondent. In practice, this means that different individuals perceive the disutility to different extents, and the panel mixed logit model accommodates this by relaxing the assumption of homogeneous preferences. Interestingly, digital comfort terms and travel time terms for age 18-24 became insignificant in this model compared to the final MNL model. The PML model's flexible structure reallocates explanatory power from observed variables (like age and digital comfort) to unobserved heterogeneity. This makes some segment-specific effects appear statistically weaker, not necessarily because the effect disappears, but because it's now masked by richer random variation in preferences.

Overall, the panel mixed logit model provides a nuanced understanding of mode choice behaviour. It effectively captures individual-level variability and reveals that unobserved factors—such as personal risk tolerance, familiarity with transport options, or hidden sociodemographic dimensions—play a substantial role in shaping mobility decisions. These insights are critical for designing more inclusive and adaptive shared mobility systems.

4.4. Model Fit

To assess the quality and explanatory power of the developed models, the key performance indicators of the Base MNL, Final MNL, and Panel Mixed Logit (PML) models are compared in Table 4.12.

As expected, the Base MNL model provides the simplest specification, with only eight estimated parameters. The Final MNL model significantly expands the specification, incorporating a richer set of explanatory variables, resulting in 15 estimated parameters. The Panel Mixed Logit model introduces a random parameter to account for unobserved heterogeneity, with a total of 13 parameters.

Table 4.12.: Comparison of Model Fit Statistics

Performance Indicator	Base MNL	Final MNL	Panel Mixed Logit
Number of estimated parameters	8	15	13
Sample size	131	126	126
Initial log-likelihood	-3560.079	-3425.49	-3422.762
Final log-likelihood	-2613.762	-2351.594	-2312.186
Likelihood ratio test	1892.634	2147.791	2221.153
Rho-square	0.266	0.314	0.324
Rho-square-bar (adjusted)	0.264	0.309	0.321
Akaike Information Criterion (AIC)	5243.524	4733.189	4650.371
Bayesian Information Criterion (BIC)	5288.707	4817.322	4687.243
Final gradient norm	0.060	0.00219	0.4437

The Final Log-Likelihood improves substantially from -2613.76 in the Base MNL to -2351.59 in the Final MNL, indicating a better model fit. The Panel Mixed Logit model achieves a further improvement in log-likelihood to -2312.19, suggesting that capturing random taste variation enhances the explanatory power of the model.

The Panel Mixed Logit (PML) model, achieves slightly better goodness-of-fit metrics with a Rho-square of 0.324 and a log-likelihood of -2312.19. However, this improvement comes at the cost of a higher gradient norm (0.4437), which suggests less precise convergence compared to the Final MNL model (0.0022). Moreover, the PML required more computational resources.

Both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) favor the Panel Mixed Logit model, with the lowest values compared to the Final MNL. These criteria balance model fit with parsimony, suggesting that, despite potential convergence concerns, the Panel Mixed Logit provides a better trade-off between explanatory power and complexity.

It is evident that the Panel model exhibits the best overall performance in terms of goodness-of-fit. It achieves the highest log-likelihood and Rho-square values while maintaining relatively low AIC and BIC values. Goodness of fit suggests how well the estimated model explains the observed data. Therefore, in addition to assessing the goodness-of-fit, it is crucial to validate the model to ensure its generalizability beyond the estimation sample.

4.5. Model Validation

To evaluate the external validity and predictive performance of the Final MNL and Panel Mixed Logit models, a modal split validation is conducted. The total respondent data is used for validation as the number of respondents is too low (see Section 3.3.3). Table 4.13 illustrates the comparison between actual mode shares and those predicted by both models. NAE values for PML and MNL are shown in Figure 4.3.

The results show that the Final MNL model predicts most modal shares with high accuracy. It slightly underpredicts ZE Bus usage, walk and shared bike. In contrast, the Panel ML model tends to overpredict shared modes (bike, e-car, and e-scooter) and bus usage, while significantly underpredicting walk, suggesting a tendency to overfit certain segments of the data. The MNL model, by contrast, produced predictions that aligned more closely with observed behaviour across all travel modes.

Although the Panel ML model better captures taste heterogeneity through the inclusion of random parameters, the Final MNL model outperforms it in terms of absolute predictive accuracy on most modes. These results emphasize that while Panel ML offers more behavioural richness, simpler models like MNL can be advantageous when the focus is on predictive reliability. The MNL specification will generalize better to new data and is therefore more reliable for policy evaluation and forecasting applications.

Table 4.13.: Modal Split Comparison: Actual vs Predicted (MNL and PML)

Mode	Actual Share (%)	Predicted MNL (%)	Predicted PML (%)	NAE for MNL (%)	NAE for PML (%)
Walk	5.34	5.18	4.09	-0.16	-1.25
Bike	21.01	21.16	20.78	0.15	-0.23
Shared bike	11.30	11.16	11.39	-0.14	0.09
Shared e-scooter	5.34	5.41	5.51	0.07	0.17
Shared e-car	18.70	19.20	19.47	0.50	0.77
ZE bus	38.32	37.89	38.76	-0.43	0.44

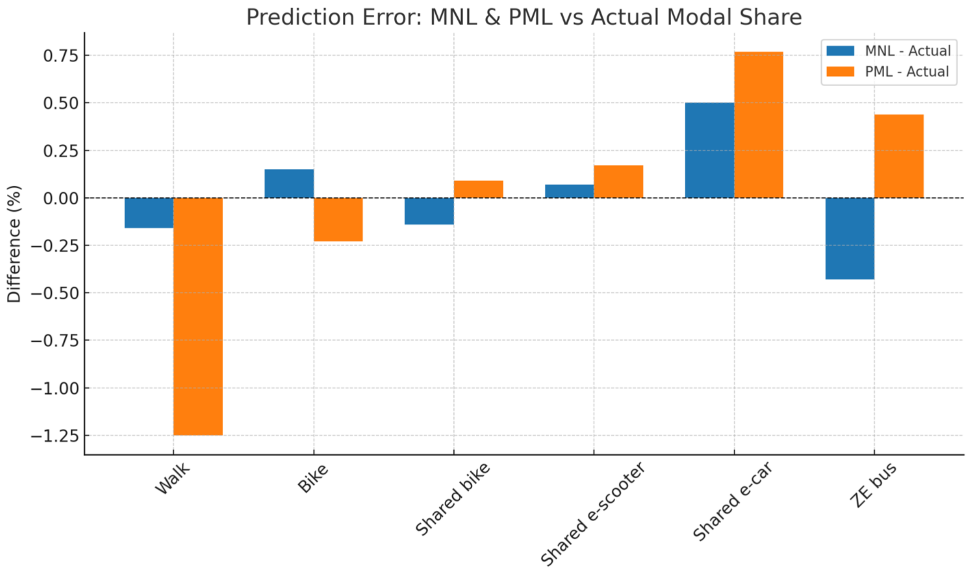


Figure 4.3.: NAE for MNL and PML model

Convergence behaviour further supports the robustness of the MNL model. It achieved optimality with a very low relative gradient of 8.76×10^{-7} and a final gradient norm of 0.00219. Moreover, the model successfully completed all Hessian evaluations, indicating numerical stability and a well-defined likelihood surface around the optimum.

PML model encountered difficulties during estimation. Specifically, it converged much slower and less precisely than the simpler MNL model. It took over 180 iterations and still ended with a high final gradient norm (0.44), signaling that it might not have reached a true global optimum. This poor convergence performance is due to the complex shape of the likelihood surface in PML models. The inclusion of random parameters makes the surface flatter and more irregular, which increases the chances of the algorithm getting stuck in local optima rather than finding the best solution. Additionally, the Monte Carlo integration required in PML further complicates convergence by introducing noise. These factors together can cause instability.

Finally, in practical applications such as policy testing, scenario simulation, and large-scale deployment, the simplicity and interpretability of the MNL model offer advantages. The absence of simulation draws or latent heterogeneity assumptions makes the MNL model not only computationally efficient but also easier to explain and justify to stakeholders.

In light of the comprehensive evaluation, the Multinomial Logit (MNL) model is selected as the final model for this study. It offers a well-balanced combination of predictive accuracy, explanatory power, computational efficiency, and interpretability—qualities that are essential for practical applications in transport policy analysis. While the Panel Mixed Logit (PML) model demonstrated a marginal improvement in certain fit statistics, such as log-likelihood and information criteria (e.g., Rho-square and BIC), these gains are offset by its more complex convergence behaviour, longer runtime, and lower prediction accuracy. Therefore, the final MNL specification is adopted for subsequent analysis to ensure reliable and realistic outcomes.

5. Model Application

This chapter applies the estimated mode choice model to target populations across different scenarios. The objectives are twofold: (i) to translate individual-level preferences into system-level modal splits for the Schiphol commuter population, and (ii) to test how key levers—such as cost, distance, waiting time, and personal characteristics—shape behavioural responses across available alternatives.

The analysis proceeds in three stages. First, a national benchmark is established by estimating baseline modal shares for the Dutch adult population. Second, the model is applied to Schiphol commuters under both a baseline and a "no private bike" scenario, in order to deal with the bias related to private bikes. Following that, sensitivity analyses are conducted to isolate the impact of key policy levers.

These applications build directly on the discrete choice model estimated in Chapter 4. While Chapter 4 identified significant behavioural parameters and quantified their effects at the individual level, this chapter scales those insights to synthetic populations. In doing so, it provides a bridge from behavioural realism to policy relevance, showing how micro-level preferences aggregate into macro-level outcomes that can guide service design, pricing policies, and targeted investment in sustainable mobility around Schiphol and comparable hubs in the Netherlands.

5.1. Model Application For Dutch Adult Population

The application is conducted on a synthetic population created by using data from the Centraal Bureau voor de Statistiek [Statistics Netherlands, nd], which provides official statistics on population distributions in the Netherlands (Table 4.1). The Netherlands experiences rain on approximately 132 days per year, representing around 40% of the year [Statista Research Department, 2023], this percentage is used as the probability of having a rainy day in this study. For the whole Dutch adult population, predicted choice probabilities for each transport mode are generated using the final model's estimated parameters.

Table 5.1.: Modal Split (% of Whole Population)

Mode	Percentage (%)
Walking	7.38
Bicycle	43.92
Shared Bicycle	9.28
Shared E-Scooter	3.82
Shared Electric Car	11.56
Zero Emission Bus	24.05

Table 5.2.: Aggregated Modal Split (% with Bike Not Available)

Mode	Percentage (%)
Walking	13.89
Bicycle	0.00
Shared Bicycle	16.59
Shared E-Scooter	6.99
Shared Electric Car	19.65
Zero Emission Bus	42.88

In the baseline scenario (Table 5.1), cycling dominates with 43.9% of trips, confirming the central role of bicycles in Dutch mobility culture (consistent with Statistics Netherlands [nd]). Zero-emission (ZE) buses follow with 24.1%, reflecting the importance of sustainable public transport as a secondary backbone. Shared e-cars (11.6%), shared bikes (9.3%), and walking (7.4%) represent relevant but smaller shares, while e-scooters remain marginal (3.8%).

When bicycles are excluded (Table 5.2), ZE buses absorb the largest shift, rising to 42.9%. This underlines their function as the primary substitute for cycling. Shared e-cars also expand (19.7%), alongside smaller increases for shared bikes (16.6%), walking (13.9%), and scooters (7.0%). These patterns suggest that electrified vehicles and buses partially offset the absence of private bikes, though likely at higher system costs and reduced physical activity benefits.

5.2. Model Application for Schiphol Commuters

To explore the implications of mobility policies in the Schiphol case study area, a synthetic population was constructed to approximate the demographic and behavioural characteristics of the real commuting population (Table 5.3). Synthetic population methods combine partial datasets (e.g., CBS registers) into a statistically coherent agent base. It allows for testing of hypothetical or future-oriented scenarios not directly observable in current data. Although this approach relies on simplifying assumptions, it is widely accepted in transport modelling contexts where privacy restrictions and fragmented data limit the feasibility of full household surveys.

According to Royal Schiphol Group [2023], the actual commuter population consists of 12.6% aged under 30, 30.7% aged 30–50, and 56.8% aged 50+. These values were redistributed into the categories used in this study, using Dutch national proportions as a reference. Weather weights were aligned with national averages like previous section, enabling scenario-based sensitivity testing. Employment shares were derived from national data in the absence of Schiphol-specific distributions.

In the baseline scenario (Table 5.4), cycling dominates with 44.0% of trips. Zero-emission (ZE) buses follow with 23.9%, indicating their role as the secondary choice. Shared e-cars (11.4%), shared bikes (9.3%), walking (7.6%), and shared e-scooters (3.8%) occupy more marginal but non-negligible shares, underscoring the multimodal character of the network.

Table 5.3.: Overview of characteristics of the synthetic Schiphol population

Attribute	Share in Population (%)
Age Groups	
18–24	7.5
25–29	5.5
30–39	16.5
40–59	33.0
60+	37.5
Weather Conditions	
Rainy	40.0
Sunny	60.0
Comfort Preference	
Low	16.0
Medium	47.0
High	37.0
Employment	
Full-time	56.3
Student	20.0

Table 5.4.: Modal split under normal availability

Mode	Share (%)
Walking	7.6
Bicycle	44.0
Shared Bicycle	9.3
Shared E-Scooter	3.8
Shared Electric Car	11.4
Zero-Emission Bus	23.9

Table 5.5.: Modal split with bike unavailable

Mode	Share (%)
Walking	14.3
Bicycle	0.0
Shared Bicycle	16.6
Shared E-Scooter	7.0
Shared Electric Car	19.4
Zero-Emission Bus	42.7

When private bicycles are excluded (Table 5.5), a pronounced modal shift occurs. ZE bus share rises to 42.7%, absorbing the majority of former cyclists, while shared e-cars increase to 19.4%. Walking and shared bikes nearly double their shares (14.3% and 16.6%, respectively), pointing to substitution potential in modes that otherwise remain secondary. These results suggest that shared and public transport modes function as the immediate fallback when cycling is unavailable. However, the shift also raises questions of system resilience: large-scale reliance on ZE buses would require substantial increases in capacity and frequency, while the substitution towards shared e-cars implies higher operational costs.

5.3. Modal Split with Weather and Bike Availability

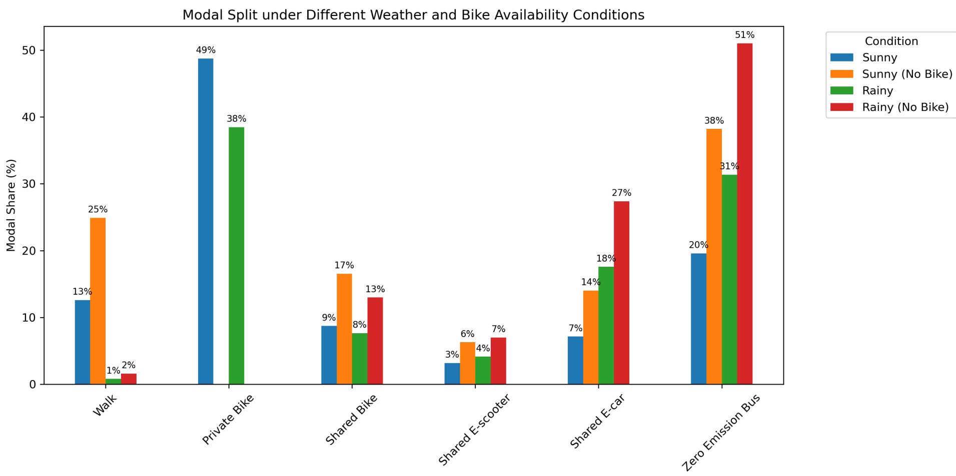


Figure 5.1.: Modal split in different weather condition and bike availability

Figure 5.1 presents the modal split predictions for Schiphol commuters derived from the final model under four different scenarios: (1) Sunny weather with bike access, (2) Sunny weather without bike access, (3) Rainy weather with bike access, and (4) Rainy weather without bike access.

The comparison between the sunny and rainy scenarios reveals a significant shift in travel behaviour. In particular, the share of private bike usage drops from 49% under sunny weather to 38% in rainy conditions, indicating the weather sensitivity of active modes. In contrast, zero-emission bus (ZE Bus) usage increases from 20% to 31% under rainy weather, reflecting a modal shift from active to motorized public modes.

When private bikes are not available, even in sunny weather, there is a considerable redistribution of mode choices. For example, shared bike usage increases to 17% (from 9% with private bike availability), demonstrating a clear substitution effect.

Under the most constrained condition (rainy weather and no private bike access), there is a notable consolidation towards public transport modes. ZE bus usage rises to 51%, becoming the dominant mode in this scenario. Similarly, shared e-car usage also climbs to 27%, reflecting a preference for sheltered, comfortable, and flexible alternatives when both weather and bike constraints are present.

Across all conditions, shared e-scooters and shared e-cars show modest but consistent increases when active travel becomes less appealing. This pattern confirms their role as intermediate alternatives between conventional public transport and private mobility.

The observed shifts confirm theoretical expectations: active modes are strongly weather-dependent, and mode availability significantly influences substitution patterns. Furthermore, the dominance of public and shared modes in adverse conditions supports the robustness of the model in simulating realistic urban travel behaviour.

5.4. Sensitivity Analysis

5.4.1. Sensitivity by Distance

To better understand how travel distance influences mode choice, a sensitivity analysis is conducted by varying the origin-destination distance from 0.5 km to 6 km in 0.5 km increments. Travel times for each mode are computed based on fixed average speeds, as summarized in Table 3.2, and adjusted accordingly at each step. All other variables (costs, weather, wait times, etc.) were held constant to isolate the effect of distance on mode preference. The resulting modal shares are visualized in Figure 5.2.

The analysis reveals several clear behavioural patterns. Walking is the dominant mode at very short distances, with over 33% share at 0.5 km. However, it declines sharply as distance increases, dropping below 10% beyond 2 km and nearing 0% around 5–6 km. This steep decline reflects the limited practicality of walking for longer distances due to its low speed and high physical effort.

Bicycles (both personal and shared) peak in preference around 1.5 km. While personal bikes exhibit a slightly higher modal share than shared bikes, both modes show a gradual decline after 2 km. This suggests that while cycling is a highly efficient option for short to medium distances, its competitiveness weakens as faster alternatives become more attractive over longer trips.

Shared e-scooters maintain a relatively small but stable share across distances. Their modal share rises slightly up to 2–3 km, indicating a niche for medium-range urban trips, but they are consistently outperformed by both bikes and e-cars.

Shared e-cars and zero-emission buses exhibit the most pronounced increase in modal share with distance. Shared e-cars become increasingly attractive, surpassing bike and scooter options around the 3.5 km mark and reaching around 34% share by 6 km. Similarly, bus usage grows consistently with distance, peaking at approximately 5 km before plateauing. This pattern reflects their high average speeds and suitability for longer, less active journeys.

Overall, the results show a distinct transition in mode choice as distance increases active modes (walking, biking) dominate up to 1.5–2 km and shared and motorized modes (e-car, bus) take over as distance increases.

These trends reinforce the importance of multimodal infrastructure planning. For short distances from the hub, enhancing pedestrian and cycling environments is key. For longer distances, reliable and well-integrated shared and public transport options are essential to sustain mode shift away from private car use.

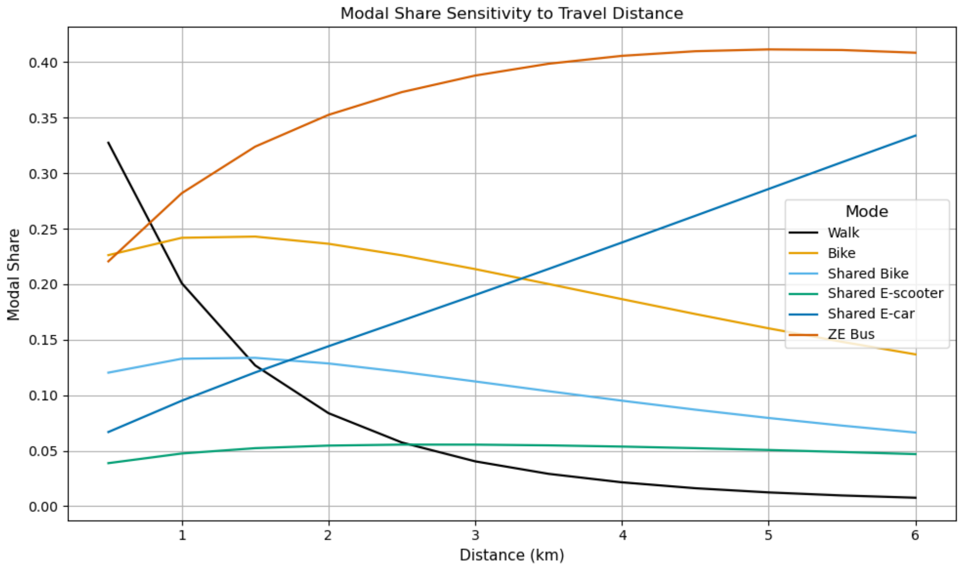


Figure 5.2.: Sensitivity by distance

5.4.2. Sensitivity by Cost

To evaluate how variations in cost influence travel behaviour, four alternative pricing scenarios were simulated and their impact on modal share was visualized in Figure 5.3. The scenarios include: Free bus (zero cost for bus travel), Shared e-car surge (increased e-car prices), Discounted shared bike and e-scooter (reduced costs for shared bikes and scooters) and Uniform cost for all shared modes (a uniform shared mode fare set at €1.5).

