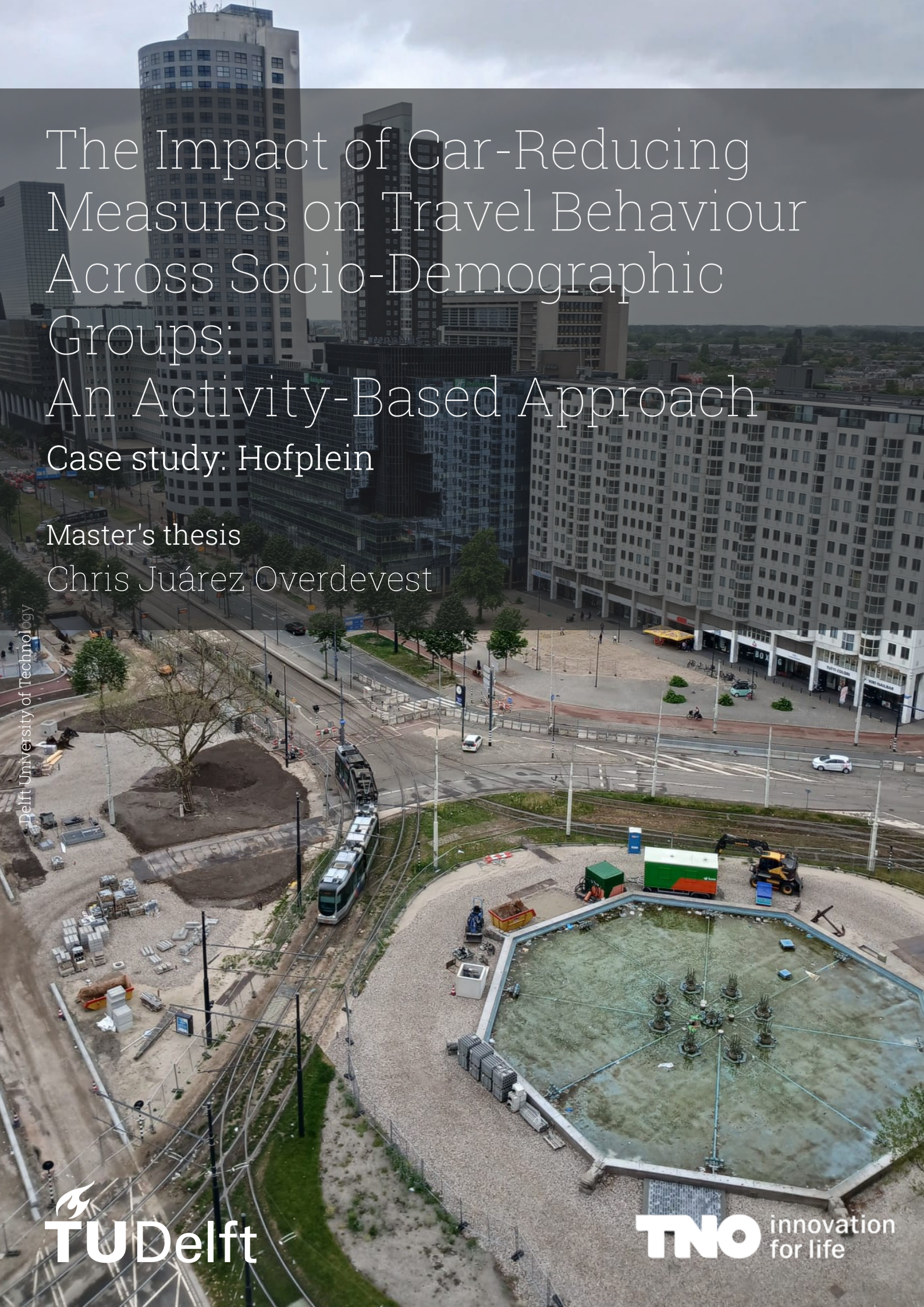
The Impact of Car-Reducing Measures on Travel Behaviour Across Socio-Demographic Groups: An Activity-Based Approach

Case study: Hofplein

Master's thesis

Chris Juárez Overdevest

Delft University of Technology



TU Delft

TNO innovation for life

The Impact of Car-Reducing Measures on Travel Behaviour Across Socio-Demographic Groups: An Activity-Based Approach

Case study: Hofplein

by

Chris Juárez Overdevest

to obtain the degree of Master of Science
at the Delft University of Technology,
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Cover: Hofplein during construction (photograph by the author).

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Preface

After seven years of studying, this thesis marks the completion of my MSc in Transport, Infrastructure and Logistics. Looking back, the journey has been both challenging and rewarding, providing me with many opportunities to learn, grow, and discover my interests. This thesis marks the completion of that period and the end of an important chapter in my life. Looking back, it feels somewhat fitting that the final destination of my studies turned out to be a thesis on transportation.

I would like to sincerely thank my supervisors, Bart van Arem, Maaike Snelder, Sander van Cranenburgh, and Han Zhou, for their guidance, critical feedback, and continuous support throughout this research. Their questions and insights helped me stay focused and challenged me to improve both the research and myself as a researcher. In particular, I would like to thank Han for his invaluable support with the modelling aspects of this thesis and for the many discussions that helped shape the final result.

I would also like to thank my colleagues at TNO and everyone else who contributed along the way. Whether through technical assistance, constructive discussions, encouragement, or simply sharing their experience, they all played a role in bringing this thesis to completion.

One reassuring outcome of this thesis is that six months of immersing myself in mobility and transport modelling did not diminish my enthusiasm for the subject. If anything, it had the opposite effect. Throughout this research, I became increasingly fascinated by the challenge of understanding how people move through cities and trying to capture that in a model. I therefore look forward to continuing in this field, this time without a thesis deadline looming in the background.

While this thesis marks the end of my student years, it does not feel like the end of the journey. Rather, it feels like arriving at a platform from which a new one begins. I look forward to starting my professional career and to discovering where the next stage will take me.

Chris Juárez Overdevest
Delft, October 2026

Summary

Introduction

Cities in the Netherlands are increasingly implementing car-reducing measures to improve sustainability, public health, and urban liveability. However, while such interventions are becoming more common, their impacts are often evaluated in terms of traffic volumes or modal share rather than the behavioural mechanisms through which travellers adapt. In particular, limited attention has been given to how responses such as modal shift, rerouting and trip suppression differ across socio-demographic groups.

This thesis addresses this gap using the redesign of Hofplein in Rotterdam as a case study. The intervention reduces road capacity by transforming a car-oriented traffic square into a multimodal public space. This reduction in capacity lowers car accessibility, which in turn triggers behavioural responses.

The central research question is:

> *What are the effects of car-reducing measures on travel behaviour across different socio-demographic groups?*

To answer this question, the study analyses both the overall behavioural impacts of reduced car accessibility and the extent to which these impacts differ between traveller groups.

Case Study Hofplein

The Hofplein redesign was selected as a representative example of an urban car-reducing intervention. By transforming a five-lane traffic square into a greener, multimodal public space, the project reduces car accessibility at a key node in Rotterdam's transport network. This creates an opportunity to investigate how travellers adapt to changing travel conditions and to assess how the resulting behavioural responses vary across different socio-demographic groups.

Methodology

Answering the research question requires understanding how travellers change their behaviour when car accessibility is reduced. However, this cannot be measured directly. Once the Hofplein redesign has been implemented, it is impossible to observe how the same travellers would have travelled if the intervention had not taken place. While traffic counts can reveal whether car use increases or decreases, they do not show how individual travellers adapted their behaviour, nor which population groups were most effected.

To address this challenge, this study uses an activity-based transport model (ActivitySim). Activity-based models simulate the travel decisions of individual travellers, making it possible to compare travel behaviour with and without the intervention. First, the accessibility impacts of the Hofplein redesign were estimated using the V-MRDH traffic assignment model. These changes in travel conditions were then incorporated into ActivitySim, allowing simulated travellers to adapt their behaviour through modal shift, rerouting, destination changes, and trip suppression.

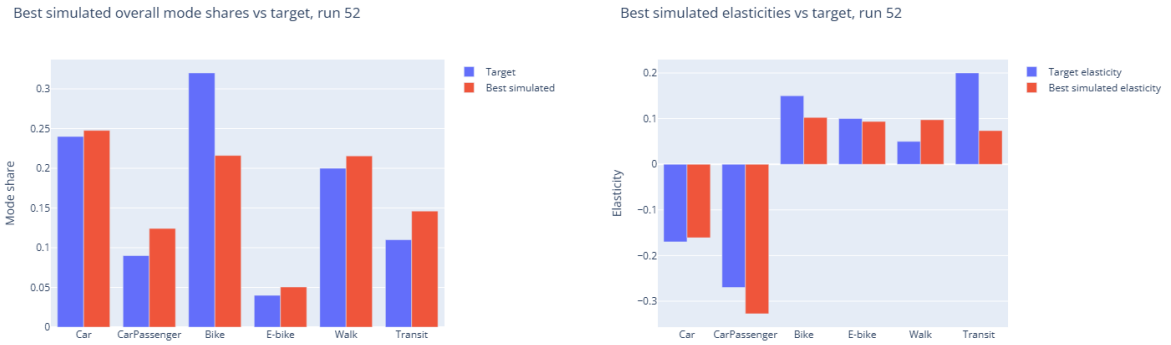
To improve behavioural realism, the model was calibrated using both observed modal shares and travel-time elasticities from the literature. Finally, simulated travellers were linked to ten KiM mobility personas, enabling behavioural responses to be analysed across different socio-demographic groups.

Model Behaviour Analysis and Calibration

The ActivitySim model used in this study was based on an existing model developed for the MRDH region. Before applying it to the Hofplein case study, it was necessary to evaluate whether the model not only reproduced observed travel patterns, but also responded realistically to changes in travel conditions.

For policy evaluation, matching observed modal shares alone is not sufficient. A model should accurately represent current travel behaviour while also producing plausible behavioural responses when accessibility changes. The analysis therefore focused on both modal shares and travel-time elasticities, providing insight into the model's behavioural realism and identifying the parameters that most strongly influence traveller decision-making.

Sensitivity analysis showed that travel-time coefficients and alternative-specific constants are the primary drivers of mode choice behaviour. Based on these findings, Bayesian optimisation was used to calibrate the model against both observed modal shares and travel-time elasticities. Figure 1 shows the performance of the selected calibration result.



(a) Modal share comparison

(b) Elasticity comparison

Figure 1: Comparison of the selected calibration result (Run 52) and the target values.

The calibration resulted in a model that reproduces both observed travel behaviour and travel-time elasticities reasonably well. Figure 1 shows that the selected calibration result aligns closely with the target values derived from CBS (2026) and Hofman (2024). The calibrated model therefore provides a credible basis for evaluating the behavioural impacts of the Hofplein intervention.

Key Findings

After calibration, the ActivitySim model was used to simulate the Hofplein redesign and estimate how travellers would respond to the resulting reduction in car accessibility. The model predicts that the intervention leads to a reduction in car use, accompanied by increases in walking, cycling, e-bike use, and public transport. However, these aggregate changes provide only a partial picture of the overall behavioural response.

The simulation results suggest that many travellers continue to travel by car despite the reduction in accessibility, often by selecting alternative routes around the intervention area. This indicates that reduced car accessibility does not necessarily lead to travellers abandoning car use, but can also result in changes to how trips are made.

For those trips that are no longer made by car, the model predicts a variety of behavioural responses. Figure 2 shows how these lost car trips are redistributed across different adaptation mechanisms, illustrating that travellers adjust their behaviour in multiple ways when car accessibility is reduced.