These four scenarios are chosen to reflect realistic and policy-relevant pricing interventions currently being discussed or piloted in European urban mobility contexts. The "Free Bus" scenario is inspired by zero-fare public transport experiments (e.g., Tallinn, Luxembourg) aimed at increasing ridership and reducing congestion. The "Shared e-car surge" scenario captures concerns over the rising cost of energy and its potential to suppress adoption of high-emission vehicle sharing options. The "Discounted shared micro-mobility" scenario responds to increasing calls for equitable access to micromobility, particularly in first-/last-mile settings. Finally, the "Uniform Cost" scenario tests fare harmonization—a principle of fare integration found in many transit systems—to examine whether standardizing costs across modes improves mode neutrality and uptake. These scenarios collectively span both user incentives and regulatory levers, enabling the exploration of behavioural elasticity under varying fare structures.

The results show significant variation in mode choice responses depending on cost assumptions. In the Free Bus scenario, bus usage peaks with a modal share of approximately 60%, indicating that eliminating fares can strongly incentivize public transport adoption. This supports broader European urban mobility strategies aimed at enhancing public transport affordability and accessibility.

Conversely, in the Shared E-car Surge scenario, a 25% price increase reduces e-car usage to near 14%, highlighting a strong price elasticity for individual shared vehicle use. This shift is

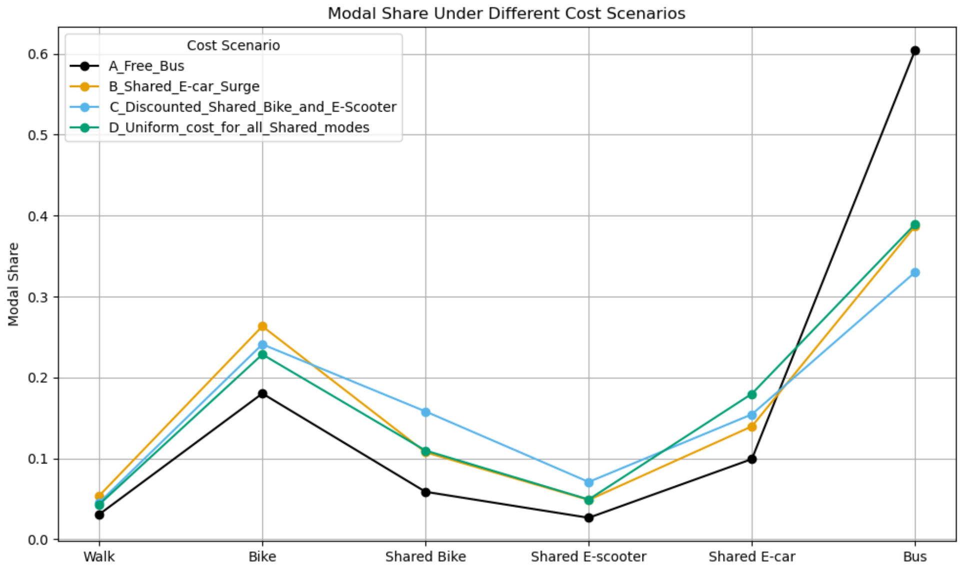


Figure 5.3.: Sensitivity by cost

accompanied by increased shares for bikes and buses, suggesting that higher operating costs for shared electric cars may prompt users to pivot to cheaper options. These findings imply that demand-based pricing or congestion charges could be effective measures to discourage high-emission modes during peak periods.

The Discounted Shared Bike and E-scooter scenario demonstrates a marked improvement in uptake for shared micromobility, especially e-scooters and shared bikes. Their usage increases notably when costs are reduced, which reinforces the case for targeted subsidies or incentive schemes for short-distance urban travel.

Meanwhile, the Uniform Cost for All Shared Modes scenario yields a more balanced modal distribution, with moderate increases in shared mode adoption (especially e-cars and scooters) without extreme shifts away from traditional modes. This suggests that a harmonized fare structure could provide predictability and fairness in pricing across services.

Overall, these findings confirm that cost levels can significantly influence modal shifts, and carefully designed pricing strategies can encourage greener mode choices. The policy implications are broad: municipalities and transit agencies can use fare incentives not just to boost ridership but also to address equity, reduce congestion, and support climate goals. Tailoring these strategies to specific demographic and spatial contexts—such as urban centers, commuter belts, or vulnerable populations—could further enhance their effectiveness.

5.4.3. Sensitivity to Bus Waiting Time

In this analysis, the wait time for the zero-emission bus mode is varied from 0 to 20 minutes in 2-minute increments, while all other parameters—including travel times, travel costs, weather conditions, and user demographics—are held constant. Figure 5.4 displays how the average modal share for each alternative responds to increasing bus wait times. The results

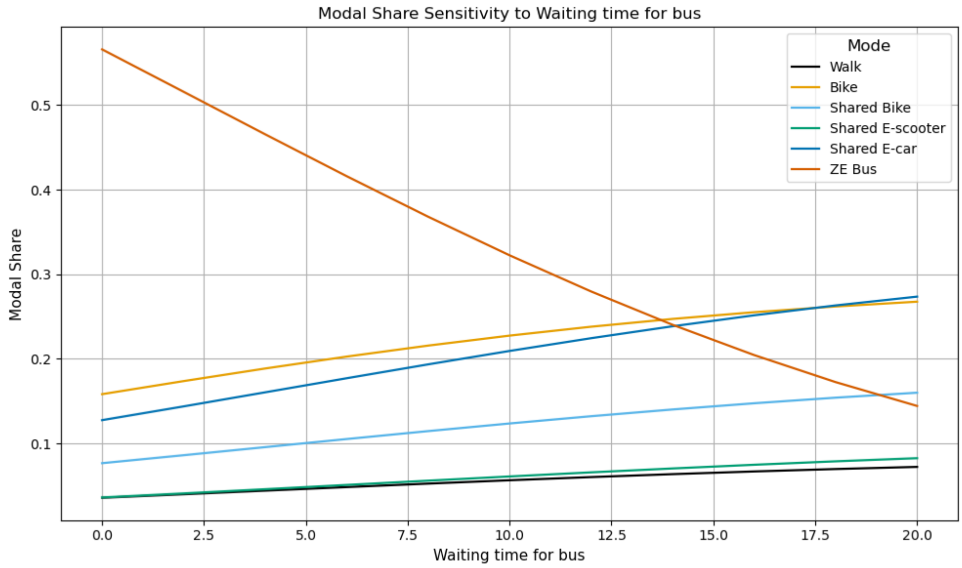


Figure 5.4.: Sensitivity by bus Wait Time

indicate that bus ridership is highly sensitive to increases in waiting time. At a zero-minute wait time, the bus captures over 55% of the total modal share, making it the dominant mode. However, as wait time increases, the share of bus trips declines rapidly and almost linearly, dropping below 15% when the wait reaches 20 minutes. This steep decline highlights the critical role of frequency and reliability in attracting riders to public transportation.

Conversely, nearly all other modes show an upward trend in modal share as bus wait time increases, although the degree of responsiveness varies. E-car and bike modes gain the most from the decline in bus usage. The e-car share grows from 13% to nearly 27%, while biking increases from 15% to 26% as bus wait time worsens. These modes act as key substitutes to public transit for users prioritizing time reliability and comfort. Shared bike also exhibits a moderate but steady rise in usage, indicating its appeal as a flexible and low-wait-time alternative. Scooter and walking, although less sensitive, also gain some share.

This behavioural shift reflects a mode substitution effect, where users abandon high-delay modes in favor of faster or more reliable options—even if those options may incur higher costs or physical effort. The near-linear nature of the decline in bus share also suggests that user perception of wait time may be linearly disutility-driven, at least within this 0–20 minute window.

5.4.4. Sensitivity to Digital Comfort and Employment Status

To evaluate how changes in employment status and digital comfort level influence travel mode choices, five distinct population scenarios were constructed. These scenarios are:

- **Young Digital Population**: A digitally fluent group, primarily composed of students and part-time workers.
- **Working Professionals**: Employed full-time with high digital comfort.

Table 5.6.: Socio-Digital Profiles of Population Groups

Cluster	Employment Distribution	Digital Comfort Level
Young Digital Population	50% students, 50% part-time/unemployed	80% high, 20% medium, 0% low
Working Professionals	90% full-time employed	70% high, 30% medium, 0% low
Retirement Community	100% retired	20% high, 50% medium, 30% low
Low-Income Urban Mix	40% students, 40% part-time/unemployed, 20% full-time	10% high, 30% medium, 60% low
Tech-Egalitarian Society	25% each: students, full-time, part-time/unemployed, retired	100% high, 0% medium, 0% low

- **Retired Community**: Older adults with varied levels of digital literacy and no active employment.
- **Low-Income Urban Mix**: A mix of students, part-time workers, and unemployed individuals with lower digital comfort.
- **Tech-Egalitarian Society**: An evenly distributed employment profile with uniformly high digital comfort.

  The distributions within the groups are given in table 5.6.The distributions are derived through an expert-informed synthesis process. Since complete joint distributions of employment status and digital comfort are not readily available for Schiphol commuters, assumptions were triangulated from national-level data (e.g., CBS statistics) and qualitative insights from relevant literature on digital inclusion. The purpose of these clusters is to enable the simulation of meaningful diversity in digital mobility readiness. For instance, the "Young Digital Population" and "Retirement Community" reflect archetypal extremes in digital comfort, allowing us to explore how green mobility adoption may differ across these ends of the spectrum. While individual cluster proportions do not aim to be statistically significant predictors on their own, their inclusion enhances behavioural plausibility within the synthetic population. Future studies with larger sample sizes could calibrate these clusters more rigorously through latent class or finite mixture models. Figure 5.5 shows that modal share distributions are relatively stable across scenarios, with bus and bike dominating in all cases. However, subtle variations are observed:

  - Walking share increases in the *Low-Income Urban Mix* and *Tech-Egalitarian Society*, suggesting a higher reliance on pedestrian travel in digitally equitable or income-constrained populations.
  - Shared micromobility modes (e.g., shared bike, scooter) remain relatively stable, with minor increases among younger or digitally proficient groups.
  - Bus use remains the dominant mode overall but slightly declines in more digitally active populations.

  These results underscore the importance of considering population structure when planning for mobility futures. Different segments of society are likely to respond

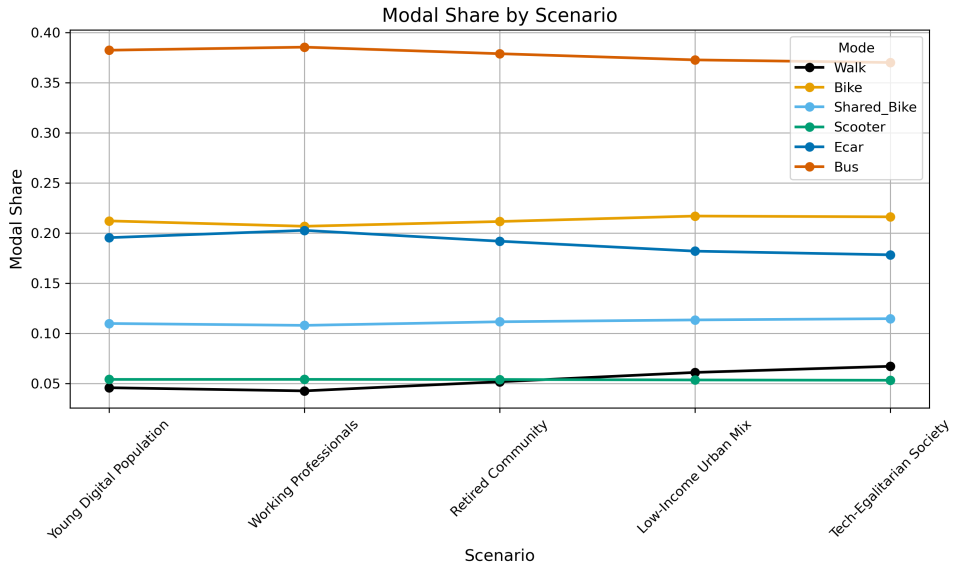


Figure 5.5.: Predicted modal share across different population scenarios.

differently to transportation policy or technology interventions. By anticipating these shifts, planners can tailor infrastructure and services to be more inclusive.

Overall, the applications in this chapter demonstrate how the estimated model scales from individual-level sensitivities to system-level outcomes for Schiphol commuters. The results consistently highlight the centrality of cycling and zero-emission buses, while also revealing strong substitution patterns when weather or bike availability constrain choices. These outcomes, however, using a synthetic commuter population and stated preference parameters mean real-world elasticities may differ. Nevertheless, the patterns provide clear policy signals: availability of different modes should be decided considering the distance between the hub and the destination, rainy conditions point to the value of flexible fleet management, and pricing remains a powerful lever for shifting demand toward greener modes. These preliminary findings set the stage for deeper critical reflection and actionable policy recommendations in the later chapters.

6. Digital Twin Simulation

This chapter presents the findings from the Digital Twin (DT) simulations conducted for the Schiphol area. The DT framework was employed to evaluate the impacts of introducing mobility hubs offering green first- and last-mile transport modes. The simulations compared two scenarios: a baseline scenario reflecting current conditions for commuter traffic without mobility hubs, and an intervention scenario incorporating two strategically located mobility hubs to omit commuter car traffic inside Schiphol Airport.

For modal splits to and from the hub, values from Table 5.4 are used. For simplification purposes and data unavailability, only car traffic of the morning peak is taken into account. Modelling this period captures the system under its highest stress, thus yielding more policy-relevant insights regarding congestion, modal shifts, and emission reduction potential.

6.1. Case Study Area: Schiphol Airport and Commuter Flows

Schiphol Airport, located southwest of Amsterdam, is the Netherlands' largest airport and one of the busiest air travel hubs in Europe. Beyond its role as an international airport, Schiphol functions as a major employment center, with approximately 65,000 people working at the airport and its immediate surroundings [Royal Schiphol Group, 2023]. The airport area hosts a wide range of businesses, including aviation operations, logistics, hospitality, retail, and office complexes, making it one of the largest single-site employment zones in the country.

This thesis focuses exclusively on the commuter traffic associated with Schiphol Airport. Commuters are defined as individuals traveling to and from the airport area for work purposes, irrespective of their mode of transport. While Schiphol experiences significant volumes of passenger and freight traffic, commuters represent a substantial share of daily movements. These movements play a critical role in shaping traffic congestion, parking demand, and overall transport system performance in the region.

The airport's strategic location near major highways (A4, A5 and A9) and its integration with the national rail network make it highly accessible. However, despite this, peak-hour congestion, limited parking availability, environmental concerns and the growing need to reduce private car dependency have further emphasized the importance of sustainable and multimodal solutions for commuting.

The Digital Twin simulations in this research are centered on this specific commuter segment, evaluating how interventions such as the introduction of mobility hubs with car restriction and green shared modes (e.g., shared bikes, e-scooters, zero-emission buses) can influence commuting patterns, reduce congestion, and improve environmental indicators for the Schiphol region. By focusing on commuters, this study provides insights into targeted mobility policies that can help alleviate pressure on the airport's transport network while supporting broader sustainability goals in the region.

6.2. Traffic Impact

The DT simulations reveal a measurable influence of mobility hubs on traffic patterns within the Schiphol area. The key traffic-related outcomes are summarized below. All the calculations are done based on one morning peak (7:00-9:00 am).

6.2.1. Commuter Car Intensity Effects During Morning Peak

Figure 6.1 visualizes the change in commuter car intensity during the morning peak hours (7:00–9:00 am) resulting from the introduction of mobility hubs. The red segments represent areas with increased car intensity, green segments indicate reductions, and grey segments show neutral change. Notably, car intensity increases significantly at the two designated mobility hub points (yellow), located along the main access routes to Schiphol. This suggests that these hubs are attracting more commuter traffic, due to park-and-transfer behaviour. In contrast, car trips inside Schiphol is replaced by offered green modes.

Even though flows increase in some areas, the intensity capacity ratios stay under 0.9. So, it does not lead to critical overloading of the road network. The existing infrastructure is generally capable of accommodating this demand without significant congestion. But this I/C ratios ignore any modes other than car for simplification reasons, so these results are very optimistic.

6.2.2. District Level Impacts on Vehicle Kilometers Travelled

To evaluate the spatial redistribution of traffic resulting from the mobility hub implementation, vehicle kilometers travelled (veh-km) were compared across administrative districts under two scenarios: with and without the hub intervention. Figure 6.2 illustrates the percentage change in veh-km per district.

The implementation of the mobility hub produced a heterogeneous impact across the regional transportation network. The district of Haarlemmermeer, experienced the most reduction in vehicle kilometers, with a decline of approximately 0.85%. This suggests that the hubs that restrict car usage, effectively diverts longer-distance private vehicle trips away from this area. More moderate reductions were observed in districts such as Haarlem and Kaag en Braassem, which exhibited decreases of 0.16% and 0.1%, respectively.

In contrast, urban districts like Amsterdam and Amstelveen showed net increases in vehicle kilometers traveled. Specifically, Amsterdam recorded a rise of approximately 3.71%, while Amstelveen saw an increase of around 2.08%. These increases are likely

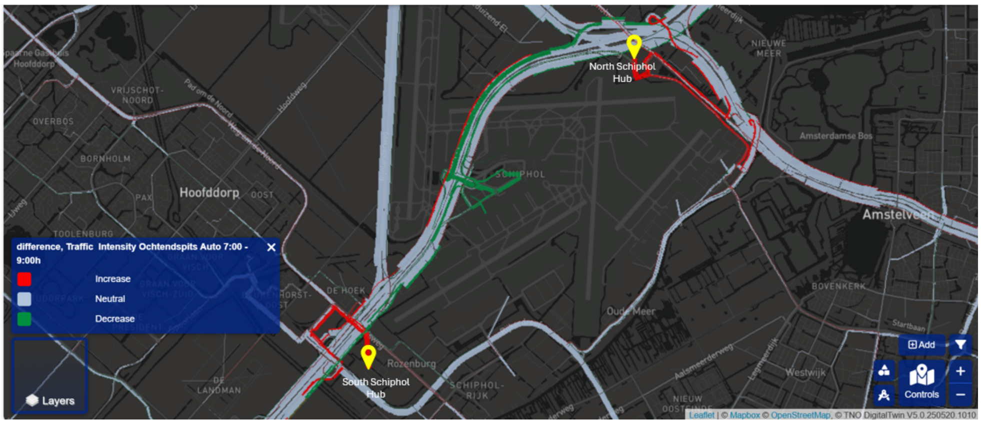


Figure 6.1.: Change in traffic intensity (Hub vs. No Hub scenario)

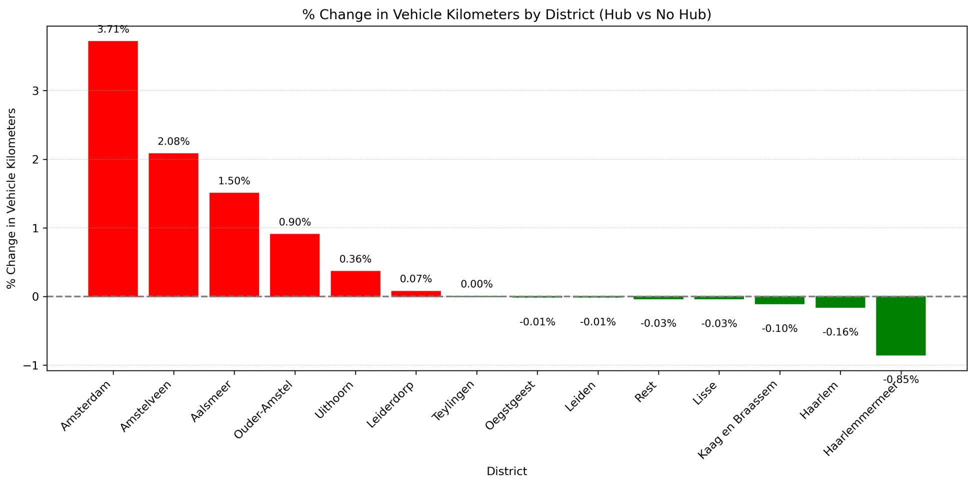


Figure 6.2.: Percentage change in veh-km by district (Hub vs. No Hub scenario)

attributable to a combination of factors, including local circulation required to access the mobility hub and the restriction of private vehicle access within Schiphol itself. As a result, travelers may be taking longer or alternative routes to reach their destinations, thereby increasing intra-urban vehicle kilometers. Additionally, this outcome could reflect induced demand effects—where improvements in network accessibility (e.g., new or enhanced connections via the hub) inadvertently make driving more attractive for certain trips.

Overall, the total vehicle kilometers across the entire network declined slightly from 34,631,470 km (without hub) to 34,621,750 km (with hub), amounting to a net reduction of approximately 9,720 km, or 0.03%. While marginal in aggregate terms, this shift underscores a broader systemic trade-off: mobility hubs can alleviate congestion and emissions in peripheral or high-throughput regions, yet simultaneously induce longer trips distance-wise. These findings highlight the necessity for spatially targeted planning and complementary policies when integrating hubs into complex urban mobility systems.

6.3. Environmental Impact

To evaluate the environmental implications of the hub strategy, three key traffic-related emissions were analyzed: NO_2, PM_{10}, and $PM_{2.5}$. Using the TNO Digital Twin platform, the difference between the hub scenario and the reference scenario was visualized for each pollutant.

6.3.1. Spatial Impact on Environmental Indicators

Figure 6.3 illustrates the spatial distribution of changes in NO_2 emissions resulting from the implementation of the hub scenario, as compared to the reference scenario. The color scale indicates the direction and magnitude of change: green areas represent emission reductions, while red areas signify increases, both measured in $\mu g/m^3$. The strong green segments, particularly along the main access routes to Schiphol Airport and the internal airport roads, suggest the benefit of having no commuter car trips inside Schiphol. This indicates a net environmental benefit around the airport core, aligning with the intended role of the hubs.

Conversely, localized red zones around the northern and southern hub locations reflect slight increases in emissions, likely due to concentrated traffic activity at the hub entry/exit points and rerouted trips. These hotspots are expected side effects of mobility consolidation and mode switching at the hubs, where users arrive to pick up or drop off shared vehicles.

Particulate Matter (PM_{10} and $PM_{2.5}$) differences reflect a similar trend. Improvements are seen especially near hub catchment areas and highway feeders into Amsterdam and Schiphol. A minor PM_{10} increase near Rozenburg is observed but is not extensive or severe. Overall, this supports the claim that the hub setup has led to healthier air quality levels in urban and peri-urban zones. The spatial maps of these environmental indicators are provided in Appendix F.

The combined environmental results strongly support the effectiveness of the mobility hub in promoting greener modal shifts. These hubs enhance air quality in a region that is typically vulnerable to pollution from heavy transport and airport-related activity. The spatial coherence of improvements across all three pollutants validates the potential of hubs as a policy tool for urban sustainability and public health.

Minor increases in emissions on specific segments suggest a need for better traffic redistribution or adaptive signaling to mitigate localized impacts. Still, the overall environmental benefit of the hub setup is clear and substantial. Even in the areas where emission increases, most of them stay below EU thresholds [European Commission, nd]. Higher than standard NO_2 emission can be seen in some zones of Schiphol Airport for aircraft related activities.

6.3.2. District Level Change in Environmental Indicators

To assess the environmental implications of the hub setup, this study analyzed the percentage change in three key vehicular emission indicators—NO_2, PM_{10}, and $PM_{2.5}$—across districts. Emission changes are represented in Figure 6.4, 6.5 and 6.6.

The results reveal a notable overall improvement in air quality in several districts due to the hub setup. The data reveal a mixed pattern of emission changes across districts, driven by spatial shifts in traffic intensity due to the logistics hub configuration. Notably, Amsterdam shows the largest increase across all pollutants, with NO_2 up by 2.51%, PM_{10} by 3.07%, and $PM_{2.5}$ by 3.19% (Table 6.2). This may be attributed to increased consolidation and traffic rerouting through major arterials in the city, reinforcing centralization effects in the hub setup.

Conversely, Haarlemmermeer shows the most significant reductions, with NO_2 down by 0.76%, and $PM_{2.5}$ by 0.89%. This suggests that decentralization of trips or rerouting away from the airport zone (Schiphol) and surrounding infrastructure may have reduced traffic load in this high-sensitivity area.

Other districts like Amstelveen, Aalsmeer, and Uithoorn exhibit moderate increases, likely due to increased local distribution activity closer to the urban fringes. Teylingen, in contrast, experiences no measurable change across any pollutant—highlighting that traffic volumes and patterns in peripheral zones remained stable under both scenarios.

Districts such as Kaag en Braassem, Leiden, and Lisse show slight decreases in emissions (typically less than 0.15%), indicating minor but beneficial traffic redistribution effects.

The findings from Table 6.2 confirm that the hub implementation causes net reduction for all the indicators. Overall, the results underscore a trade-off—central urban zones may see increased emissions due to aggregation and distribution efficiencies, but the total emissions go lower due to improvement in other corridors (Table 6.1). These findings support the need for district-specific air quality policies (i.e., low-emission zones, vehicle access restrictions in dense cores, differentiated pricing based on emissions class, or targeted electrification of urban freight fleets) and better spatial planning, ensuring that efficiency gains at the regional scale do not come at the cost of localized environmental degradation.

Figure 6.3.: Difference in traffic-related NO_2 emissions (in $\mu g/m^3$) between the mobility hub scenario and the reference scenario (Red indicates emission increase; green indicates reduction).

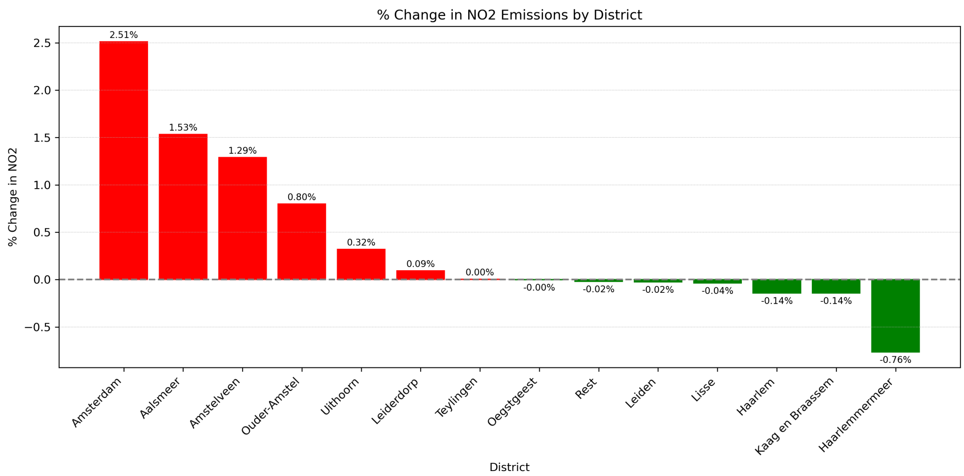


Figure 6.4.: District-wise Change in NO_2 emission

Table 6.1.: Total Emission Reduction Due to Mobility Hub (in Metric Tonnes and Percentage)

Pollutant	**Total Change (tonnes)**	**Total Change (%)**
NO_2	-4.92×10^{-6}	-0.021%
PM_{10}	-1.57×10^{-5}	-0.028%
$PM_{2.5}$	-4.33×10^{-6}	-0.027%

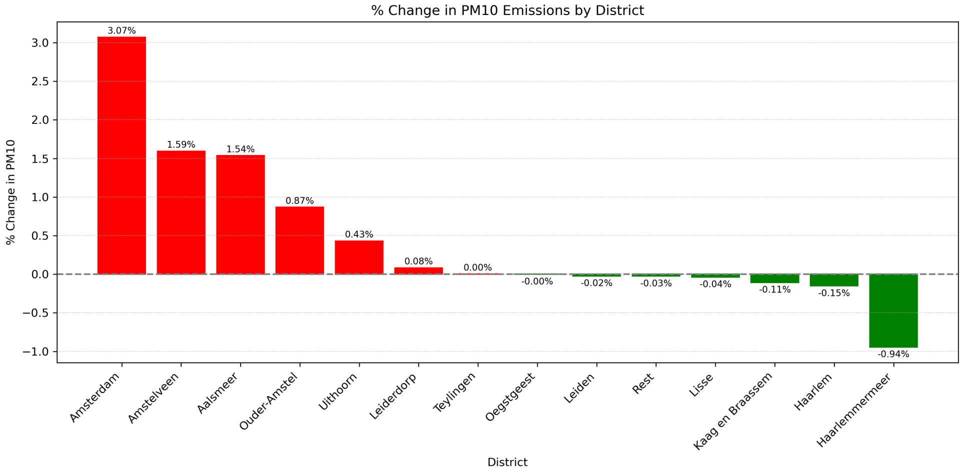


Figure 6.5.: District-wise Change in PM_{10} emission

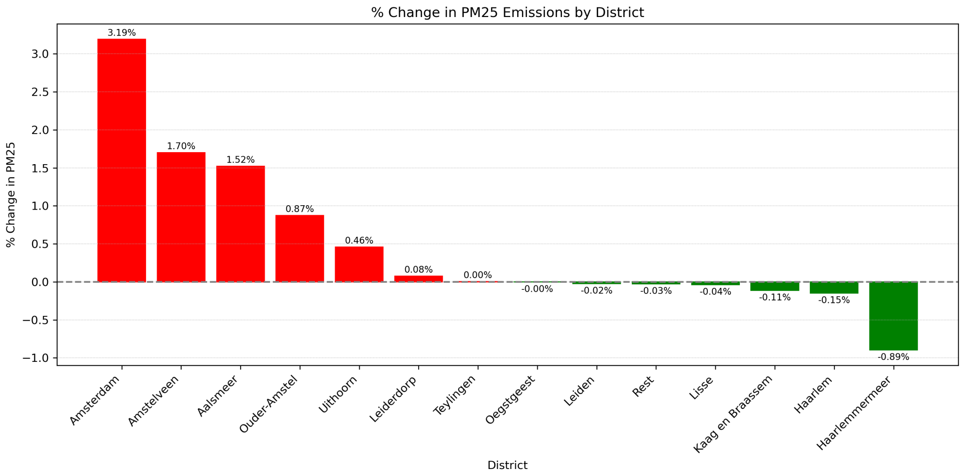


Figure 6.6.: District-wise Change in $PM_{2.5}$ emission

Table 6.2.: Percentage Change in Emissions by District (%)

District	**NO_2**	**PM_{10}**	**$PM_{2.5}$**
Haarlemmermeer	-0.76	-0.94	-0.89
Amsterdam	2.51	3.07	3.19
Leiden	-0.02	-0.02	-0.02
Kaag en Braassem	-0.14	-0.11	-0.11
Ouder-Amstel	0.80	0.87	0.87
Aalsmeer	1.53	1.54	1.52
Lisse	-0.04	-0.04	-0.04
Amstelveen	1.29	1.59	1.70
Uithoorn	0.32	0.43	0.46
Leiderdorp	0.09	0.08	0.08
Oegstgeest	-0.00	-0.00	-0.00
Haarlem	-0.14	-0.15	-0.15
Rest	-0.02	-0.03	-0.03
Teylingen	0.00	0.00	0.00

7. Discussion and Limitations

This chapter discusses the key findings and implications of the study, focusing on user behaviour insights, the performance of green mobility modes, environmental and traffic impacts, and the limitations of the study.

7.1. Discussion

The findings from both the discrete choice modelling and the digital twin simulation provide valuable insights into commuter travel preferences, behavioural sensitivities, and the broader effects of green mobility hub implementation.

Cost and time emerged as dominant factors in mode choice, but their influence is far from uniform across individuals or contexts. The discrete choice modelling revealed strong cost elasticity, with zero-fare bus scenarios producing large modal shifts. This underscores affordability as a decisive barrier, consistent with studies in similar contexts [Sanders, 2015; Torabi et al., 2023]. However, even with uniform costs, mode shares differ—reflecting intrinsic preferences, perceived travel time, and sociodemographics. This indicates financial incentives alone cannot fully reshape travel behaviour, as underlying constraints and preferences continue to play an important role. At the same time, the strong response to free or subsidised fares raises questions about financial sustainability: while such measures can substantially boost uptake, they require durable funding mechanisms to avoid policy backfire once subsidies are withdrawn.

Similarly, waiting time emerged as a critical disutility. Around 14 minutes of waiting, bus usage falls below both bike and shared e-car usage, reinforcing earlier evidence that travellers tolerate only a 3–15 minute transfer window as acceptable [Schakenbos et al., 2016]. Long waits push commuters towards modes they can control directly (bike, shared car), despite longer travel times.

Weather sensitivities revealed a notable asymmetry: during adverse conditions, time sensitivity increased while cost sensitivity decreased. This shows that commuters prioritise reliability and comfort over monetary savings when exposed to discomfort. In practice, this means that dynamic pricing alone may be less effective in sustaining ridership during adverse weather. Instead, a combined strategy is needed: on one hand, operators could experiment with weather-responsive pricing schemes (e.g., temporary discounts, flexible fare capping, or bundled services during rainfall or snowfall) to cushion demand drops; on the other hand, infrastructural measures such as sheltered bike lanes, heated pavements, or covered transfer zones are critical to address the resilience gap. Sustainable modes like cycling and shared micromobility are more vulnerable to weather shocks, meaning that hubs risk becoming over-dependent on bus capacity if these vulnerabilities are not mitigated.

Both younger, digitally comfortable individuals and older, digitally uncomfortable individuals displayed similar preferences for shared modes, according to the sensitivity analysis. This underscores an often-overlooked design principle: inclusivity in shared mobility systems is not just about physical accessibility or pricing—it's also about interface clarity, onboarding simplicity, and perceived reliability. Without these features, systems may inadvertently favour younger, higher-educated, and tech-savvy users, reinforcing digital divides. Designing for universal usability (e.g., multilingual apps, cash options, simplified trip planning) will ensure equitable uptake among different groups. Although these findings remain indicative, as older and less digitally skilled commuters were underrepresented in the sample.

Parameters associated with trip purpose, gender, and shared vehicle frequencies are found to be statistically insignificant in the model specifications, even though they were relevant in similar studies (See section 2.2). However, this should not be interpreted as evidence that these factors do not influence travel behaviour. Rather, this outcome may be attributed to sample limitations or cognitive fatigue among respondents, particularly given the number of attributes and the complexity of the survey tasks. It is possible that some factors were subconsciously ignored or given less attention, resulting in weaker statistical effects. Consequently, these attributes are excluded from the final model, although their real-world relevance remains plausible.

A critical implication of hub-based interventions is the localised increase in traffic flows around mobility hub nodes. While the overall system shows reductions in vehicle kilometres travelled (VKT) and emissions, the design of the hubs inherently concentrates certain trips—particularly drop-offs, pickups, and last-mile transfers—around specific access points. This spatial redistribution creates trade-offs: at the regional scale, congestion and emissions decline, but locally, access roads, intersections, and forecourts may face disproportionate peak demand, raising safety concerns and potentially undermining user satisfaction. These "pressure points" require active management to ensure that local surges do not erode systemic benefits. However, as long as these local flows remain below the infrastructural capacity threshold, the net benefits of hub implementation—such as emissions reduction, reduced VKT, and improved accessibility—are preserved. Careful traffic engineering, dynamic access control, dedicated bus lanes, and smart kerb or occupancy management are essential to prevent congestion spillbacks and safety hazards, thereby preserving the wider gains of hub implementation.

In terms of modelling decisions, the Multinomial Logit (MNL) model is selected for the final application phase due to its better prediction power and stability. However, this choice also warrants reflection. As shown in Section 4.5, the Panel Mixed Logit (PML) model outperformed the MNL model in terms of goodness-of-fit. PML also accounts for individual-level random effects and repeated observations, which are especially relevant in a stated preference setting. The MNL framework assumes homogeneous preferences across individuals and adheres to the Independence of Irrelevant Alternatives (IIA) property, meaning that the relative odds of choosing between two options remain unchanged with the introduction or removal of other alternatives. This assumption is particularly problematic in the context of introducing new shared mobility modes that have overlapping attributes. By ignoring correlated unobserved factors across alternatives and inter-individual taste variation, the MNL model may misestimate modal share patterns. This risks inflating or suppressing the potential uptake of specific services under hypothetical conditions. By neglecting panel dynamics, the

MNL model may provide clean but over-simplified estimates that mask nuanced behavioural patterns—particularly important when simulating long-term adoption trajectories for emerging mobility technologies. Thus, MNL's behavioural validity in capturing the richness of mode choice psychology remains limited, warranting caution in interpretation, particularly in policy contexts where substitution patterns between related services matter. The inability to account for unobserved preference correlations may lead to over-optimistic demand forecasts. This means that policies relying on MNL-based projections should be treated cautiously, as they may misrepresent substitution effects between closely related services.

One concern is the potential impact of visual and textual framing. Even though efforts were made to present all alternatives neutrally, variations in how shared mobility modes were described or depicted may inadvertently amplify their perceived attractiveness. Such framing effects can affect choices, inflating the preference for technologically novel or environmentally appealing options. Another layer of bias stems from the hypothetical nature of SP experiments. While the cost and time attributes were grounded in real-world data, the stakes for respondents were hypothetical. In the absence of real monetary or temporal consequences, individuals may not fully internalize the trade-offs, potentially overstating sensitivity to variables like cost or underestimating inconveniences such as waiting time or weather exposure. These two concerns can mean respondents' choice in the survey may diverge significantly from revealed real-world choices, which may mean the uptake percentage is inflated for certain green modes. This raises concerns about external validity—how well these stated preferences will map onto revealed choices when the services are actually available.

Moreover, scenario simplifications—such as assuming universal availability of shared services or constant weather conditions in DT and MNL—fail to capture the volatility and constraints of real-world mobility ecosystems. These assumptions may result in overly optimistic projections of mode adoption, particularly for resource-constrained populations or less urbanized settings where service reliability is a key determinant of behaviour.

The improvement results from the hubs are valid within the confines of assumptions mentioned before. Most notably, the outputs of the Digital Twin—such as VKT, I/C ratios, and emissions—are not validated against observed traffic or environmental data for the Schiphol region. This absence of empirical grounding means that while the trends appear behaviourally plausible, they should be interpreted as indicative rather than predictive, limiting their utility in high-stakes policy forecasting.

This study provides actionable insights for mobility hub planning and green mode design. By integrating discrete choice models with large-scale traffic simulation, it offers a reproducible, scalable approach for assessing multi-modal strategies. The findings suggest that when designed with cost sensitivity, time efficiency, and digital inclusivity in mind, shared mobility interventions can generate both behavioural and systemic benefits. Future work should build on this integrative foundation with dynamic agent-based models and real-world validation to close the gap between simulation and reality.

7.2. Limitations

While this study provides a novel integrative framework combining discrete choice modelling and digital traffic simulation, several methodological, behavioural, and modelling limitations must be acknowledged when interpreting the findings.

A key methodological challenge is ensuring that the collected data adequately represents the target population's travel behaviour. The study aimed for 240 responses to enable robust model estimation, but only 131 valid responses were obtained. This shortfall limits the ability to capture heterogeneity in mobility preferences. The respondent profile—mainly younger, highly educated, and digitally literate individuals—further constrains representativeness. While these groups reflect early adopters of shared and sustainable mobility, their preferences may not align with the broader commuting population. The sample's deviation from population norms (as shown in Section 4.1) implies underrepresentation of older adults, lower-income groups, and individuals with lower digital comfort or education. Several subgroups had fewer than 30 observations, weakening the ability to detect effects such as age-related digital discomfort or age-related sensitivity to waiting time. As a result, model estimates likely overstate adoption of digitally mediated green modes. A larger, more balanced sample would likely yield different parameter values, particularly regarding technology use, waiting-time sensitivity, and willingness to pay.