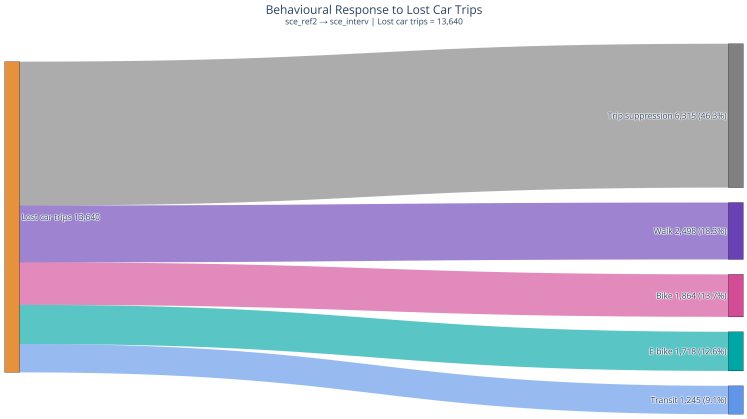


Figure 2: Behavioural response of lost car trips.

The persona analysis further showed that these impacts are distributed unevenly across the population. By linking simulated travellers to KiM mobility personas, it was possible to examine how different traveller groups responded to the intervention. Figure 3 compares the modelled modal shares before and after the intervention for each persona.

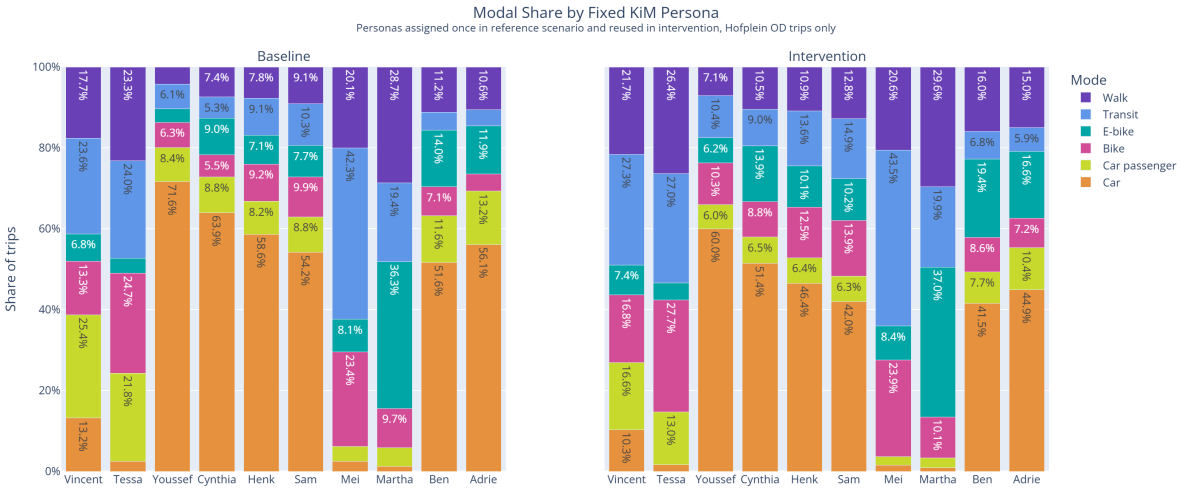


Figure 3: Baseline and intervention modal shares by persona.

The strongest behavioural responses were predicted for car-oriented personas such as Cynthia, Henk, Sam, Ben, and Adrie, whereas already multimodal personas such as Vincent, Tessa, Mei, and Martha experienced comparatively small changes. Travellers who were most dependent on the car generally experienced the largest reductions in accessibility and consequently exhibited the strongest behavioural adaptation. These findings suggest that the effects of car-reducing measures depend not only on the intervention itself, but also on the characteristics and travel patterns of the travellers effected.

Scientific Contributions

This thesis contributes to both transport modelling and sustainable mobility research.

First, it demonstrates the importance of behavioural realism in transport modelling. A calibration approach was developed that combines observed modal shares with travel-time elasticities, ensuring that the model not only reproduces current travel patterns but also responds plausibly to changes in travel conditions.

Second, the study shows how activity-based modelling and persona segmentation can be combined to analyse behavioural responses at the level of individual travellers. This makes it possible to identify how different population groups adapt to transport interventions and how impacts are distributed across society.

Finally, the research provides insight into the mechanisms underlying traffic evaporation. Rather than being explained by modal shift alone, reductions in car use emerge through a combination of rerouting, destination changes, trip suppression, and shifts to alternative transport modes.

Policy Recommendations

The findings highlight an important trade-off in the evaluation of car-reducing measures. Interventions such as the Hofplein redesign can contribute to urban liveability, traffic safety, and environmental sustainability, but they may also reduce accessibility for certain traveller groups.

The results suggest that these accessibility impacts are distributed unevenly across the population. While many travellers can adapt through alternative routes or transport modes, car-dependent travellers experience the largest accessibility reductions and are more likely to suppress trips altogether. Policymakers should therefore evaluate not only the overall benefits of car-reducing measures, but also who bears the resulting accessibility impacts. Ensuring that attractive and accessible alternatives are available is particularly important for travellers who rely most heavily on the car.

Conclusions

This thesis examined how travellers respond to reduced car accessibility using the Hofplein redesign in Rotterdam as a case study. The results suggest that car-reducing measures influence travel behaviour through multiple adaptation mechanisms, including rerouting, modal shift and trip suppression.

Importantly, these responses are not distributed evenly across the population. Travellers who rely heavily on the car experience the largest accessibility impacts and exhibit the strongest behavioural responses, whereas already multimodal travellers are effected to a much smaller extent. Understanding these differences is therefore essential when evaluating the effectiveness and equity implications of car-reducing measures.