The demographic bias is reinforced by survey distribution methods. Most responses came from urban populations with well-developed public transport and limited car ownership. Distribution through personal networks also produced a concentration of highly educated respondents, many with professional backgrounds in sustainable transport or urban mobility. This group's stronger environmental awareness and pro-sustainability attitudes may inflate willingness to adopt some green modes and heighten sensitivity to parameters such as cost and environmental impact, compared to the general commuting population.

One important simplification in the utility specification is the omission of transfer penalties, such as perceived transfer time, uncertainty, or walking time between modes. Extensive literature indicates that transfers are a key deterrent in multi-modal journeys, often exerting a disutility larger than in-vehicle travel time [Torabi et al., 2023; Zuurbier, 2023]. Incorporating transfer penalties would likely reduce the attractiveness of certain green modes—thereby yielding more conservative and realistic adoption forecasts. This omission likely inflates projected uptake and limits the precision of scenario-specific policy insights. In future iterations, fixed and context-sensitive transfer costs should be included to better reflect user experience and support accurate hub-level design assessments.

Model validation is performed on the same dataset used for model estimation due to the small sample size (n = 131). This approach, though suggested by literature, limits the ability to assess out-of-sample predictive power, increasing the risk of overfitting. When models are evaluated on the same data they are trained on, performance metrics such as Rho-square bar or log-likelihood may overestimate generalizability. As a result, while the model fits the current data well, its ability to accurately predict mode choice behaviour in different populations or future conditions remains uncertain, limiting confidence in applying these coefficients to other contexts or policy forecasts.

In modelling the synthetic Schiphol commuter population, not all relevant user characteristics—such as employment status or digital comfort—were available from existing data sources. These attributes were therefore approximated or borrowed from broader Dutch population statistics. While this approach enables demographic realism at an aggregate level, it masks important local heterogeneities that could significantly influence mode choice and behavioural sensitivities. Schiphol is a unique employment hub with atypical travel profiles: it includes shift workers, aviation staff subject to security constraints, and part-time service personnel with irregular schedules. Such nuances are not well captured through national averages. As a result, the mode choice predictions derived from the discrete choice model, when scaled onto this synthetic population, may overgeneralise behavioural patterns and fail to account for niche but policy-relevant commuter groups (e.g., night-shift workers reliant on car access due to poor off-peak transit). More broadly, synthetic populations provide structural demographic realism but cannot capture individual-level variability in decision-making—especially under context-specific constraints such as childcare responsibilities or flexible work schedules. This means that simulations may reproduce aggregate travel patterns but miss behavioural edge cases that are critical for targeted interventions.

Commuters who go to Schiphol by train are not considered in the study. Also, if hub usage is mandatory, some people might shift to trains. This shift is not considered in the study. Excluding the possibility of modal shift to trains can result in an overestimation of the attractiveness or uptake of hub-based green modes. This limitation should be considered when interpreting the scalability of mobility hub interventions in highly connected regions like Schiphol.

In translating behavioural insights to the digital twin (DT) simulation, several structural assumptions are made. The simulation relies on fixed OD flows and modal splits, omitting important feedback mechanisms—such as congestion deterring car use or poor weather reducing micro-mobility viability. These omitted dynamics mean that the simulation does not model long-term behavioural adaptation or nonlinear system effects in real life, which are particularly relevant for interventions aimed at system-wide transformation. For example, the simulation does not account for potential spillover effects. When a hub reduces congestion on a route, that improvement could encourage more people to start driving again, creating a rebound effect. This rebound might cancel out some of the original benefits like reduced emissions or traffic. Because the Digital Twin does not simulate these second-order or delayed responses, it may paint an overly optimistic picture of the long-term impact. In reality, the system might react in more complex, non-linear ways as travellers adapt their choices over time.

Another methodological constraint lies in how trips are conceptualized and operationalized within the Digital Twin (DT) simulation. Specifically, the DT assumes trips begin and end neatly within predefined origin-destination (OD) zones, with no allowance for intermediate stops, spontaneous detours, or real-world trip chaining behaviours (e.g., daycare drop-offs, grocery errands, or work-related detours). This clean-slate modelling structure does not reflect how multi-purpose, multi-modal daily trips are actually constructed by users. As a result, the model potentially underrepresents the true complexity of urban mobility, especially for individuals who rely on flexible or time-constrained travel. This simplification carries real implications: shared or green modes may appear more attractive in the simulation than in real life, where the inability to accommodate secondary trip purposes would discourage adoption. It also neglects mid-trip mode shifts (e.g., biking to a transit station and taking a shared shuttle from there), which are relevant in mode choice decisions as well.

The temporal scope of input data imposes an additional limitation. The simulation is calibrated using only morning peak-hour car traffic data, which was the most readily available and complete dataset at the time of analysis. It ignores mode-switchers who may enter the zone using non-car modes and switch to shared or green options within the hub. These flows are especially important for understanding the full burden on first and last-mile infrastructure. The omission of these flows can lead to underestimation of total network volume, intersection-level congestion, and emissions, particularly at critical intermodal nodes like mobility hubs or station forecourts. I/C ratios, which are used as key indicators of network strain, may appear artificially low—resulting in overly optimistic conclusions about system resilience. Likewise, emissions calculated may fail to capture idling times, or modal interactions that occur at real-world convergence points. Since the simulation is based solely on morning peak car traffic, it captures only part of the daily mobility picture. This limits the assessment of full-day impacts such as return commute patterns. As a result, both congestion and environmental effects may be understated, and policy insights derived from the model should be interpreted as lower-bound estimates.

Additionally, the DT does not model the operational flow and emissions from conventional buses currently running within Schiphol's internal network. This exclusion underestimates both the total emissions and the I/C ratios, particularly in zones where conventional bus congestion or idling is known to be substantial. As a result, the simulation may underrepresent existing pressures in the transport network, but the net environmental and traffic gains of this study remain correct. Future work should consider incorporating these transit flows.

AON and VA assignment strategies, while computationally tractable, have known drawbacks. AON assigns all traffic between an OD pair to the single least-cost path, ignoring route diversity and user heterogeneity. This over-concentrates flows along selected corridors, artificially inflating I/C ratios. In scenarios involving mode shifts or increased access traffic (e.g., at hub entry points), this leads to exaggerated stress on particular network links without accounting for users' natural route dispersion in response to congestion. The volume averaging method, though a step toward realism, smooths over localized bottlenecks. By distributing volumes based on averaged conditions, it can under-represent congestion-induced delay or network vulnerability, especially under peak pressure. This may result in underestimation of emission hotspots or system inefficiencies during real-world operation. But for strategic decision making, static AON or VA assignment results are considered accurate enough in practice.

Emission estimation within the DT framework also involves key limitations. Emissions are calculated based on vehicle volumes, mode type, and standard emission factors, without dynamically accounting for important modifiers such as stop-and-go traffic, acceleration profiles, cold starts, or road gradient. This simplified estimation might not fully reflect real-life scenarios, thus the calculated change in emissions will not be the same as observed values. Despite these simplifications, the integration of behavioural modelling with a digital twin still offers more realism than most existing studies, but future work should address these constraints.

The study evaluates only two hub scenarios, both of which are based on fixed assumptions regarding location, design features (e.g., parking capacity, green mode availability), and integration with surrounding land use and transit networks. While these serve as useful proof-of-concept cases, they do not reflect the full design space of mobility hubs, nor the range of behavioural and infrastructural responses that could emerge in different contexts. Hub performance is highly sensitive to spatial and socioeconomic context. A hub located in a high-density urban corridor with strong rail access will yield very different usage patterns and network effects compared to one in a low-density suburban area with limited transit integration. Factors such as walkability, perceived safety, land value, and complementary amenities (e.g., bike repair stations, retail options) also play critical roles in determining a hub's attractiveness and systemic impact. The two scenarios modelled here cannot capture this geographic and operational heterogeneity.

Moreover, hub design itself is held constant across scenarios in terms of service offerings, operational hours, and pricing strategies. In reality, such parameters may vary based on local government priorities, operator business models, and user demographics. For instance, a hub offering real-time ride-matching and secure bike parking could perform markedly better than one without these features, especially in areas with high theft or low digital trust. These nuances are not captured in the current static hub typology, which limits the policy specificity of the results.

This simplification also overlooks the possibility of non-linear or threshold effects—i.e., that mobility hubs may only trigger meaningful modal shifts once a critical mass of service integration, user density, or fare subsidy is reached. By testing only two scenarios, the analysis may produce disproportionately large behavioural or systemic responses.

These limitations suggest that while the study offers important preliminary findings, further research is needed to validate and expand upon them. Future research should prioritise combining revealed and stated preference data, improving demographic representativeness, and validating simulation outcomes against real-world pilot hubs, to strengthen both behavioural validity and policy applicability.

8. Conclusions & Recommendations

This research investigates how mobility hubs offering green first- and last-mile transport modes can influence travel behaviour, traffic conditions, and environmental outcomes. Through a stated preference survey, discrete choice modelling, and integration with a digital twin traffic simulation, the study provides data-driven insights for planning sustainable mobility hubs. This chapter summarizes key findings, beginning with answers to the research questions, followed by practical recommendations for implementation and future research directions.

8.1. Answers to the Research Questions

1. *Which traffic and environmental indicators are suitable for assessing the impacts of a mobility hub, and why, according to existing literature?*

   From literature, the traffic and environmental indicators that will be affected by a mobility hub are listed. The primary traffic indicators affected include vehicle kilometers traveled (VKT), intensity-capacity ratios, and traffic flows. Environmental indicators are concentration of NO_2, PM_{10} and $PM_{2.5}$. These indicators are policy-relevant because they are routinely monitored in transport and environmental planning frameworks and provide a direct link between user behaviour, network efficiency, and environmental quality.

2. *What are the different decision makers' and alternatives' attributes that affect people's decision to choose between the available mode options?*

   A literature study on mode choice behaviour is conducted to identify the key characteristics that influence travellers' mode choice decisions, particularly within the context of green mobility hubs. These influencing factors include: passenger-specific (decision-maker) attributes and alternative-specific (mode-related) attributes.

   Three attributes of the transport modes are found in the literature to greatly influence choice. Travel cost consistently emerges as the most impactful factor in most studies. Travel time is another crucial factor; travellers tend to prefer options that minimize door-to-door journey time. Public transport frequency has been shown to influence choice, as users are more likely to select buses or trains that run frequently, minimizing wait times.

   Weather conditions, particularly rain or cold, strongly deter users from choosing exposed modes like walking or biking. In such cases, users often shift toward sheltered, reliable modes such as buses.

The literature confirms that mode choice is shaped by complex interactions between individual characteristics and mode-specific features. Eight personal characteristics are selected in this study: Age, Gender, Education, Employment status, trip purpose, comfort with digital mode, primary mode and shared transport usage frequency. Successful mobility hubs must therefore cater to diverse needs—by offering affordable, fast, digitally accessible, and weather-resilient transport modes—while also aligning with the behaviour patterns and capabilities of the population they serve.

3. *What is the most appropriate model for capturing individual mode choice behaviour in the context of a mobility hub?*

   Several discrete choice models were developed and tested to capture individual mode choice behaviour. Among them, the Multinomial Logit (MNL) model was selected as the most appropriate due to its balance of statistical performance, interpretability, and robustness for integration with traffic simulations. The modelling process began with a base MNL specification including only alternative-specific constants and mode-level attributes (cost, distance, and waiting time). The final MNL model was estimated through a forward stepwise procedure, sequentially incorporating statistically significant socio-demographic variables such as age group, employment status, digital comfort, and weather sensitivity. This specification substantially improved model performance, achieving a Rho-square bar of 0.309.

   A Panel Mixed Logit (PML) model was also estimated to account for repeated observations and unobserved heterogeneity, and indeed achieved superior in-sample fit. However, the PML suffered from convergence instability and limited predictive robustness when applied in simulation, raising concerns about reliability in scenario-based policy evaluation. In contrast, the MNL model offered stable convergence and consistent predictions across varying hub scenarios.

   Thus, despite its restrictive assumptions—such as homogeneous preferences and the independence of irrelevant alternatives—the MNL emerged as the most suitable framework in this context. It strikes a pragmatic balance between capturing key behavioural effects and ensuring robust predictive power and stability for policy applications. This trade-off is consistent with the goal of the study, where predictive power is prioritised for informing planning and hub design.

4. *To what extent do the identified mode attributes and individual characteristics influence mode choice behaviour?*

   The strength and direction of each factor are captured through the final utility functions. Travel cost emerged as one of the most influential attributes, with consistently negative coefficients. Students were the most cost-sensitive group. Rainy weather has lower cost sensitivity—indicating that, under adverse conditions, commuters prioritise comfort and reliability over monetary savings. Younger individuals were particularly sensitive to travel time, while shared e-cars and e-scooters carried negative intrinsic preferences compared to other modes, reflecting underlying scepticism or perceived inconvenience.

Digital comfort also shaped behaviour: respondents highly comfortable with digital tools displayed strong negative sensitivity to travel time, while students and full-time employees were especially time-critical. The significant random panel parameter in PML further confirmed heterogeneity in cost perceptions, justifying the inclusion of a panel specification.

Sensitivity analyses reinforced these findings. Active modes declined sharply beyond 2–3 km, while motorised alternatives gained share. Increases in cost uniformly reduced modal shares, while longer bus waiting times shifted demand towards more controllable modes such as cycling or car-sharing. Interestingly, individuals with lower digital comfort were also willing to adopt shared modes in a hub setting, suggesting that inclusive design features can broaden uptake.

Together, these results demonstrate that mode choice is not simply a function of isolated attributes, but emerges from the interaction between mode based factors (cost, time, waiting time) and personal characteristics (age, digital comfort, employment status). By incorporating interaction effects and contextual variables such as weather and trip length, the model captured behavioural responses that varied predictably across user types—highlighting the importance of tailoring hub design to heterogeneous commuter needs.

5. *How is demand redistributed among available modes when the mobility hub is introduced?*

The introduction of two green mobility options at the hub produced a clear redistribution of commuter demand across modes, confirmed by both discrete choice estimates and simulation outputs. During the morning peak (07:00–09:00), a total of 4,845 trips with Schiphol as destination were reallocated according to the modelled modal shares (Table 8.1).

Table 8.1.: Mode-wise Distribution of Total Trips

Mode	**Total Trips**	**Percentage (%)**
Walking	358	7.38
Bike	2127	43.91
Shared Bike	450	9.28
Shared E-scooter	185	3.82
Shared E-car	560	11.56
Zero Emission Bus	1165	24.05
Total	4845	100.00

Similar redistributions were observed for outbound trips. Collectively, this redistribution supports broader sustainability goals by lowering system-wide emissions, easing congestion pressure, and promoting more inclusive and multimodal mobility ecosystems.

Answer to the Main Research Question

What are the traffic and environmental impacts of introducing multimodal green mobility hubs for first- and last-mile travel?

The results demonstrate that green mobility hubs can deliver measurable traffic and environmental benefits. By integrating the estimated mode choice model into the TNO Digital Twin simulation, the study shows that hubs reduce vehicle kilometres travelled (VKT), network intensity, and emissions such as NO_2 and PM. Replacing commuter car trips with active and shared modes produces a quantifiable decline in system-wide congestion and air pollution, consistent with earlier evidence on the role of hubs in promoting sustainable travel behaviour.

On the traffic side, the hub triggered a spatial redistribution of vehicle kilometres. Peripheral municipalities such as Haarlemmermeer (–0.85%), Haarlem (–0.14%) and Kaag en Braassem (–0.12%) experienced reductions, reflecting a diversion of long-distance through-traffic. In contrast, central urban zones like Amsterdam and Amstelveen recorded modest increases (up to +3.7%), largely attributable to local redistribution and rerouting linked to car-restricted zones around Schiphol. Despite these localised shifts, the overall network registered a net reduction in veh-km and flow, indicating that hubs act as a lever for improving traffic network.

On the environmental front, the hub produced consistent net reductions in major pollutants across the region. District-level analysis confirmed improvements in Haarlemmermeer, Haarlem, and Kaag en Braassem, while emission maps highlighted widespread decreases in NO_2 and PM concentrations along major corridors such as the A4 and A10. Localised hotspots emerged in a few urban areas, but these were outweighed by regional-scale benefits.

Overall, the intervention validates mobility hubs as effective instruments for advancing sustainability goals. Yet, their success depends on careful spatial planning, integration with zero-emission modes, car-access restrictions, and coordinated traffic management to mitigate displacement effects. Properly implemented, hubs can simultaneously improve accessibility, reduce emissions, and support long-term modal shift in first- and last-mile travel.

8.2. Recommendations

8.2.1. Recommendations for Practice

Several practical recommendations can be made to guide the development and implementation of green mobility hubs—particularly around major fixed destinations such as airports and city centers based on the study.

The survey results show that travel behaviour is highly influenced by weather, cost, and travel distance. Therefore, mobility hubs should provide a balanced mix of modes to suit a range of preferences and conditions. Zero Emission Buses (ZE buses) should operate at high frequencies, particularly during peak hours, with minimal waiting times to attract users who prioritize comfort and weather protection. Shared micromobility options (e-scooters, bikes) should be placed under covered or indoor docking stations to mitigate weather-related aversion. Pricing strategies should incentivize sustainable choices—e.g., lower fees for shared e-bikes, or time-based discounts for off-peak travel.

Since digital comfort plays a significant role in mode choice, policymakers must ensure that access to shared mobility is inclusive. Providing multi-channel access to shared services (e.g., physical kiosks or OV-chip integration for those uncomfortable with apps) and offering digital literacy workshops or simple onboarding as part of the hub experience can be helpful. Ensure that mobility hubs are equipped with intuitive signage, accessible design features, and real-time information displays to support confident navigation for all users.

The digital twin analysis reveal notable reductions in emissions and congestion when green modes are adopted. Hubs should be strategically located where they can intercept car traffic (e.g., outer ring roads, P+R facilities), enabling early modal shift and integrated into existing PT and cycling networks, with safe, direct routes to key destinations. They should also be monitored and dynamically adjusted over time using simulation-based tools like the digital twin to adapt to seasonal, demographic, and demand changes.

Policies should address equity and uptake across diverse user groups. As the survey results indicate, younger and digitally skilled travellers are currently more inclined to adopt shared modes. To broaden adoption, targeted benefits such as subscription discounts for students or seniors could be introduced. Partnerships with large employers (e.g., Schiphol Airport) can further support uptake through subsidised memberships (e.g., shared bikes, ZE bus passes) for their staff. Marketing and behaviour change campaigns should build on real usage data and local insights to normalise shared and active mobility choices.

Finally, mobility hubs can serve as enablers of wider regulatory measures. Zero-emission zones (ZEZs) and car-free areas are increasingly important policy tools for reducing urban emissions. Well-designed hubs can help these measures by providing reliable and attractive alternatives to private car use, ensuring that restrictions on car access are paired with viable, convenient substitutes.

8.2.2. Recommendations for Research

While this study offers valuable findings, several directions for further research can strengthen the depth, realism, and policy relevance of mode choice modelling in the context of mobility hubs. A first step should be to expand the number and diversity of respondents. Greater coverage of age groups, educational backgrounds, and geographical areas—especially non-urban and digitally less-engaged populations—would reduce sampling bias and improve representativeness. Weighting techniques could also be applied to adjust for imbalance in representativeness, and validation against a different dataset would provide a stronger test of predictive robustness. In addition, extending the scope of analysis to incorporate a wider set of green modes and socio-demographic factors would allow more comprehensive behavioural insights.

Future research should also focus on addressing hypothetical bias inherent in stated preference (SP) surveys. Pairing SP data with revealed preference (RP) data—such as usage records from mobility-as-a-service platforms, operator datasets, or municipal traffic sensors—would enable more accurate calibration of utility functions. Attributes that were not statistically significant in this study, potentially due to survey fatigue or task complexity, could be re-examined through simplified or focused survey designs that isolate these variables. Moreover, alternative modelling approaches such as Latent Class Models could be employed to reveal hidden traveller segments with differing sensitivities that are not visible in aggregate analysis.