More broadly, the research demonstrates the value of activity-based transport models for policy evaluation. By representing travel decisions at the level of individual travellers, activity-based models can reveal behavioural responses and distributional impacts that remain hidden in aggregate analyses. As cities continue to pursue more sustainable transport systems, such insights can help policymakers better balance the societal benefits of car-reducing measures against their accessibility impacts for different traveller groups.

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1

Introduction

This chapter first presents the context of the thesis, followed by the scope that defines the boundaries of the research. Then it introduces the Hofplein case study, after which the connection to the XCARCITY program is outlined. The chapter continues with presenting the main research question, together with a set of sub-questions and concludes with an outline of the thesis.

1.1. Context

Urban car use is an increasingly pressing challenge for cities worldwide. Private cars contribute significantly to greenhouse gas emissions (IPCC, 2023), air pollution, heat island effect and road safety risks. At the same time, they occupy valuable urban space that could otherwise support more sustainable uses (Saeidizand et al., 2022). These issues align closely with the European Union's ambition to achieve more than 100 climate-neutral and smart cities by 2030 (European Commission, 2025).
In response to these challenges, Dutch municipalities are increasingly implementing policies that restrict or discourage car use in urban areas (Jorritsma et al., 2023). These measures are typically not pursued as an objective in themselves, but rather as part of a broader effort to create more liveable cities. A concrete example of this broader transition is the ongoing redesign of Hofplein in Rotterdam. In this project, the *verkeersplein* in the city centre, which currently accommodates a five-lane arterial road, is being reduced to two lanes. The reclaimed space is allocated to pedestrians, cyclists and more than 100 trees, with the aim of lowering traffic volumes and improving the quality of urban space.

The Hofplein project is not a one-of-a-kind initiative, but rather part of a broader range of measures aimed at reducing car use. These interventions can take different forms, such as pricing and parking schemes, but this thesis focuses specifically on road reallocation at major urban intersections. Such interventions are relevant in the Dutch context, as similar projects are being implemented in cities like The Hague (Rijswijkseplein) (Den Haag FM, 2025) and Utrecht (Lombokplein) (Municipality Utrecht, n.d.). By reducing road capacity, these measures decrease car accessibility and thereby encourage travellers to make more sustainable choices. Because these intersections play a central role in urban networks, such interventions are typically large in scale and can significantly disrupt traffic flows.

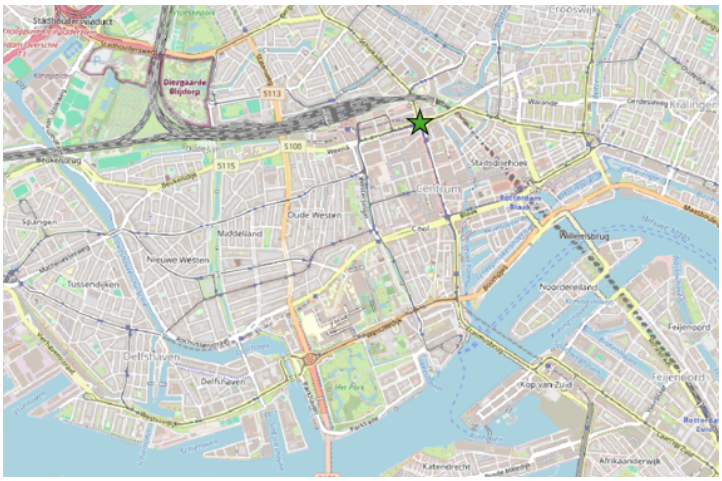
Given this growing implementation of car-reducing measures, it is important to understand their impacts. There is increasing evidence that car-reducing measures, such as the Hofplein redesign, can generate positive environmental, health, social equity, and livability outcomes (Mouratidis, 2025). However, Mouratidis (2025) also highlights that these measures may lead to unintended negative consequences for individuals who are involuntarily prevented from using their car. This raises the question of how people actually respond to such interventions in practice. It remains unclear how travel behaviour adapts: do former car users switch to alternative modes, choose different routes, or stop from making certain trips altogether?
Understanding these behavioural responses is essential, as travel behaviour strongly influences the performance and sustainability of urban transport systems (Pourramazani & Miralles-Garcia, 2022). In the context of car-reducing interventions, changes in observed traffic volumes are often used as an

indicator of success. However, it is not always clear whether these reductions reflect a genuine shift to more sustainable modes or are the result of other behavioural adaptations.
In addition, these responses may not be evenly distributed across society. Travel behaviour is known to vary across socio-demographic groups (Di Ciommo & Shiftan, 2017), which raises the question of whether certain populations are disproportionately effected by car-reducing measures. This distinction is particularly important, as individuals who are already disadvantaged may have fewer alternatives when car accessibility is reduced. Despite its fact, this equity dimension remains relatively underexplored in the context of such interventions.
To address this gap, this thesis examines the effects of urban car-reducing measures across socio-demographic groups. It focuses on how travel behaviour adapts to the Hofplein intervention and evaluates the broader implications for sustainable and equitable urban transport systems.

1.2. Scope

To begin with, it is important to clearly define the nature of the Hofplein intervention. It is characterised as a purely infrastructural project aimed at reducing car accessibility in order to encourage more sustainable travel behaviour. More specifically, it can be classified as a road reallocation measure applied to a major urban intersection. Such interventions are often accompanied by adjacent developments, such as new housing projects that make use of the space freed up by reduced car infrastructure. Although these developments are not formally part of the intervention itself, they are often considered as complementary projects.