Another priority is improving the behavioural realism of the simulation framework. The current digital twin relies on static and deterministic assumptions, whereas future iterations should incorporate stochastic service availability, and capacity-constrained assignment. Such enhancements would better capture real-world conditions such as temporary vehicle shortages, surge effects during peak hours, or weather-induced service disruptions. Agent-based or micro-simulation methods could further enrich the analysis by modelling individual-level heterogeneity, adaptive re-routing, and direct interactions with hub infrastructure.

Finally, future studies should broaden the policy scope beyond infrastructure and travel attributes. Policies such as dynamic tolling or low-emission zone charges, when combined with mobility hub design, could be tested for their synergistic effects. The role of bundled mobility services—for example, integrating e-scooter access with train subscriptions—also warrants further investigation. Equally, behavioural interventions such as nudges, default settings, and loyalty programmes should be studied as potentially powerful tools to influence less conscious travel decisions. In addition, the interaction between mobility hubs and larger regulatory measures, such as the introduction of zero-emission or car-free zones, could be examined to understand their joint impact on system performance.

Together, these recommendations highlight the importance of combining richer datasets, advanced modelling techniques, and integrative policy analysis. Advancing along these lines would bridge the gap between theoretical models and practical implementation, positioning mobility hubs not merely as infrastructure but as strategic instruments for reducing emissions, enhancing accessibility, and shaping equitable urban mobility futures. By linking individual behavioural insights with system-level outcomes, this thesis moves beyond traditional hub studies and provides actionable evidence for designing zero-emission zones around airports and city centres.

A. NGENE Syntax

```
design
;alts = Walk, Bike, Shared_Bike, Shared_E-Car, Shared_E-Scooter, ZE_Bus
;rows = 8
;orth = sim
;model:
U(Walk) = ASC_Walk /
U(Bike) = ASC_Bike /
U(Shared_Bike) = ASC_Shared_Bike + b_cost*cost[0,1] /
U(Shared_E-Car) = ASC_Shared_E-Car + b_cost*cost /
U(Shared_E-Scooter) = ASC_Shared_E-Scooter + b_cost*cost /
U(ZE_Bus) = b_cost*cost + b_PT_Freq*PT_Freq[5,10]
```

B. Survey

One out four blocks of the survey is attached on the next pages as an example:

Consent Block

Welcome to the Survey for ‘Modeling of Mobility Hubs’!
This study is being done by Tabia Binta Farazi from the TU Delft, in collaboration with TNO.

Your response will improve future mobility hubs and make transportation more sustainable. We will ask you 16 transportation mode choice questions and some sociodemographic questions. The survey takes about 10 minutes.

Your participation in this study is entirely voluntary and completely anonymous. If you have any questions regarding this research, please contact Tabia Binta Farazi (T.B.Farazi@student.tudelft.nl).

By clicking 'Next' and proceeding with the survey, you confirm that you agree to give your valuable input — thank you for participating!

✔ The mobility hub considered in this study is a location where you can switch to different transport modes to go to key destinations like city centers or airports.

✔ You can not take your own car to the destination. You can park your car at the hub or arrive by other means to switch to one of the given options.

✔ A private bike is your own bike, and you can park it at the destination. For shared options, you pick them up at the hub, drive them yourself, and drop them off at the destination.

✔ You get six mode options for every question, but the cost for each mode and waiting time for the zero emission bus varies.

✔ Imagine it's raining 🌧 and the destination is **2 Km** away from the mobility hub. You will be given 4 questions to choose your mode preference:

Type text here

Choose one of the following six options for your journey:

Walking

24 min

€ 0

Shared E-scooter

6 min

€ 0

Private Bike

8 min

€ 0

Shared E-car

3 min

€ 3.6

Shared Bike

8 min

€ 4.55

Zero Emission Bus

5 min

€ 0

Waiting time
5 mins

Choose one of the following six options for your journey:

Walking

24 min

€ 0

Shared E-scooter

6 min

€ 0

Private Bike

8 min

€ 0

Shared E-car

3 min

€ 0

Shared Bike

8 min

€ 0

Zero Emission Bus

5 min

€ 0

Waiting time
10 mins

Choose one of the following six options for your journey:

Walking

24 min

€ 0

Shared E-scooter

6 min

€ 0

Private Bike

8 min

€ 0

Shared E-car

3 min

€ 0

Shared Bike

8 min

€ 4.55

Zero Emission Bus

5 min

€ 1.54

Waiting time
5 mins

Choose one of the following six options for your journey:

- ○ **Walking** — 24 min, € 0
- ○ **Shared E-scooter** — 6 min, € 0
- ○ **Private Bike** — 8 min, € 0
- ○ **Shared E-car** — 3 min, € 3.6
- ○ **Shared Bike** — 8 min, € 0
- ○ **Zero Emission Bus** — 5 min, € 1.54, Waiting time 10 mins

Now consider the same mobility hub (**2 km** away) but in sunny weather. You will be given 4 questions to choose your mode preference:

Choose one of the following six options for your journey:

- Walking — 24 min — € 0
- Shared E-scooter — 6 min — € 2.98
- Private Bike — 8 min — € 0
- Shared E-car — 3 min — € 3.6

Shared Bike

8 min

€ 0

Zero Emission Bus

5 min

€ 0

Waiting time
5 mins

Choose one of the following six options for your journey:

Walking

24 min

€ 0

Shared E-scooter

6 min

€ 2.98

Private Bike

8 min

€ 0

Shared E-car

3 min

€ 0

Shared Bike

8 min

€ 4.55

Zero Emission Bus

5 min

€ 0

Waiting time
10 mins

Choose one of the following six options for your journey:

Walking

24 min

€ 0

Shared E-scooter

6 min

€ 2.98

Private Bike

8 min

€ 0

Shared E-car

3 min

€ 0

Shared Bike

8 min

€ 0

Zero Emission Bus

5 min

€ 1.54

Waiting time
5 mins

Choose one of the following six options for your journey:

Walking

24 min

€ 0

Shared E-scooter

6 min

€ 2.98

Private Bike

8 min

€ 0

Shared E-car

3 min

€ 3.6

○ Shared Bike

8 min

€ 4.55

○ Zero Emission Bus

5 min

€ 1.54

Waiting time
10 mins

✔ Now we imagine another mobility hub **4 Km** away from the destination in sunny 🌞 weather. You will be given 4 questions to choose your mode preference:

Choose one of the following six options for your journey:

Walking

48 min

€ 0

Shared E-scooter

12 min

€ 0

Private Bike

16 min

€ 0

Shared E-car

6 min

€ 3.6

Shared Bike

16 min

€ 4.55

Zero Emission Bus

10 min

€ 0

Waiting time
5 mins

Choose one of the following six options for your journey:

Walking

48 min

€ 0

Shared E-scooter

12 min

€ 0

Private Bike

16 min

€ 0

Shared E-car

6 min

€ 0

Shared Bike

16 min

€ 0

Zero Emission Bus

10 min

€ 0

Waiting time
10 mins

Choose one of the following six options for your journey:

Walking

○ 48 min

€ 0

Private Bike

○ 16 min

€ 0

Shared Bike

○ 16 min

€ 4.55

Shared E-scooter

○ 12 min

€ 0

Shared E-car

○ 6 min

€ 0

Zero Emission Bus

○ 10 min

€ 1.95

Waiting time
5 mins

Choose one of the following six options for your journey:

- ○ **Walking** — 48 min, € 0
- ○ **Shared E-scooter** — 12 min, € 0
- ○ **Private Bike** — 16 min, € 0
- ○ **Shared E-car** — 6 min, € 3.6
- ○ **Shared Bike** — 16 min, € 0
- ○ **Zero Emission Bus** — 10 min, € 1.95, Waiting time 10 mins

Now consider the same mobility hub (**4 km** away) but in rainy weather. You will be given 4 questions to choose your mode preference:

Choose one of the following six options for your journey:

- Walking
  - 48 min
  - € 0
- Shared E-scooter
  - 12 min
  - € 4.96
- Private Bike
  - 16 min
  - € 0
- Shared E-car
  - 6 min
  - € 3.6
- Shared Bike
  - 16 min
  - € 0
- Zero Emission Bus
  - 10 min
  - € 0
  - Waiting time 5 mins

Choose one of the following six options for your journey:

- ○ **Walking** — 48 min — € 0
- ○ **Shared E-scooter** — 12 min — € 4.96
- ○ **Private Bike** — 16 min — € 0
- ○ **Shared E-car** — 6 min — € 0
- ○ **Shared Bike** — 16 min — € 4.55
- ○ **Zero Emission Bus** — 10 min — € 0 — Waiting time 10 mins

Choose one of the following six options for your journey:

Walking

48 min

€ 0

Shared E-scooter

12 min

€ 4.96

Private Bike

16 min

€ 0

Shared E-car

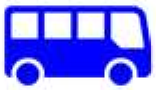
6 min

€ 0

Shared Bike

16 min

€ 0



Zero Emission Bus

10 min

€ 1.95

Waiting time
5 mins

Choose one of the following six options for your journey:

Walking

48 min

€ 0

Shared E-scooter

12 min

€ 4.96

Private Bike

16 min

€ 0

Shared E-car

6 min

€ 3.6

Shared Bike

16 min

€ 4.55

Zero Emission Bus

10 min

€ 1.95

Waiting time
10 mins

Default Question Block

What is your age?

○ 18-24

- 25-29
- 30-39
- 40-49
- 50-59
- 60-64
- 65-69
- 70+
- Prefer not to say

What is your gender?

- Male
- Female
- Other
- Prefer not to say

What is your highest education level?

- High School Diploma
- MBO Diploma
- HBO/ University Bachelor Diploma/ Bachelor
- Master's+
- None
- Prefer not to say

Which of the following describe your current employment status most?

- ○ Full-time
- ○ Part-time
- ○ Unemployed
- ○ Student
- ○ Retired
- ○ Prefer not to say

For which of the following purposes you are more likely to use a mobility hub? (You can select more than one option)

- ☐ Work
- ☐ Leisure
- ☐ Shopping
- ☐ Education
- ☐ [ ] Other
- ☐ I would never use a hub

How frequently have you used shared mobility in the past 6 months?

- ○ More than 3 times
- ○ 1-3 times

- ○ Never

What is your primary mode of transport?

- ○ Car (Driver)
- ○ Car (Passenger)
- ○ Public Transport
- ○ Walking
- ○ Biking
- ○ ____________ Others

How comfortable are you using digital apps for transport?

- ○ Extremely uncomfortable
- ○ Somewhat uncomfortable
- ○ Neither comfortable nor uncomfortable
- ○ Somewhat comfortable
- ○ Extremely comfortable

C. Base Model Code

Listing C.1: Python code used for base model estimation

```
#Importing packages
import numpy as np
import pandas as pd
import biogeme
import biogeme.database as db
import biogeme.biogeme as bio
from biogeme import models
import biogeme.tools as tools
from biogeme.expressions import Beta, Variable , log, exp
import pandas as pd
import numpy as np
import math
import datetime
import os



#loading data frame
df = pd.read_csv("df_final.csv")
#Creating general database
database = db.Database('Survey_answers', df)

#Defining variables
globals().update(database.variables)

# Defining betas
ASC_walk = Beta('ASC_walk', 0, None, None, 0)
ASC_bike = Beta('ASC_bike', 0, None, None, 0)
ASC_shared_bike = Beta('ASC_shared_bike', 0, None, None, 0)
ASC_shared_escooter = Beta('ASC_shared_escooter', 0, None, None, 0)
ASC_shared_ecar = Beta('ASC_shared_ecar', 0, None, None, 0)


beta_cost = Beta('beta_cost', 0, None, None, 0)
beta_wait_time_bus = Beta('beta_wait_time_bus', 0, None, None, 0)
beta_travel_time = Beta('beta_travel_time', 0, None, None, 0)
```

```
#Defining utility functions

V_walk = (ASC_walk +beta_travel_time * TT0)

V_bike = (ASC_bike +beta_travel_time * TT1)

V_shared_bike = (ASC_shared_bike +beta_travel_time * TT2+
beta_cost * TC2)

V_shared_escooter = (ASC_shared_escooter +
beta_travel_time * TT3 +
beta_cost * TC3)

V_shared_ecar = (ASC_shared_ecar +
beta_travel_time * TT4 +
beta_cost * TC4)

V_ze_bus = (beta_travel_time * TT5 +
beta_cost * TC5+ beta_wait_time_bus * WT5)


# Associate utility functions with the alternatives
V = {0: V_walk, 1: V_bike , 2: V_shared_bike , 3: V_shared_escooter ,
        4: V_shared_ecar , 5: V_ze_bus}




# Define Biogeme Variables
avail_walk = Variable('avail_walk')
avail_bike = Variable('avail_bike')
avail_shared_bike = Variable('avail_shared_bike')
avail_shared_escooter = Variable('avail_shared_escooter')
avail_shared_ecar = Variable('avail_shared_ecar')
avail_ze_bus = Variable('avail_ze_bus')

# Define availability dictionary linked to each alternative
av = {
    0: avail_walk,
    1: avail_bike,
    2: avail_shared_bike,
    3: avail_shared_escooter,
    4: avail_shared_ecar,
    5: avail_ze_bus
}
```

```
# The choice model is a logit model with availability conditions
logprob = models.loglogit(V, av, choice)


# Define the Biogeme object
biogeme = bio.BIOGEME(database , logprob)

#Setting reporting files
biogeme.generate_pickle = False
biogeme.generate_html = True
biogeme.saveIterations = True

#Naming and estimating the model
biogeme.modelName = "Base model"

results = biogeme.estimate()

# Get general statistics and estimated parameters
print(results.printGeneralStatistics())
pandasResults = results.getEstimatedParameters()
display(pandasResults)
```

D. Final Model Code

This appendix includes the complete Python code for Final Model.

```
 #Importing packages
import numpy as np
import pandas as pd
import biogeme
import biogeme.database as db
import biogeme.biogeme as bio
from biogeme import models
import biogeme.tools as tools
from biogeme.expressions import Beta, Variable , log, exp
import pandas as pd
import numpy as np
import math
import datetime
import os



#loading data frame
df = pd.read_csv("df_final.csv")
 #Creating general database




# ------------------
# Setup for dataset
# ------------------
filtered_df_4 = df[(df['PreferNotSay_Age'] != 1) & (df['Emp_PreferNotSay'] != 1)
    .copy()
filtered_df_4['Emp_PartTimeOrUnemployed'] = filtered_df_4['Emp_PartTime'] +
    filtered_df_4['Emp_Unemployed']
filtered_df_4['Emp_PartTimeOrUnemployed'] = filtered_df_4['Emp_PartTimeOrUnemployed']
    .clip(upper=1)
database = db.Database("Final_Model_4", filtered_df_4)
globals().update(database.variables)

# ---------------
# Variable Setup
# ---------------
TT0, TT1, TT2, TT3, TT4, TT5 = Variable('TT0'), Variable('TT1'), Variable('TT2'),
```

```
    Variable('TT3'), Variable('TT4'), Variable('TT5')
TC2, TC3, TC4, TC5 = Variable('TC2'), Variable('TC3'), Variable('TC4'),
    Variable('TC5')
WT5 = Variable('WT5')
choice = Variable('choice')

# Availability
av = {
    0: avail_walk,
    1: avail_bike,
    2: avail_shared_bike,
    3: avail_shared_escooter,
    4: avail_shared_ecar,
    5: avail_ze_bus
}

# Constants

ASC_shared_bike = Beta('ASC_shared_bike', 0, None, None, 0)
ASC_shared_escooter = Beta('ASC_shared_escooter', 0, None, None, 0)
ASC_shared_ecar = Beta('ASC_shared_ecar', 0, None, None, 0)
beta_wait_time_bus = Beta('beta_wait_time_bus', 0, None, None, 0)

# ----------------------
# Weather Interactions
# ----------------------
beta_tt_weather_rainy = Beta('beta_tt_weather_rainy', 0, None, None, 0)
beta_cost_weather_rainy = Beta('beta_cost_weather_rainy', 0, None, None, 0)
beta_cost_weather_sunny = Beta('beta_cost_weather_sunny', 0, None, None, 0)


# ------------------
# Age Interactions
# ------------------
beta_travel_time_age_18_24 = Beta('beta_travel_time_age_18_24', 0, None, None, 0)
beta_travel_time_age_25_29 = Beta('beta_travel_time_age_25_29', 0, None, None, 0)
beta_travel_time_age_30_39 = Beta('beta_travel_time_age_30_39', 0, None, None, 0)



# Employment Interactions
# ----------------------
beta_tt_emp_fulltime = Beta('beta_tt_emp_fulltime', 0, None, None, 0)
beta_tt_emp_student = Beta('beta_tt_emp_student', 0, None, None, 0)
beta_cost_emp_student = Beta('beta_cost_emp_student', 0, None, None, 0)


beta_tt_comfort_high = Beta('beta_tt_comfort_high', 0, None, None, 0)
beta_tt_comfort_mid = Beta('beta_tt_comfort_mid', 0, None, None, 0)
```

```
# Define blocks

def weather_block(TT, TC):
    return (
        beta_tt_weather_rainy * TT * rainy + beta_cost_weather_rainy * TC * rainy +
        beta_cost_weather_sunny * TC * sunny
    )
def age_block(TT, TC):
    return (
        beta_travel_time_age_18_24 * TT * Age_18_24 +
        beta_travel_time_age_25_29 * TT * Age_25_29 +
        beta_travel_time_age_30_39 * TT * Age_30_39
    )
def comfort_block(TT,TC):
    return (
        beta_tt_comfort_high * TT * Comfort_High +
        beta_tt_comfort_mid * TT * Comfort_Mid
    )
def employment_block(TT, TC):
    return (
        beta_tt_emp_fulltime * TT * Emp_FullTime +
        beta_tt_emp_student * TT * Emp_Student +
        beta_cost_emp_student * TC * Emp_Student
    )



# Define utilities
V = {
    0: weather_block(TT0, 0)+age_block(TT0, 0)+comfort_block(TT0,0)
    +employment_block(TT0, 0),
    1: weather_block(TT1, 0)+age_block(TT1, 0)+comfort_block(TT1,0)
        +employment_block(TT1, 0),
    2: ASC_shared_bike + weather_block(TT2, TC2)+age_block(TT2, TC2)+comfort_block(TT2,TC2)
        +employment_block(TT2, TC2),
    3: ASC_shared_escooter + weather_block(TT3, TC3)+age_block(TT3, TC3)
        +comfort_block(TT3,TC3)+employment_block(TT3, TC3),
    4: ASC_shared_ecar + weather_block(TT4, TC4)+age_block(TT4, TC4)+comfort_block(TT4,TC4)
        +employment_block(TT4, TC4),
    5: weather_block(TT5, TC5)+age_block(TT5, TC5)+comfort_block(TT5,TC5)
        +employment_block(TT5, TC5)+ beta_wait_time_bus * WT5,
}
# Availability dictionary
av = {
    0: avail_walk,
    1: avail_bike,
    2: avail_shared_bike,
    3: avail_shared_escooter,
    4: avail_shared_ecar,
    5: avail_ze_bus
```

```
}

# Model estimation
logprob = models.loglogit(V, av, choice)
biogeme = bio.BIOGEME(database, logprob)
biogeme.seed = 1234
biogeme.generate_pickle = False
biogeme.generate_html = True
biogeme.saveIterations = True
biogeme.modelName = "Final_Model_tTest"

Final_Model_results = biogeme.estimate()

# Output
print(Final_Model_results.printGeneralStatistics())
pandasResults = Final_Model_results.getEstimatedParameters()
display(pandasResults)
```