To ensure feasibility and clarity, the scope of this study is defined along several dimensions. First, the analysis focuses exclusively on physical car reduction measures related to street design and infrastructure, such as road narrowing, the reallocation of space, or road closures. Other policy instruments, including parking regulations, pricing strategies, or economic incentives, are explicitly excluded. This is discussed in more detail in Section 2.2.
Second, the spatial scope is defined at two levels. The physical intervention itself is limited to the Hofplein, which is located in the city centre of Rotterdam (Figure 1.1). However, the study area covers the entire Metropoolregio Rotterdam Den Haag (MRDH, n.d.-a), as individuals effected by the redesign may travel from a wide range of origins and destinations. The manner in which this broader spatial extent is incorporated and constrained within the analysis is explained in Chapter 4.
Third, the analysis of travel behaviour is restricted to a predefined set of alternatives, including private car use, cycling, walking, public transport, e-bike and car passenger. Behavioural responses to the redesign are examined in terms of whether individuals continue using the same route, choose an alternative route, switch to a different mode of transport, or decide not to make the trip altogether. This is further elaborated in Section 2.3.

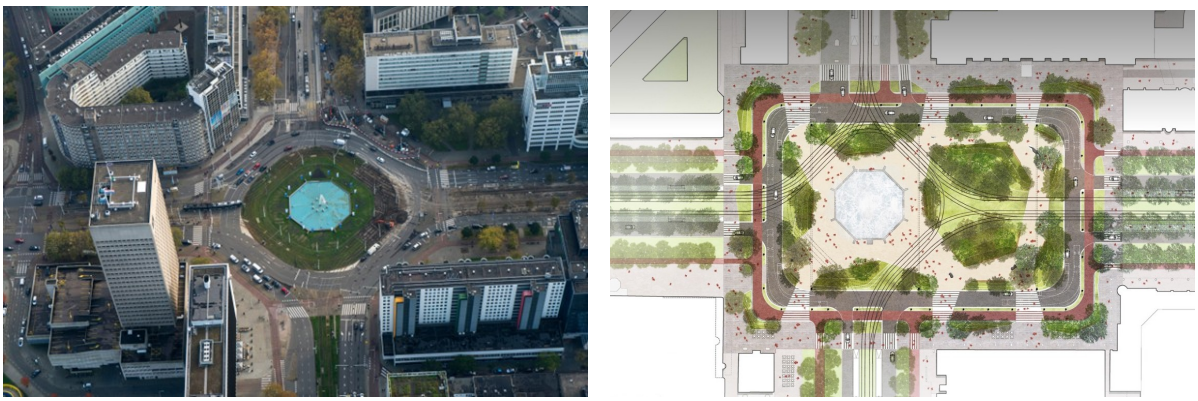

Centrum
Oude Westen
Middelland
Nieuwe Westen
Tussendijken
Delfshaven
Noordereiland
Feijenoord
Kop van Zuid
Katendrecht
Afrikaanderwijk
Kralingen
Crooswijk
Blijdorp
Cool
Witte Dorp
Rotterdam Blaak
Stadsdriehoek
Weena
Coolsingel
Westblaak
Delftsevaart
Mathenesserlaan
Maasboulevard
Willemsbrug
Erasmusbrug
Wijnhaven
Parkhaven
Oude Haven
Nieuwe Haven
Veerhaven
Wijnhaven
Spijkenisse
Vlaardingen
Schiedam
Rotterdam Airport
Rotterdam Ahoy
Diergaarde Blijdorp
Stadhuis
Hofplein
Blaak
Beurs
Delftsplein
Keilehaven
Schiehaven
Nieuwe Maas
Oude Maas
Waalhaven
Eemhaven
Merwehaven
Botlek
Europoort
Maasvlakte
Hoek van Holland
Vlaardingen
Schiedam
Spijkenisse
Ridderkerk
Barendrecht
Capelle aan den IJssel
Krimpen aan den IJssel
Hoogvliet
Pernis
Charlois
Ommoord
Prins Alexander
Zuidplein
Kralingse Bos
Kralingse Plas
Oudedijk
Nieuwe Binnenweg
Oude Binnenweg
Witte de Withstraat
Schouwburgplein
Meent
Coolsingel
Aert van Nesstraat
Lijnbaan
Binnenrotte
Grotemarkt
Hoogstraat
Leuvehaven
Boompjes
Wilhelminakade
Parkhaven
Delfsh

Finally, the study considers differences between population groups based on selected socio-demographic characteristics. In particular, income, car ownership, age, gender and migration background are included as key variables to assess whether the impacts of the car reducing measures are distributed unevenly across different segments of the population. Further details are provided in Section 2.4.

1.3. Hofplein

This thesis focuses on the Hofplein, one of the most iconic public spaces in Rotterdam. Traditionally, the square has functioned as a car-oriented *verkeersplein*, where motorised traffic was prioritised over active modes and public space that is attractive and accessible for people. In recent years, however, this role has been reconsidered. In line with the municipality's ambition to reduce mobility-related carbon emissions to zero by 2040 (Municipality Rotterdam, 2020), the Hofplein has been identified as a key location for intervention and is currently undergoing a major redesign.

At the time of writing, this redesign is still under construction. The planned transformation represents a clear shift away from car dominance towards a more balanced urban space, with improved conditions for pedestrians, cyclists, and public use. This transition is shown in Figure 1.2, which compares the original layout with the proposed redesign.



(a) Original situation **(b)** Redesigned layout (Juurlink+Geluk, 2020)

Figure 1.2: Hofplein before and after the redesign

The Hofplein intervention forms part of Rotterdam's broader Verkeerscirculatieplan (VCP), which aims to reduce car accessibility in the city centre while promoting walking, cycling, and public transport (Municipality Rotterdam, 2005). At the same time, the area is a major focus of urban densification, with approximately 10,000 new dwellings planned in and around the city centre, including the Rotterdam Central District surrounding Hofplein (Municipality Rotterdam, n.d.-a). The combination of increasing residential density and reduced car accessibility makes Hofplein a particularly relevant case for examining how changes in accessibility may influence travel behaviour. While the additional population associated with the planned housing is not explicitly modelled in this thesis, future densification should be kept in mind when interpreting the results. This relevance is further strengthened by Rotterdam's socio-demographic diversity, which allows behavioural responses to be studied across a wide range of population groups (Cushman & Wakefield, 2024).
For these reasons, the Hofplein intervention provides an interesting and relevant case study for evaluating this thesis and will be discussed in greater detail in Chapter 3.