E. Descriptive statistics

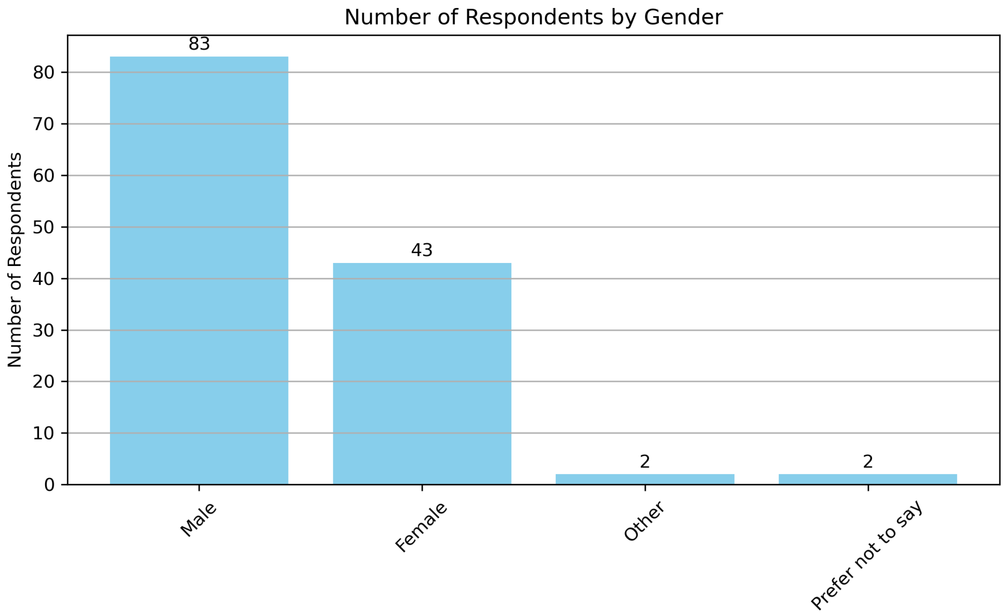


Figure E.1.: Gender distribution among respondents

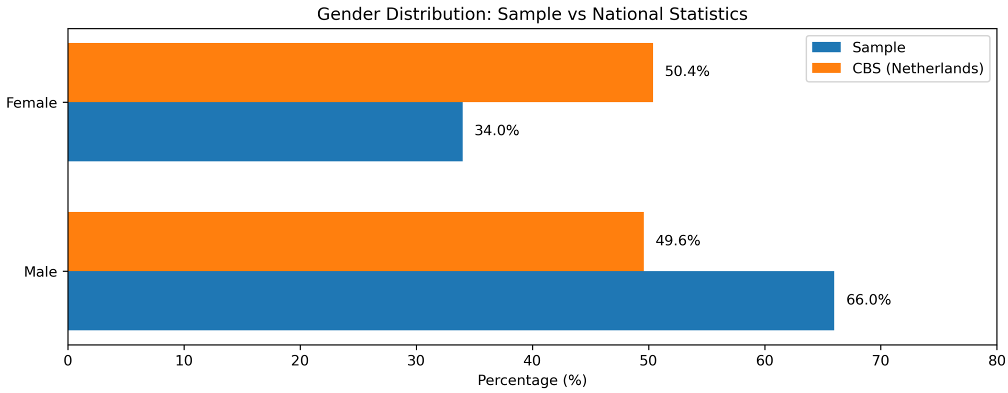


Figure E.2.: Gender distribution among respondents vs CBS

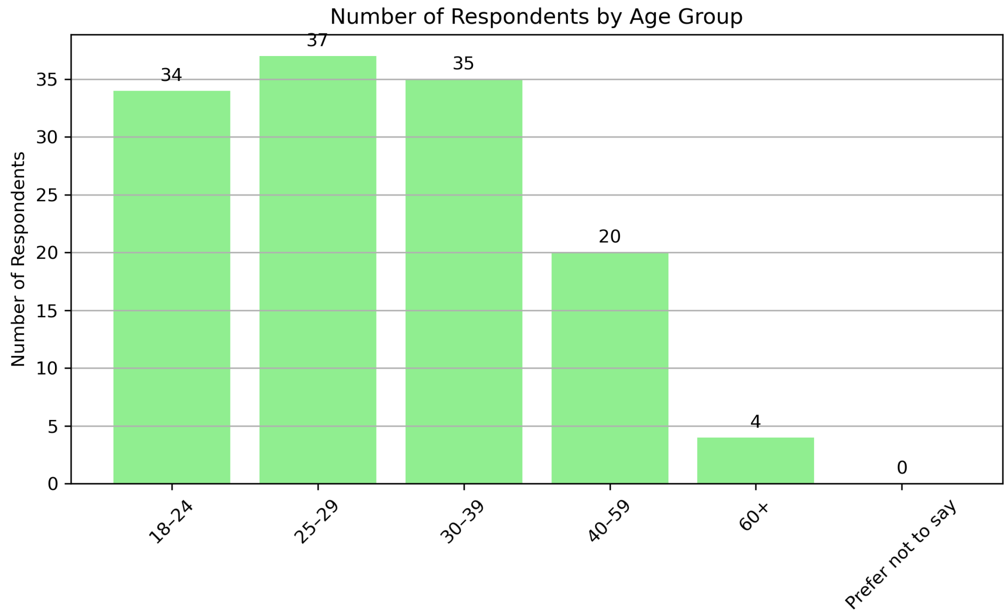


Figure E.3.: Age distribution among respondents

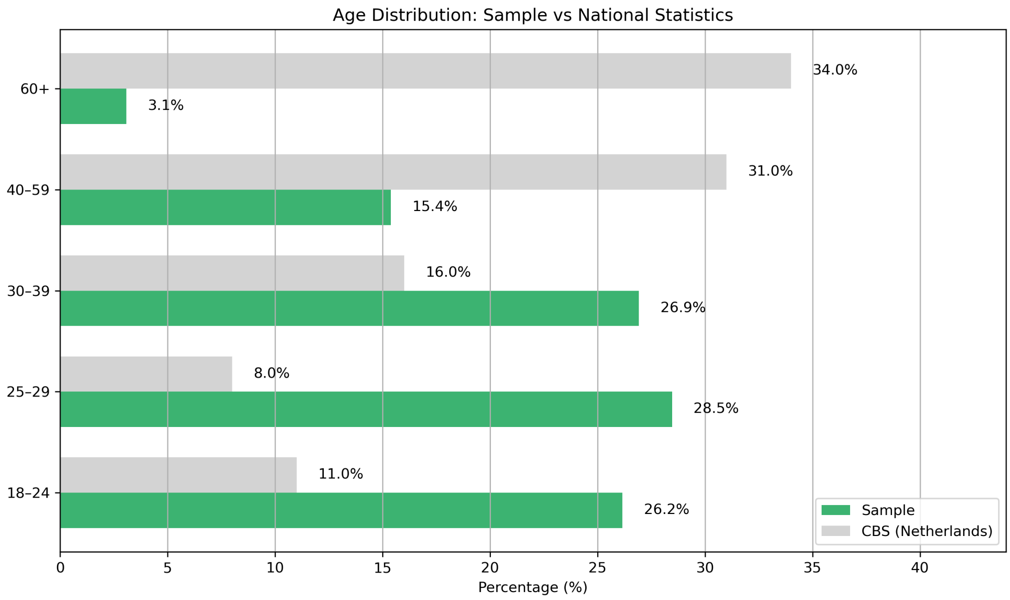


Figure E.4.: Age distribution among respondents vs CBS

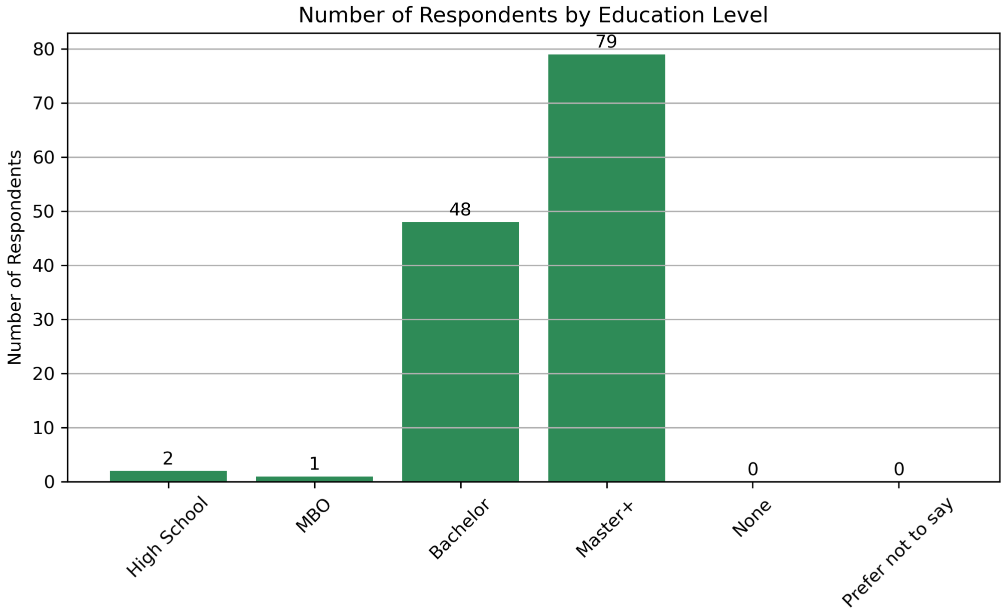


Figure E.5.: Education distribution among respondents

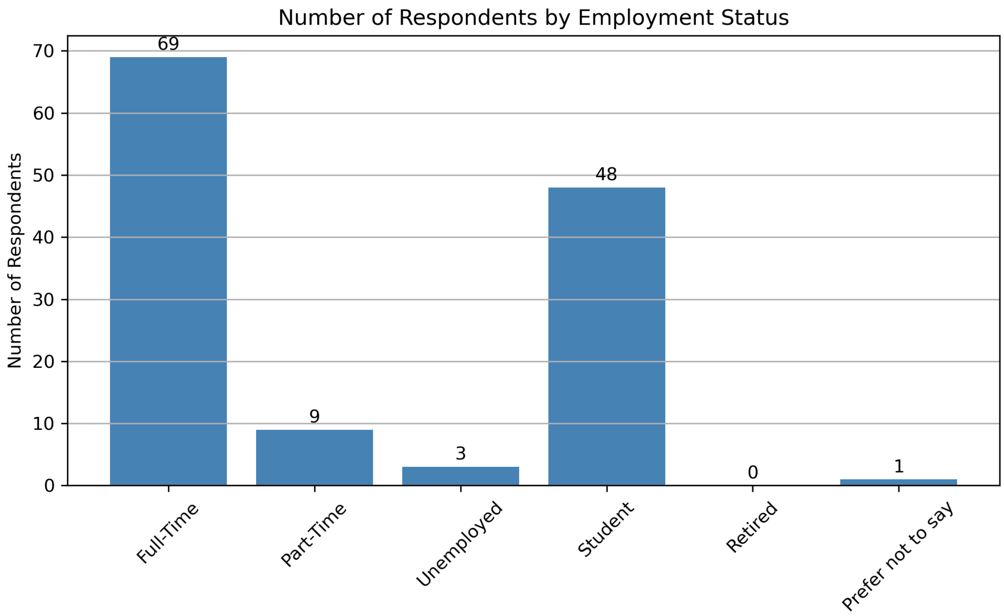


Figure E.6.: Employment status distribution among respondents

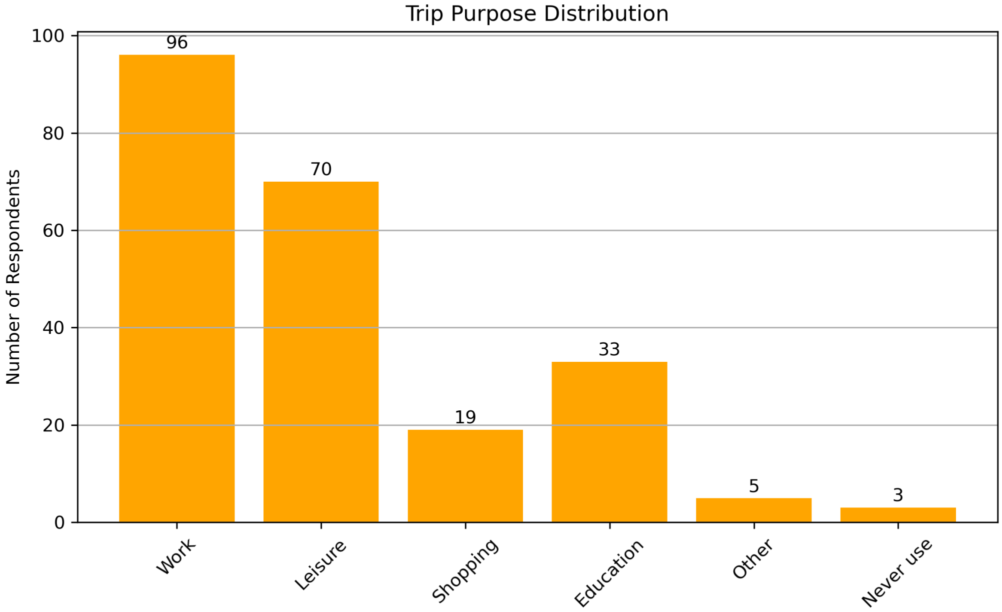


Figure E.7.: Trip purpose distribution among respondents

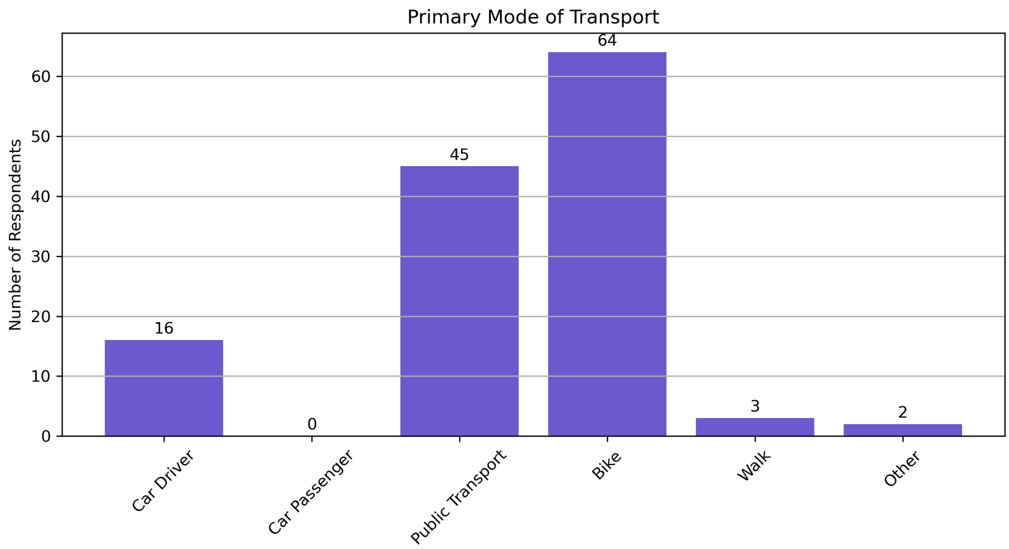


Figure E.8.: Primary mode distribution among respondents

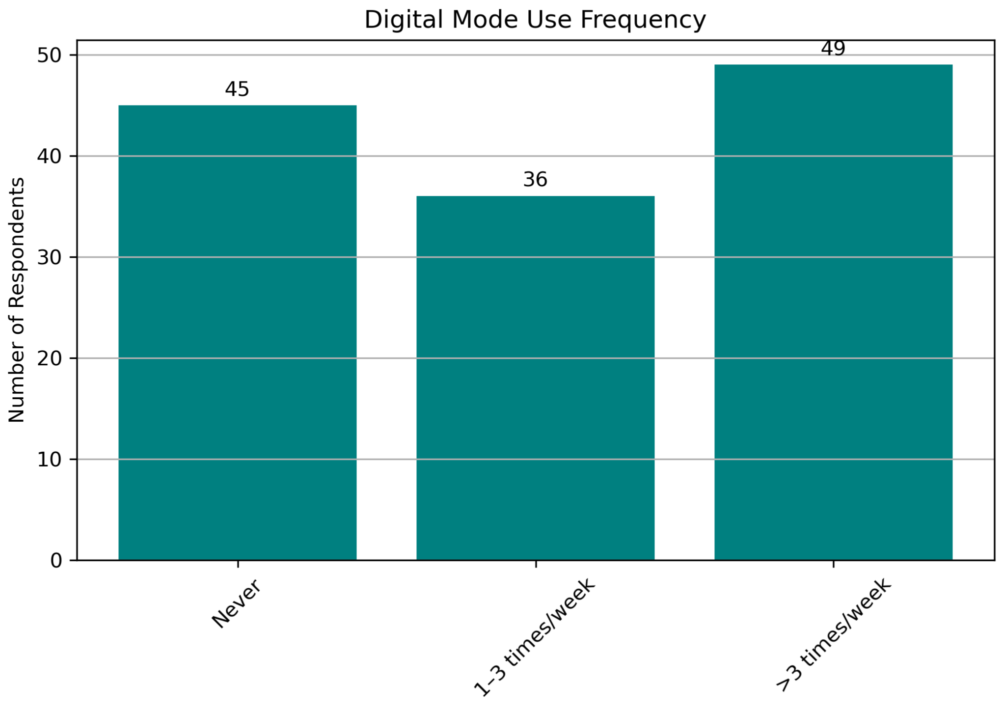


Figure E.9.: Shared mobility usage frequency distribution among respondents

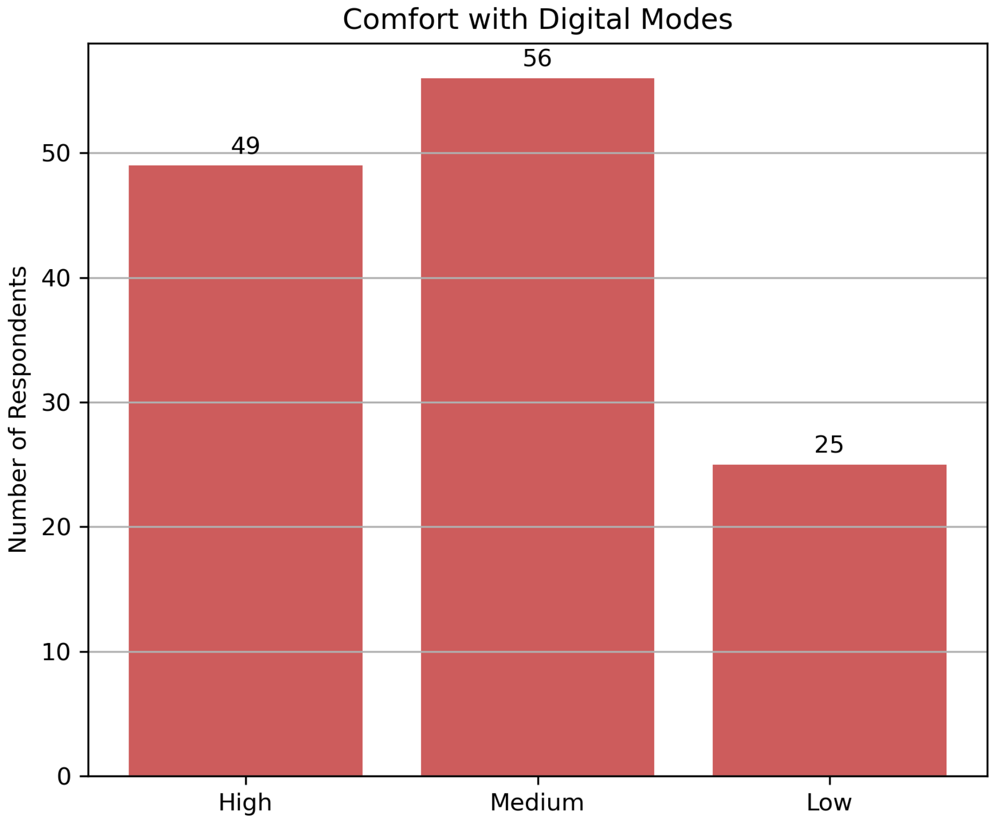


Figure E.10.: Comfort with digital transport apps distribution among respondents

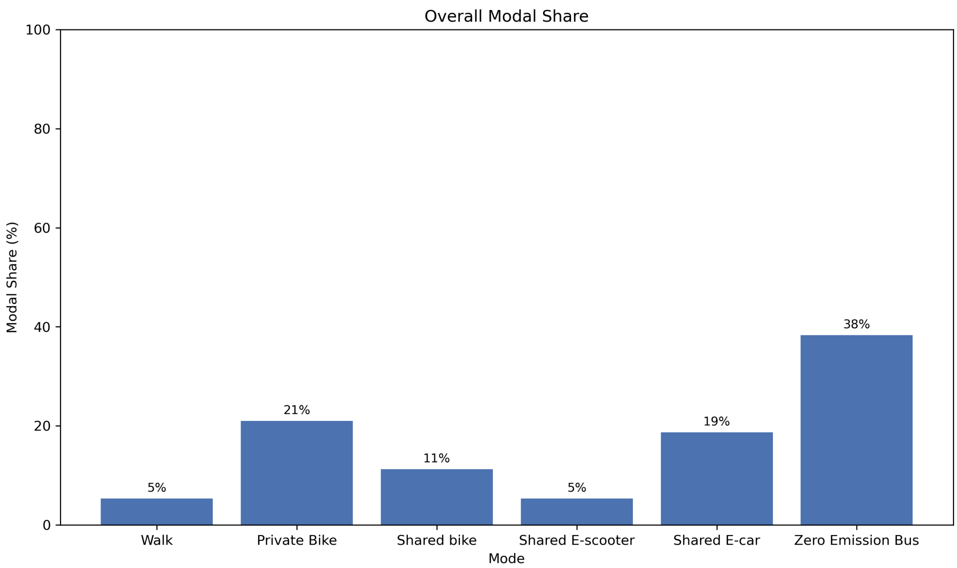


Figure E.11.: Modal Share in survey answers

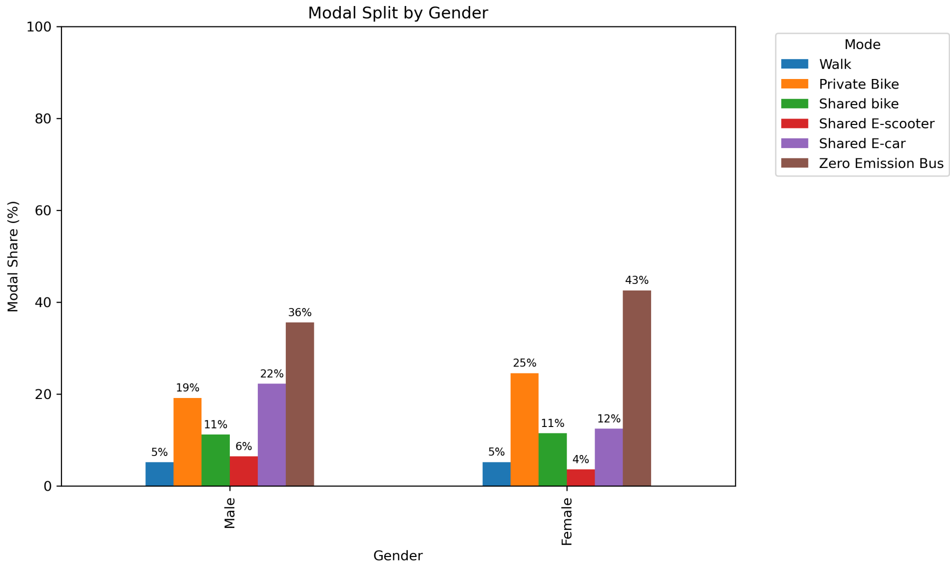


Figure E.12.: Modal choice distribution by gender.

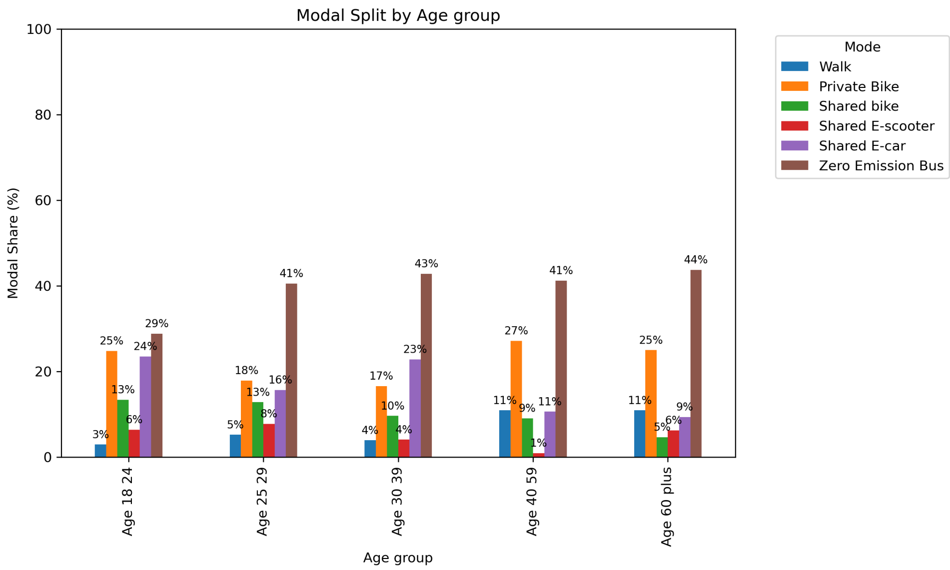


Figure E.13.: Modal choice distribution by age group.

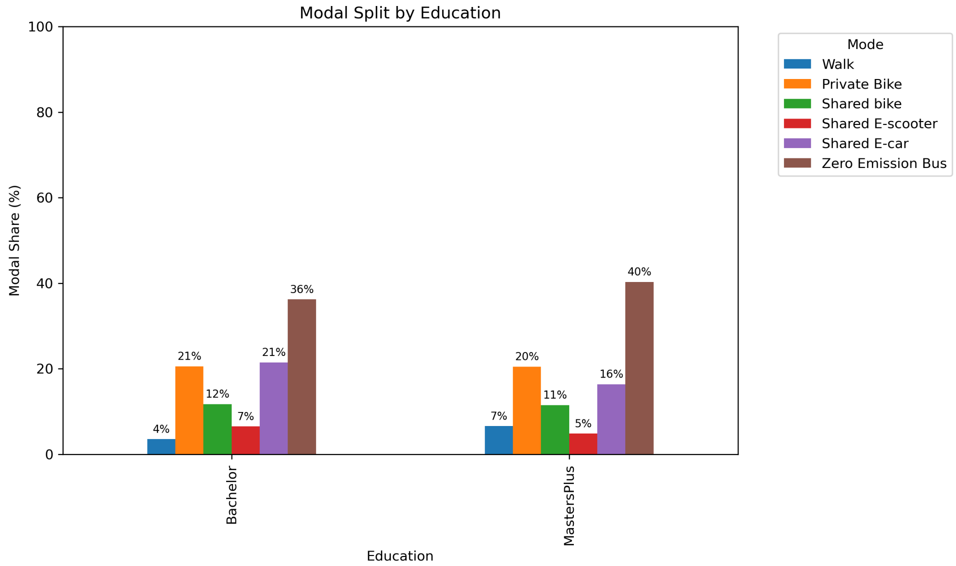


Figure E.14.: Modal choice by education level.

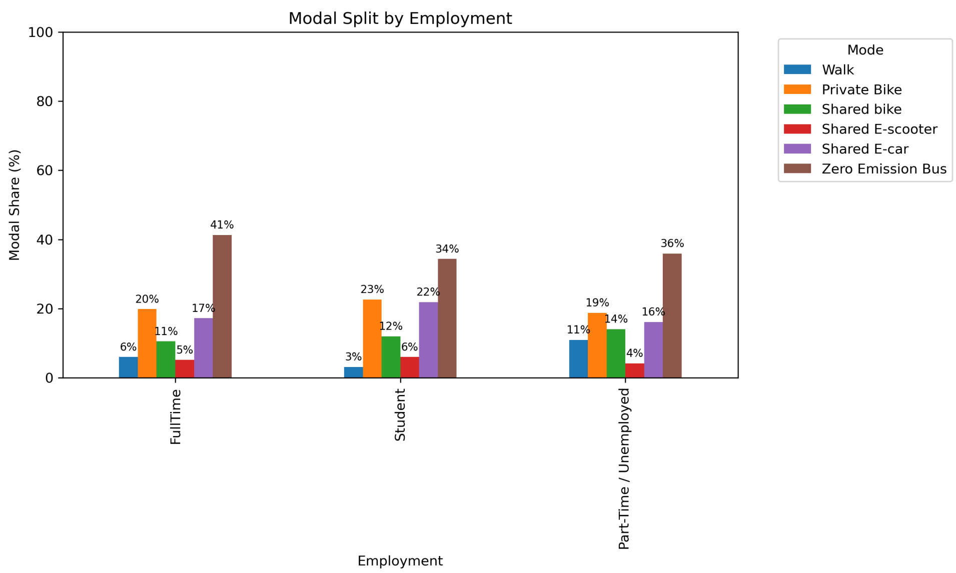


Figure E.15.: Modal choice by employment status.

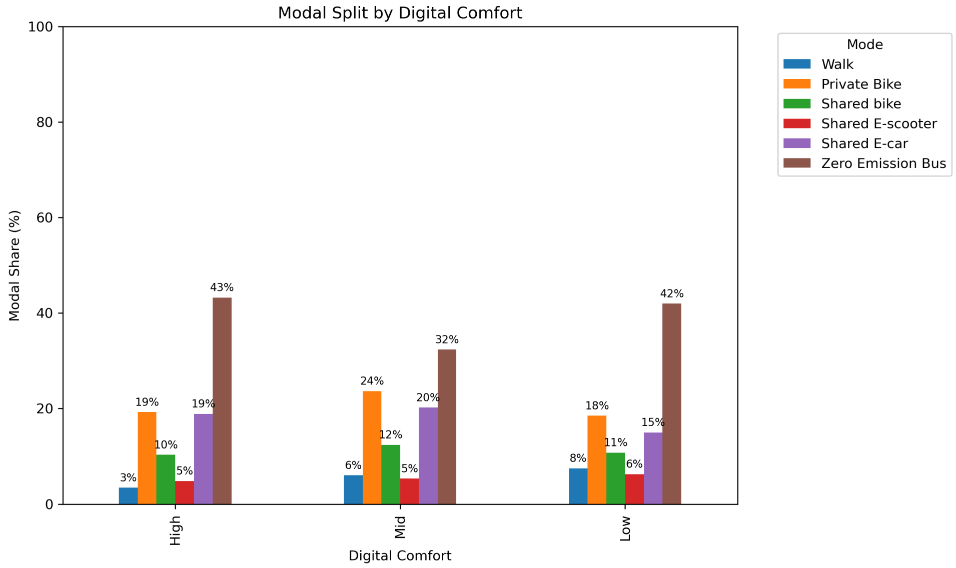


Figure E.16.: Modal choice by digital comfort level.

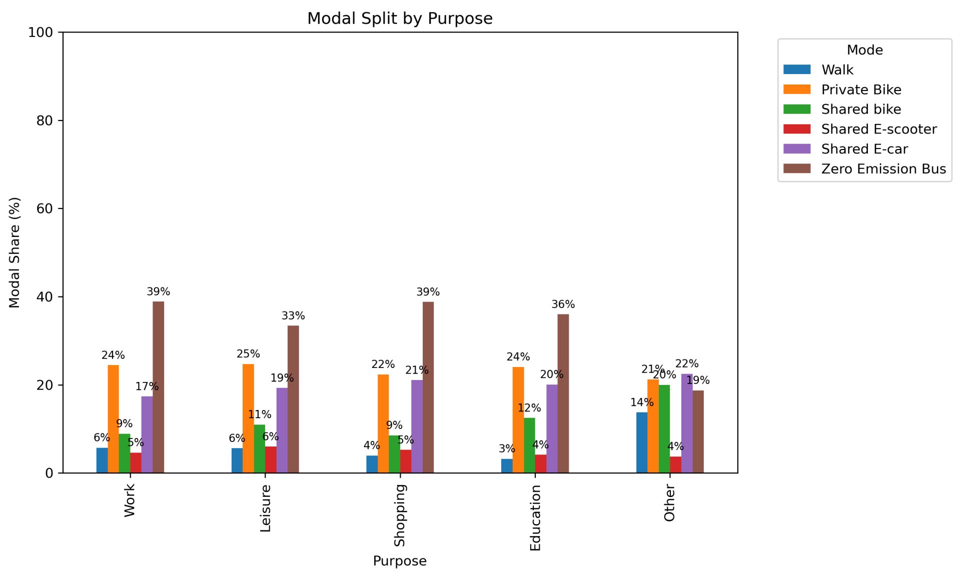


Figure E.17.: Modal choice by travel purpose.

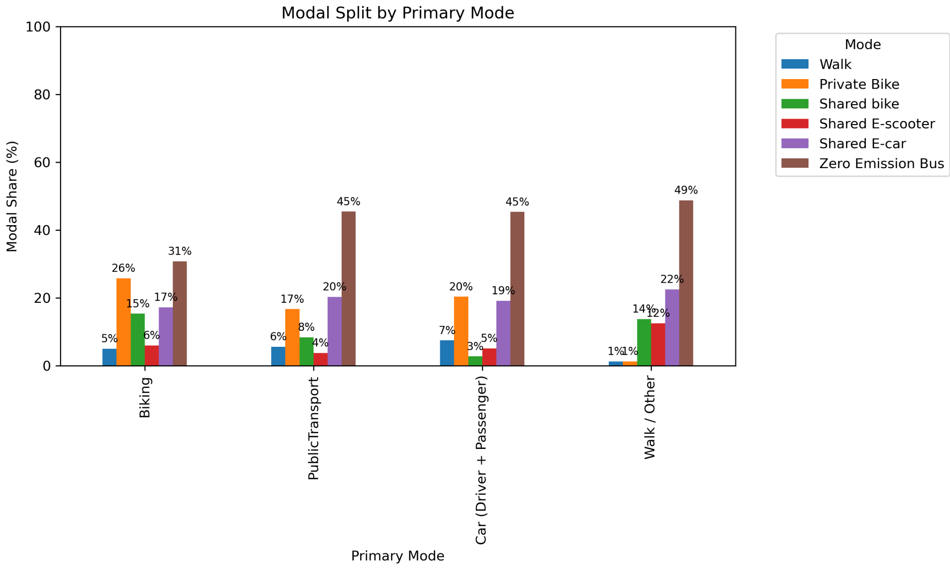


Figure E.18.: Self-reported primary mode vs. task-level choice.

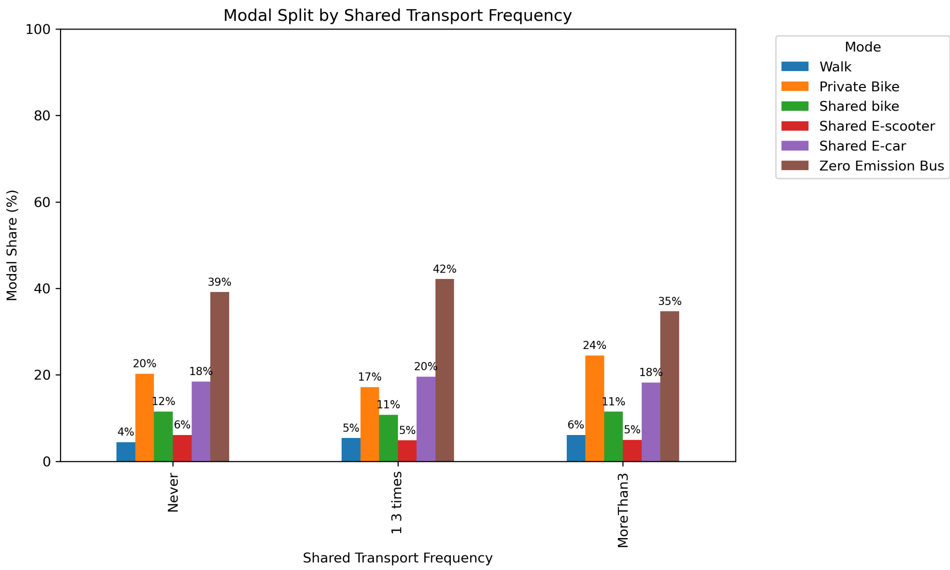


Figure E.19.: Modal choice by frequency of shared transport use.

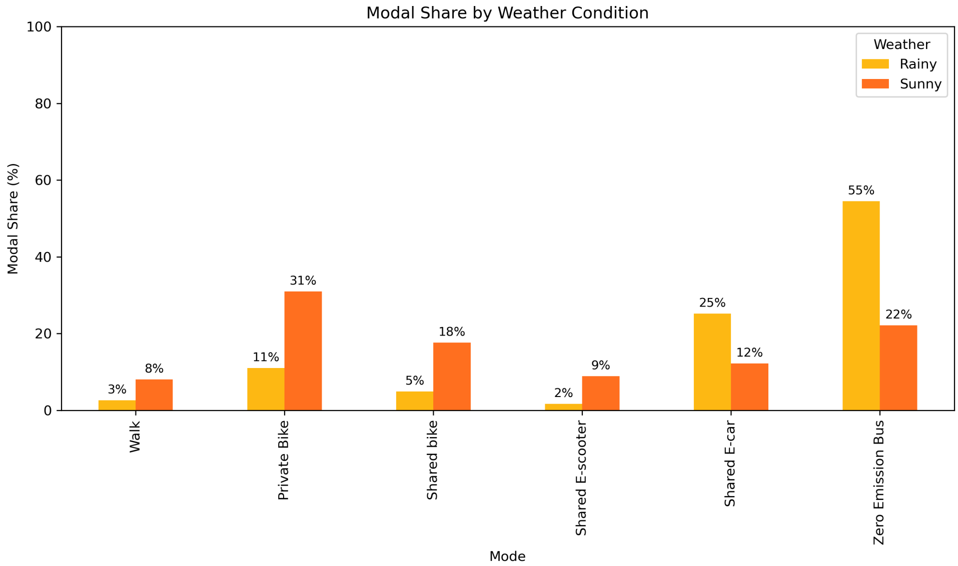


Figure E.20.: Modal choice by weather.

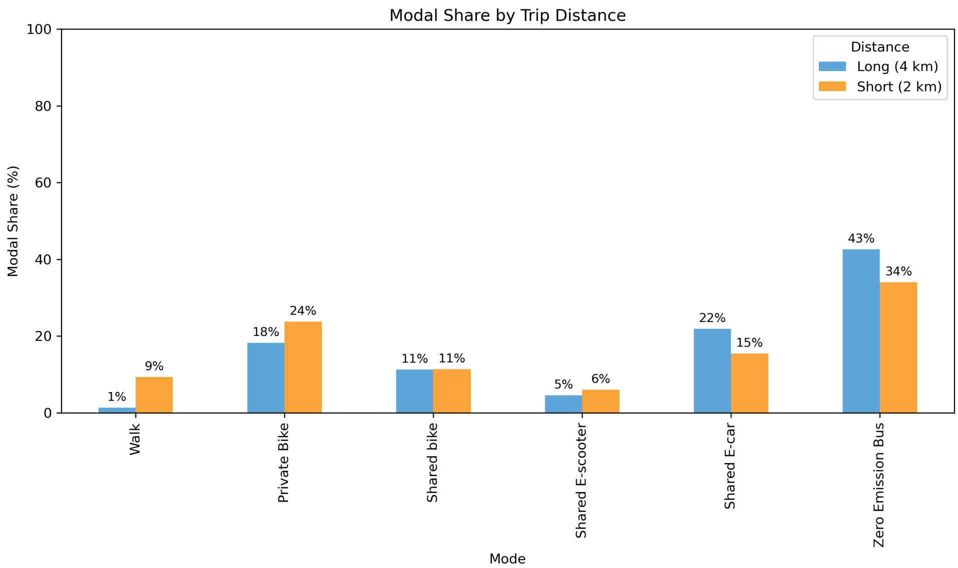


Figure E.21.: Modal choice by distance.

F. Environmental Impact Maps: Mobility Hub Intervention

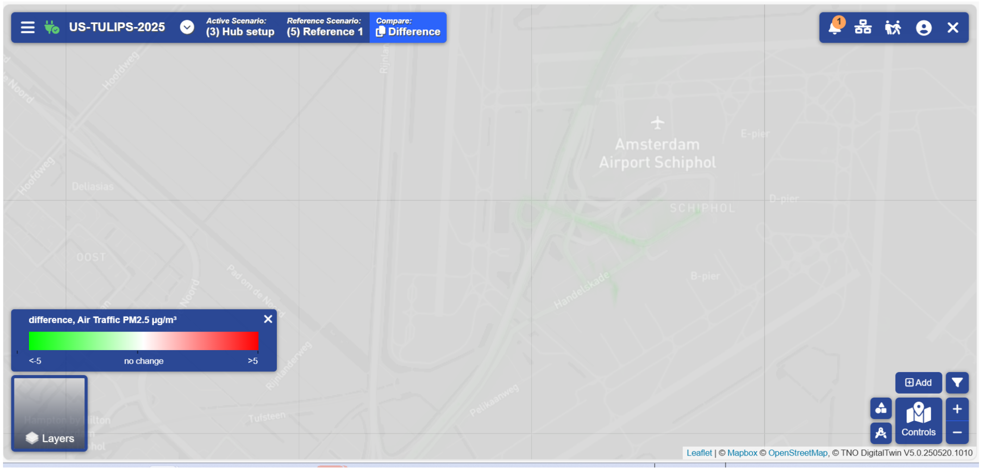


Figure F.1.: Change in $PM_{2.5}$ concentration ($\mu g/m^3$) due to the mobility hub scenario.