1.4. XCARCITY

This thesis is conducted as part of XCARCITY, a five year research program supporting sustainable urban mobility in car low cities. Within this program, digital twins, or transport models, are used to provide insight into both the direct and indirect effects of car reducing measures on urban mobility systems. This research contributes directly to the program's goals by examining how car-reducing measures influence travel behaviour and transport equity, while also providing insight into how these effects and behavioural responses differ across socio-demographic groups.

1.5. Research questions

This study examines the effects of car reducing measures, such as the redesign of the Hofplein, on travel behaviour and it investigates how these effects vary across different socio-demographic groups. Accordingly, the central research question of this study is:

> *What are the effects of car-reducing measures on travel behaviour across different socio-demographic groups?*

To address this main research question, the study is guided by the following sub-questions:

1. What is the most appropriate approach to analyse changes in aggregate travel behaviour resulting from car-reducing measures, and how can these changes in travel behaviour be split out for different socio-demographic groups?
2. To what extent does the selected approach reproduce realistic travel behaviour, and how can its behavioural performance be improved through calibration?
3. How does the Hofplein redesign effect travel behaviour in terms of mode choice, route choice, and trip generation, including the decision to forgo trips?
4. Which population groups are most sensitive to the Hofplein intervention and how do they adapt their travel behaviour?

1.6. Thesis outline

This thesis is structured as follows.

Chapter 2 reviews the literature on car-reducing transport measures and travel behaviour. It discusses the range of behavioural responses that may occur following changes to road capacity, including modal shift, route choice adaptation, destination changes, and trip suppression. The chapter also examines differences in responses across population groups and reviews methodological approaches for analysing behavioural change, with particular attention to activity-based transport models.

Chapter 3 introduces the Hofplein case study. It describes the area's historical development, transport system and policy context within Rotterdam's mobility strategy, before presenting the planned intervention. Finally, observed traffic intensities before and during the intervention are analysed to provide insight into its real-world traffic impacts.

Chapter 4 presents the methodology used to address Sub-question 1. It describes the modelling framework, including the choice for ActivitySim, the synthetic population, and the traffic assignment model, as well as the scenario design and model evaluation and calibration procedures. The chapter concludes by introducing the persona-based approach used to analyse socio-demographic differences in behavioural responses.

Chapter 5, *Model Behaviour Analysis and Calibration*, addresses Sub-question 2 by evaluating the behaviour of the model. The chapter presents the results of the sensitivity analysis, examines travel-time elasticities, and discusses the outcomes of the calibration procedure. The performance of the model is subsequently assessed against findings reported in the literature.

Chapter 6 presents the main results of the study and addresses Sub-questions 3 and 4. The chapter first discusses the traffic assignment outcomes. It then analyses the behavioural responses resulting from the intervention, including changes in mode choice, route choice, destination choice, and activity participation. Finally, the chapter presents the results of the persona analysis, highlighting differences in behavioural adaptation across traveller groups.

Chapter 7 discusses the findings and their broader implications. The chapter reflects on the implications of car-reducing measures for transport policy, and discusses the opportunities and challenges of using activity-based transport models for policy evaluation. It also examines the key assumptions and limitations of the modelling approach and provides recommendations for future research.

Chapter 8 concludes the thesis by answering the research questions and synthesising the key findings. The chapter also discusses the broader relevance of the results for urban transport planning.

2

Literature review

This chapter reviews the literature relevant to this thesis. It starts by explaining the literature review methodology, followed by background on car-reducing measures. The chapter then discusses different types of travel behaviour responses, including modal shift, rerouting, and trip suppression. Differences across population groups and equity impacts are also examined. Next, methods for studying travel behaviour change are reviewed, with a focus on transport modelling and activity-based models. The chapter concludes with the main insights from the literature.

2.1. Literature review methodology

To obtain a thorough understanding of the existing research on car-reducing measures, a systematic and sufficiently detailed literature review was conducted. The search method was guided by the framework proposed by Van Wee and Banister (2024), and the main databases used to identify relevant literature were Google Scholar and Scopus.

The review was carried out in several stages, each focusing on a specific aspect of car-reducing measures. First, studies analysing the occurrence and effects of such measures were identified using keywords such as ”car-reduced”, ”car-reducing measures”, and ”car-lite”. Building on this, literature examining their observed impacts was reviewed using terms such as ”disappearing traffic” and ”traffic evaporation”. Subsequently, the underlying behavioural mechanisms were explored through keywords including ”modal shift”, ”traffic rerouting”, and ”transport poverty”. Attention was then given to studies on heterogeneity in travel behaviour across population groups, using search terms such as ”transport equity”. Finally, to support the methodological approach of this thesis, additional literature was identified using keywords such as ”transport modelling”, ”activity-based”, and ”activity-based modelling”.

For all search stages, both backward and forward snowballing techniques (Van Wee & Banister, 2016) were applied to identify additional relevant studies based on the reference lists and citations of the selected papers.

2.2. Car-reducing measures

Urban transport systems play a central role in shaping cities. In the past century, car use has become dominant in many urban areas, providing flexibility and accessibility, but also generating a range of negative externalities. As cities aim to become more sustainable, the private car in urban environments has come under growing scrutiny. This section examines the reasons for car-reducing measures, the different types of measures that can be implemented, and their observed effects.

2.2.1. Reasons for car reduction

The negative externalities associated with car traffic effect human health, the environment, and overall societal well-being in several ways, which will be discussed in this section.