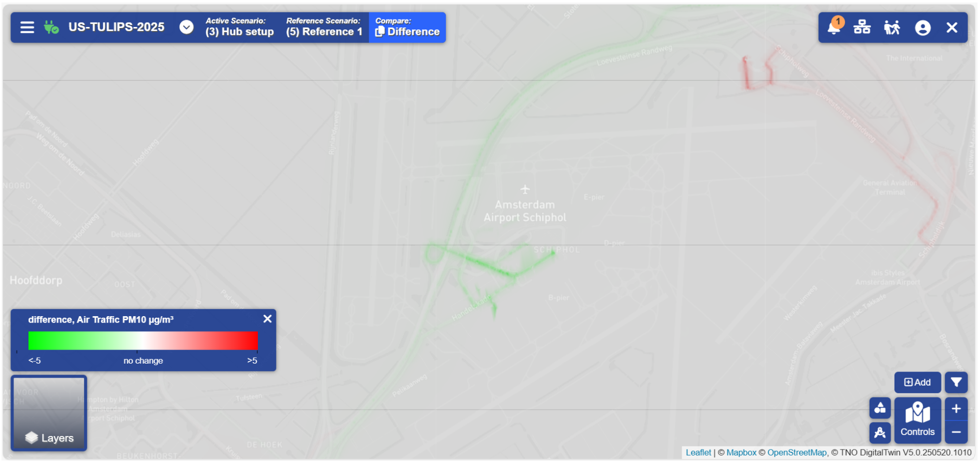


Figure F.2.: Change in PM_{10} concentration ($\mu g/m^3$) between scenarios.

Bibliography

(2024). Biogeme: Open-source software for discrete choice modeling. https://biogeme.epfl.ch. Accessed: 21 June 2025.

Abe, R. (2021). Preferences of urban rail users for first- and last-mile autonomous vehicles: Price and service elasticities of demand in a multimodal environment. *Transportation Research Part C: Emerging Technologies*, 126:103105.

Aguilera-García, , Gomez, J., and Sobrino, N. (2020). Exploring the adoption of moped scooter-sharing systems in spanish urban areas. 96:102424.

Alpkokin, P. (2012). Historical and critical review of spatial and transport planning in the netherlands. *Land Use Policy*, 29(3):536–547.

Aono, S. (2019). Identifying best practices for mobility hubs. https://sustain.ubc.ca/sites/default/files/Sustainability%20Scholars/2018_Sustainability_Scholars/Reports/2018-71%20Identifying%20Best%20Practices%20for%20Mobility%20Hubs_Aono.pdf.

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

Becker, S. and Rudolf, C. (2018). Exploring the potential of free cargo-bikesharing for sustainable mobility. *GAIA - Ecol. Perspect. Sci. Soc.*, 27:156–164.

Ben-Akiva, M. and Bierlaire, M. (2003). Discrete choice methods and their applications. In Hall, R. G., editor, *Handbook of Transportation Science, Second Edition*, pages 5–34. Kluwer Academic Publishers.

Ben-Akiva, M., McFadden, D., and Train, K. (2019). Foundations of stated preference elicitation: Consumer behavior and choice-based conjoint analysis. *Foundations and Trends® in Econometrics*, 10(1-2):1–144.

Bertolini, L. (2008). Station areas as nodes and places in urban networks: An analytical tool and alternative development strategies. In Bruinsma, F., Pels, E., Rietveld, P., Priemus, H., and van Wee, B., editors, *Railway Development*, pages xx–xx. Physica-Verlag HD.

Böcker, L., Anderson, E., Uteng, T., and Throndsen, T. (2020). Bike sharing use in conjunction to public transport: Exploring spatiotemporal, age and gender dimensions in oslo, norway. *Transportation Research Part A: Policy and Practice*, 138:389–401.

Chan, K. and Farber, S. (2020). Factors underlying the connections between active transportation and public transit at commuter rail in the greater toronto and hamilton area. *Transportation*, 47:2157–2178.

Chen, S., Wang, H., and Meng, Q. (2020). Solving the first-mile ridesharing problem using autonomous vehicles. *Computer-Aided Civil and Infrastructure Engineering*, 35:45–60.

Correia, G. and Antunes, A. (2012). Optimisation approach to depot location and trip selection in one-way car-sharing systems. *Transportation Research Part E: Logistics and Transportation Review*, 48(1):233–247.

de Haas, M., Kroesen, M., and Chorus, C. (2021). E-bike user groups and substitution effects: Evidence from longitudinal travel data in the netherlands.

Dubey, S., Cats, O., and Hoogendoorn, S. (2024). Understanding preferences for mobility-on-demand services through a context-aware survey and non-compensatory strategy. *Transportation Research Part C: Emerging Technologies*.

European Commission (n.d.). Eu air quality standards.

Frank, L., Dirks, N., and Walther, G. (2021). Improving rural accessibility by locating multimodal mobility hubs.

Garritsen, K., Grigolon, A., and Geurs, K. (2024). The role of digital mobility skills in the uptake of shared modes at mobility hubs.

Garritsen, K. E., Grigolon, A. B., and Geurs, K. T. (2023). The role of digital mobility skills in the uptake of shared modes at mobility hubs. *Transportation Research Part A: Policy and Practice*, 169:103531.

Gavriilidou, A. (2024). Discrete choice model comparison. https://example.com. PowerPoint slides. CIEM6110-A1: Empirical Analysis for TTE, Technical University of Delft.

GreenWheels (2023). Rates - greenwheels. https://www.greenwheels.nl/en-us/rates. Accessed: 2023-04-03.

Guo, Y., Chen, Z., Stuart, A., Li, X., and Zhang, Y. (2020). A systematic overview of transportation equity in terms of accessibility, traffic emissions, and safety outcomes: From conventional to emerging technologies. *Transport Research Interdisciplinary Perspectives*, 4:100091.

GVB (2025). Stops and timetable. https://www.gvb.nl/en/travel-information/stops-and-timetable. Accessed: 2025-06-25.

Habib, K. N., Morency, C., and Trépanier, M. (2012). Modeling commuters' mode choice behaviour with explicit consideration of carpooling and carsharing. *Transportation*, 39:345–365.

Hachette, M., L'Hostis, A., and Gragera, A. (2024). Exploring the concept of 'mobility hubs' and assessing their impacts in two european cities. https://doi.org/10.1007/978-3-031-35664-3_1.

Halldórsdóttir, K., Nielsen, O., and Prato, C. (2017). Home-end and activity-end preferences for access to and egress from train stations in the copenhagen region. *International Journal of Sustainable Transportation*, 11(10):776–786.

Henry, L. and Marsh, D. (2008). Intermodal surface public transport hubs: Harnessing synergy for success in america's urban and intercity travel. In *APTA Bus & Paratransit Conference*, Austin, USA. American Public Transportation Association.

Hensher, D., Wei, E., Liu, W., and Balbontin, C. (2024). Profiling future passenger transport initiatives to identify the growing role of active and micro-mobility modes. https://doi.org/10.1016/j.tra.2024.104172.

Heufke Kantelaar, M., Molin, E., Cats, O., Donners, B., and Wee, B. V. (2022). Willingness to use night trains for long-distance travel. *Travel Behaviour and Society*, 29:339–349.

Hochmair, H. (2015). Assessment of bicycle service areas around transit stations. *International Journal of Sustainable Transportation*, 9:15–29.

Horjus, J., Gkiotsalitis, K., Nijënstein, S., and Geurs, K. (2024). Integration of shared transport at a public transport stop: mode choice intentions of different user segments at a mobility hub. *Transportation Research Part A: Policy and Practice*.

Hosseini, K., Choudhari, T., Stefaniec, A., O'Mahony, M., and Caulfield, B. (2024). E-bike to the future: Scalability, emission-saving, and eco-efficiency assessment of shared electric mobility hubs.

Jahanshahi, D., Tabibi, Z., and van Wee, B. (2020). Factors influencing the acceptance and use of a bicycle sharing system: Applying an extended unified theory of acceptance and use of technology (utaut). *Case Studies on Transport Policy*, 8:1212–1223.

Ji, Y., Fan, Y., Ermagun, A., Cao, X., Wang, W., and Das, K. (2017). The public bicycle as a feeder mode to rail transit in china: The role of gender, age, income, trip purpose, and bicycle theft experience. *International Journal of Sustainable Transportation*, 11(4):308–317.

Jiao, J. and Bai, S. (2020). Understanding the shared e-scooter travels in austin, tx. *ISPRS International Journal of Geo-Information*, 9(2).

Jiao, J. and Wang, F. (2021). Shared mobility and transit-dependent population: A new equity opportunity or issue? *International Journal of Sustainable Transportation*, 15:294–305.

Jonkeren, O., Kager, R., Harms, L., and Brömmelstroet, M. t. (2021). The bicycle-train travellers in the netherlands: Personal profiles and travel choices. *Transportation*, 48:455–476.

Jorge, D. and Correia, G. (2013). Car-sharing systems demand estimation and defined operations: a literature review. *European Journal of Transport and Infrastructure Research*, 13(3):201–220.

Jorritsma, P., Witte, J., Alonso González, M., and Hamersma, M. (2021). Deelauto- en deelfietsmobiliteit in nederland. ontwikkelingen, effecten en potentie.

Kondor, D., Zhang, H., Tachet, R., Santi, P., and Ratti, C. (2019). Estimating savings in parking demand using shared vehicles for home-work commuting. *IEEE Transactions on Intelligent Transportation Systems*, 20:2903–2912.

Kouwenhoven, M., de Jong, G. C., Koster, P., van den Berg, V. A. C., Verhoef, E. T., Bates, J., and Warffemius, P. (2014). New values of time and reliability in passenger transport in the netherlands. Technical report, Significance and KiM Netherlands Institute for Transport Policy Analysis. Report for the Ministry of Infrastructure and the Environment, Netherlands.

Kroesen, M. (2017). To what extent do e-bikes substitute travel by other modes? evidence from the netherlands. *Transportation Research Part D: Transport and Environment*, 53:377–387.

Kroesen, M. (2023). Sen1721: Travel behaviour research lecture 1 - 2. Lecture.

Liao, F., Vleugel, J., Bösehans, G., Dissanayake, D., Thorpe, N., Bell, M., van Arem, B., and Correia, G. (2023). Mode substitution induced by electric mobility hubs: Results from amsterdam. *Transportation Research Part D (In Press)*.

Lohman, W., C. H. B. J. K. R. A. Y. . W. E. (2023). Building digital twins of cities using the inter model broker framework. future generation computer systems. *International Journal of Geographical Information Science*, (148):501–513.

Ma, X., Yuan, Y., van Oort, N., and Hoogendoorn, S. (2020). Bike-sharing systems' impact on modal shift: A case study in delft, the netherlands. *Journal of Cleaner Production*, 259:120846.

Meijkamp, R. (2000). Car sharing means more travel with less pollution: Eco-efficient services—stop selling cars; sell kilometres instead. *Delft Outlook*.

Meng, M., Koh, P., and Wong, Y. (2016). Influence of socio-demography and operating streetscape on last-mile mode choice. *Journal of Public Transportation*, 19(2):38–54.

Micromobiliteit.nl (2024). Mobike deelfietsen. Accessed: 2025-08-02.

Molin, E. (2023). Sen1721: Travel behaviour research lecture 6. Lecture.

Molin, E. (2024). Introduction to experimental designs - lecture 1 (sen1221 – part ii).

Molin, E. J. E. and 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.

Non, M., Dinkova, M., and Dahmen, B. (2023). Skill up or get left behind? digital skills and labor market outcomes in the netherlands. Technical report, CPB Netherlands Bureau for Economic Policy Analysis. Working Paper.

NS (2023a). E-scooter - door to door. `https://www.ns.nl/en/business/door-to-door/e-scooter`. Accessed: 2023-04-03.

NS (2023b). Ov-fiets - door to door. `https://www.ns.nl/en/door-to-door/ov-fiets`. Accessed: 2023-04-03.

OECD (2013). *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD Publishing, Paris.

Oeschger, G., Carroll, P., and Caulfield, B. (2023). First- and last-mile connections to public transport in dublin: analysis of pre-covid19 mobility patterns and user experiences. `https://doi.org/10.1016/j.trpro.2023.11.517`.

Ohnemus, M. and Perl, A. (2016). Shared autonomous vehicles: Catalyst of new mobility for the last mile? *Built Environment*. This issue.

Orme, B. (2010). *Sample Size Issues for Conjoint Analysis*. Research Publishers LLC, Madison, Wisconsin.

Ortúzar, J. D. D. and Willumsen, L. G. (2011). *Modelling Transport (1st ed.)*. Wiley.

Park, S., Kang, J., and Choi, K. (2014). Finding determinants of transit users' walking and biking access trips to the station: A pilot case study. *KSCE Journal of Civil Engineering*, 18:651–658.

PBL Netherlands Environmental Assessment Agency (n.d.). Landelijk model systeem verkeer en vervoer (lms). Online. https://www.pbl.nl/modellen/landelijk-model-systeem-verkeer-en-vervoer-lms.

Pham, D. (2023). Mobility design strategies for sustainable development in peripheral urban areas: A case study in travel choice behaviour for rijnenburg, utrecht. Master's thesis, Delft University of Technology.

Pitsiava-Latinopoulou, M. and Iordanopoulos, P. (2012). Intermodal passengers terminals: Design standards for better level of service. *Procedia – Social and Behavioral Sciences*, 48:3297–3306.

Puello, L. and Geurs, K. (2015). Modelling observed and unobserved factors in cycling to railway stations: application to transit-oriented-developments in the netherlands. *European Journal of Transport and Infrastructure Research*, 15(1):27–50.

Qualtrics (n.d.). Experience management software. https://www.qualtrics.com/.

Rongen, T., Tillema, T., Arts, J., Alonso-González, M., and Witte, J. (2024). An analysis of the mobility hub concept in the netherlands: Historical lessons for its implementation.

Royal Schiphol Group (2023). Annual report 2023. https://www.royalschipholgroup.com/en/reports/annual-report-2023/. Accessed: June 21, 2025.

Ryley, T. J., Stanley, P. A., Enoch, M. P., Zanni, A. M., and Quddus, M. A. (2014). Investigating the contribution of demand responsive transport to a sustainable local public transport system. *Research in Transportation Economics*, 48:364–372.

Sanders, K. (2015). The role of pre-transport in travelers' transportation mode choice: A study conducted in the region of the railway station of eindhoven. Master's thesis, Eindhoven University of Technology.

Schakenbos, R., Paix, L. L., Nijenstein, S., and Geurs, K. T. (2016). Valuation of a transfer in a multi-modal public transport trip. *Transport Policy*, 46:72–81.

Scheltes, A. and Correia, G. (2017). Exploring the use of automated vehicles as last mile connection of train trips through an agent-based simulation model: An application to delft, the netherlands. *International Journal of Transportation Science and Technology*, 6(1):28–41.

Shaheen, S., Bell, C., Cohen, A., and Yelchuru, B. (2017). Travel behavior: Shared mobility and transportation equity. Report PL-18-007, U.S. Department of Transportation.

Shaheen, S. and Chan, N. (2016). Mobility and the sharing economy: Potential to facilitate the first- and last-mile public transit connections. *TR News*, 42(4).

Shelat, S., Huisman, R., and Oort, N. (2018). Analysing the trip and user characteristics of the combined bicycle and transit mode. *Research in Transportation Economics*, 69.

Smit, R., Mieghem, R., and Hensema, A. (2006). Algemene PM10, NOx en NO2 Emissiefactoren voor Nederlandse Snelwegen. Technical Report 06.OR.PT.029.1/RS, TNO. [In Dutch].

Smit, R., Mieghem, R., Hensema, A., Rabé, E., and Eijk, A. (2007). VERSIT+ Emissiefactoren voor Standaardrekenmethode 1 (CAR II). Technical Report MON-RPT-033-DTS-2007-00709, TNO. [In Dutch].

Stam, B., van Oort, N., van Strijp-Harms, H. J., van der Spek, S. C., and Hoogendoorn, S. P. (2021). Travellers' preferences towards existing and emerging means of first/last mile transport: A case study for the almere centrum railway station in the netherlands. *European Transport Research Review*, 13(1):56.

Statista Research Department (2023). Number of rain days in the netherlands from 1990 to 2022. https://www.statista.com/statistics/1012831/number-of-rain-days-in-the-netherlands/.

Statistics Netherlands (n.d.). Home. https://www.cbs.nl/. Accessed June 2025.

Sun, Q., Feng, T., Kemperman, A., and Spahn, A. (2020). Modal shift implications of e-bike use in the netherlands: Moving towards sustainability? *Transportation Research Part D: Transport and Environment*, 78:102202.

Sytsma, J. and Stulen, L. (2018). Maas laat leidsche rijn stromen: de meerwaarde van maas in een vinex-wijk. In *CVS 2018*.

Tikoudis, I., Martinez, L., Farrow, K., Bouyssou, C., Petrik, O., and Oueslati, W. (2021). Exploring the impact of shared mobility services on co2. Technical Report 175, OECD Environment Working Papers, Paris.

Tona, D., Duives, D. C., Cats, O., Hoogendoorn-Lanser, S., and Hoogendoorn, S. P. (2024). Determinants of mode choice in the netherlands. *Transportation Research Part A: Policy and Practice*.

Torabi, F., Araghi, Y., van Oort, N., and Hoogendoorn, S. (2023). Passengers' preferences for using emerging modes as first/last mile transport to and from a multimodal hub: Case study delft campus railway station. *Transport Research Part A (In Press)*.

Train, K. E. (2002). *Discrete Choice Methods with Simulation*. Cambridge University Press, Cambridge.

Tran, M., Zhang, J., and Fujiwara, A. (2014). Can we reduce the access by motorcycles to mass transit systems in future hanoi? *Procedia – Social and Behavioral Sciences*, 138:623–631.

Van Kuijk, R., Homem de Almeida Correia, G., van Oort, N., and van Arem, B. (2024). Preferences for first and last mile shared mobility between stops and activity locations: A case study of local public transport users in utrecht, the netherlands.

van Langevelde van Bergen, C. C. (2023). Public support for tradable peak credits as an instrument to reduce congestion: A stated choice experiment that is simultaneously used to investigate the influence of content and medium of stated choice introductions. Master's thesis, Delft University of Technology. MSc Thesis, Complex Systems Engineering and Management.

Van Mil, J., Leferink, T., Annema, J., and Van Oort, N. (2020). Insights into factors affecting the combined bicycle-transit mode. *Public Transport*.

Vervoerregio Amsterdam (2024). Regionaal verkeersmodel venom. Accessed: 2025-08-02.

Wang, W., Zhang, Q., Peng, Z., Shao, Z., and Li, X. (2020). An empirical evaluation of different usage pattern between car-sharing battery electric vehicles and private ones. *Transportation Research Part A: Policy and Practice*, 135:115–129.

Wesseling, J. and Zandveld, P. (2006). Pluim Snelweg. Technical Report 2006/A/R/00675/A, TNO. [In Dutch].

Wu, Y., Kang, L., Hsu, Y., and Wang, P. (2019). Exploring trip characteristics of bike-sharing system uses: Effects of land-use patterns and pricing scheme change. *International Journal of Transportation Science and Technology*, 8:318–331.

Xanthopoulos, A., Bösehans, M., and Thomas, F. (2024). Optimization of the location and capacity of shared multimodal mobility hubs to maximize travel utility in urban areas.

Yap, M., Correia, G., and van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice*, 94:1–16.

Zhou, H., Dorsman, J., Mandjes, M., and Snelder, M. (2023). Sustainable mobility strategies and their impact: A case study using a multimodal activity based model.

Zijlstra, T., Durand, A., Hoogendoorn-Lanser, S., and Harms, L. (2020). Early adopters of mobility-as-a-service in the netherlands. *Transport Policy*, 97:197–209.

Zuurbier, M. N. (2023). The multimodal mobility hub and preferred facilities: Its potential for sustainable travel behavior.

Colophon

This document was typeset using LaTeX, using the KOMA-Script class `scrbook`. The main font is Palatino. Chatgpt is used for coding and idea generation.

TU Delft