Motorised vehicles have a substantial impact on human health. Road traffic is a major source of urban air pollution, which is strongly linked to respiratory and cardiovascular diseases (WHO, n.d.). What

makes this particularly concerning is that exposure during travel is disproportionately high: although people spend only 6% of their time in transport, it accounts for 21% of their total exposure and around 30% of their inhaled dose of harmful black carbon particles (Dons et al., 2012). On top of that, traffic noise adds another layer of harm, as long-term exposure has been associated with sleep disturbances, increased stress, anxiety, and higher risks of cardiovascular disease (Yavuz et al., 2024).
Beyond these long-term health effects, motorised transport also leads to immediate and severe consequences through traffic crashes. Together with pollution linked to automobility, these impacts are estimated to account for approximately one in every 34 deaths worldwide (Miner et al., 2024). Taken together, this underscores the substantial human cost of car-dominated transport systems, effecting both everyday health and the risk of premature death.

Furthermore, car use contributes to broader environmental problems, most notably climate change. The transport sector is a major source of greenhouse gas emissions, accounting for approximately a quarter of total CO_2 emissions in the European Union in 2019. It is also the only sector in which emissions have increased over recent decades (European Parliament, 2019). In addition to emissions, the extensive spatial requirements of car infrastructure reduce opportunities for green space, public areas, and alternative transport modes. This negatively effects urban liveability and limits the potential for more sustainable urban environments.

These impacts are also reflected in the broader societal costs of car use. From an economic perspective, each kilometer traveled by car imposes a social cost of approximately €0.50, which is more than six times higher than the cost of cycling (€0.08 per kilometer) (Gössling & Choi, 2015). These costs include impacts related to pollution, congestion, infrastructure use, safety, and health damage.

Taken together, these externalities highlight the wide-ranging societal impacts of car use. Because these effects manifest across multiple domains and scales, reducing car use is increasingly considered a necessary policy response to address these challenges (Nieuwenhuijsen, 2020). The potential benefits of car-reducing measures are therefore commonly discussed across multiple domains, including environmental quality, public health, social equity, and urban liveability (Mouratidis, 2025). Empirical evidence from case studies supports this perspective, showing that such measures can lead to improvements in air quality, reductions in noise exposure, increased green space, and higher levels of physical activity (Nieuwenhuijsen, 2021).

2.2.2. Types of car-reducing measures

In response to these challenges, a wide range of policy measures has been developed to reduce car use. These measures have become increasingly prominent in European cities, as well as in Dutch municipalities (KiM, 2023). However, the academic debate on car-use reduction has a longer history. Earlier work by Priemus (1995) distinguishes four broad categories of policy instruments: (1) push measures that discourage car use, (2) pull measures that improve alternative modes, (3) physical planning interventions, and (4) communication-based strategies.

Building on this earlier classification, a more recent report on car-reducing measures in the Netherlands by Jorritsma et al. (2023) adopts a more spatially oriented perspective. It distinguishes three main categories: changes in the built environment (such as densification and mixed-use neighbourhoods), changes in parking facilities (including the removal of parking spaces and increases in parking prices), and changes to roads and streets (such as street redesigns, lowering traffic speeds, or restricting car access entirely).
Since the redesign of the Hofplein serves as the case study for this research and falls within the category of changes to roads and streets, the remainder of this study focuses specifically on measures that physically reallocate space from cars to other modes of transport.

2.2.3. Traffic evaporation

As these measures are increasingly implemented, a key question concerns their effectiveness in actually reducing car use. While it was previously assumed that reducing road capacity would primarily lead to increased congestion, growing empirical evidence shows that total traffic volumes often decline instead. This phenomenon, commonly referred to as *traffic evaporation* or disappearing traffic, can be understood as the opposite of induced demand (Cairns et al., 2002; van Heyningen et al., 2025). Evidence from real-world interventions supports this effect. For instance, street redesigns in Barcelona

led to a 23% reduction in traffic volumes on intervention streets in absolute terms, and a 14% reduction relative to comparable control streets (Nello-Deakin, 2022). Similarly, in the Netherlands, a pilot project involving a “knip” on the Weesperstraat in Amsterdam resulted in an 18% decrease in the number of unique cars, alongside a 10% reduction in vehicle kilometres travelled (Municipality Amsterdam, 2024). These findings suggest that road reallocation projects do more than simply displace traffic; they can fundamentally change travel behaviour. The mechanisms underlying these behavioural responses, such as changes in mode choice, rerouting and trip suppression, are explored in more detail in Section 2.3. At the same time, these aggregate reductions may hide important differences between population groups, raising questions about who is able to adapt and who may be disproportionately effected.

2.2.4. Accessibility

The previous section demonstrated that reducing road capacity does not necessarily lead to a one-to-one redistribution of traffic. Instead, part of the traffic often disappears through changes in travel behaviour. To understand why travellers make these adjustments, it is necessary to consider the underlying mechanism through which car-reducing measures influence travel behaviour.

Road reallocation, as a class of car-reducing measures, primarily effects travel behaviour by reducing accessibility for car users. These measures increase travel times and congestion, making destinations more difficult to reach by car (Tennøy & Hagen, 2021). As accessibility declines, travellers may reconsider how, when, where, or whether they travel, ultimately producing the behavioural adaptations that contribute to traffic evaporation.

To understand these effects more precisely, it is first necessary to clarify what is meant by accessibility. Over time, numerous definitions and methods for evaluating accessibility have been developed, which has made the concept somewhat ambiguous (Bocarejo S. & Oviedo H., 2012). This lack of clarity was also noted by Geurs and van Wee (2004), who proposed the following overarching definition, which is adopted in this thesis:

> *Accessibility is the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s).*

This definition emphasises that accessibility is not a fixed value, but varies depending on the characteristics of individuals or groups. These variations are partly driven by socio-demographic differences, but also by the concept of perceived accessibility. Perceived accessibility captures how accessible a transport system is experienced at the individual level. Unlike objective measures, it incorporates personal perceptions and experiences (Van der Vlugt et al., 2019). This distinction becomes particularly relevant when implementing car-reducing measures. While objective accessibility may change in measurable ways, perceived accessibility among car users can decline more sharply when their available travel options are restricted. This effect is likely to be strongest for frequent car users, who already rely less on sustainable transport modes (Lättman et al., 2020).

2.3. Travel behaviour responses to car-reducing measures

The effectiveness of car-reducing measures ultimately depends on how travellers respond to the changes in accessibility these interventions create. If accessibility by car declines, travellers must adapt their behaviour in order to maintain participation in daily activities. A key question, therefore, is which types of behavioural responses emerge when car-reducing measures are implemented. Nello-Deakin (2022) identifies three broad categories:

(1) Modal shift

(2) Trip rerouting

(3) Trip suppression

The latter can take multiple forms, including changes in destination, working from home, or the complete elimination of trips. A similar, but more detailed, framework is provided by Hunt et al. (2002), which distinguishes a wider range of possible responses, including changes in driving behaviour (increased speeds or shorter headways), route choice, departure times, mode choice, trip origin or destination, and trip chaining, as well as full trip elimination.

This research adopts the framework of Nello-Deakin (2022) as a primary structure for simplicity and clarity. At the same time, it recognises that the category of trip suppression encompasses several of the more detailed behavioural responses identified by Hunt et al. (2002), such as changes in departure time, trip chaining, and trip elimination. In this section, these potential behavioural responses are evaluated in terms of their likelihood of occurrence and their effects, based on existing literature.

2.3.1. Modal shift

Promoting a modal shift away from private car use toward more sustainable modes of transport is often a central objective of many car-reducing measures. These policies typically combine two complementary strategies: push measures that reduce the convenience or attractiveness of car use, and pull measures that enhance the appeal of alternatives such as walking, cycling, and public transport (Adamidis et al., 2025; Batty et al., 2015).

Evidence on the effectiveness of these strategies in achieving substantial modal shift remains mixed. Several studies nevertheless report positive behavioral responses to well-designed interventions. In Brussels, for example, the introduction of pedestrian zones led 36% of surveyed residents to change their transport choices when visiting the city center, with about 15% increasing their use of public transport (Keserü et al., 2018). More broadly, pedestrianisation is widely regarded as an effective instrument for limiting car use while simultaneously improving the quality of pedestrian environments (Batty et al., 2015).

At the same time, the literature highlights important limitations to the effectiveness of car-reducing measures. Reducing space for cars in isolation, without complementary investments in alternative modes, often fails to induce meaningful changes in travel behavior (Jorritsma et al., 2023). Even when street redesign redistributes space to pedestrians, cyclists, or public transport, observed modal shifts are sometimes modest (Hagen & Tennøy, 2021). This is partly explained by the strong influence of individual preferences and social factors on modal choice: research in highly accessible, walkable, and transit-oriented areas shows that nearly one-third of residents continue to identify as habitual car users, suggesting that car use often reflects personal preference rather than necessity (Núñez et al., 2024). In addition, socio-demographic characteristics shape individuals' willingness to adapt their travel behavior. Evidence from the "Madrid Central" low-emission zone indicates that low-income respondents (earning less than €1,300 per month) are more likely to reduce or abandon private car use than higher-income groups, while households with dependent children, elderly relatives, or persons with disabilities tend to continue using private vehicles due to specific mobility needs (Tarriño-Ortiz et al., 2022).

Importantly, even when substantial modal shift is limited, car-reducing measures often generate broader benefits. These include environmental improvements, enhanced traffic safety, and more positive experiences of urban space (Batty et al., 2015). Similarly, such interventions can increase commute satisfaction and perceived accessibility for walking and cycling, even if changes in mode choice remain modest, while conditions for car users may become less favorable (Hagen & Tennøy, 2021).

2.3.2. Trip rerouting

Another possible behavioural response is trip rerouting, whereby travellers adjust their routes to avoid the intervention area. This type of behaviour is often considered undesirable, as it can shift traffic to alternative routes rather than reducing overall car use. In this context, an important distinction arises between local and supra-local effects. While interventions may successfully reduce car traffic within a specific street or neighbourhood, they can simultaneously displace traffic to adjacent areas (Jorritsma et al., 2023). For instance, road closures or access restrictions can lead to detour traffic along alternative routes. As a result, the local benefits of reduced traffic may be partly offset by increased pressure on other parts of the urban road network.

However, empirical evidence on the extent of such rerouting effects is limited. In a study of interventions in Barcelona, the observed impacts were relatively limited. Traffic increased slightly on streets immediately adjacent to the intervention area (approximately +2%), while traffic levels on other streets within a wider 500 m buffer did not differ significantly from those in the control group (Nello-Deakin, 2022). These findings indicate that rerouting does occur, but is not necessarily the dominant behavioural response.

2.3.3. Trip suppression

Beyond modal shift and rerouting, car-reducing measures may also lead travellers to forgo trips altogether. This is commonly referred to as *trip suppression* (Nello-Deakin, 2022). In practice, this can happen in several ways. For this research, three forms are considered: changes in trip origin or destination, increased use of trip chaining, and complete trip elimination.

Among these, trip elimination is particularly relevant from an equity perspective. It means that people decide not to make a trip at all because travelling by car has become less accessible or less convenient. In such cases, individuals may no longer be able to reach certain activities. While the link between car-reducing measures and transport poverty is not yet well established, it is occasionally mentioned in the literature. it is addressed explicitly in a master's thesis by Knaap (2022), while Nello-Deakin (2020) questions implications for social equity due to car-reducing measures. This is however an important concern, as access to key destinations, such as work, is essential for participation in society. For instance, car ownership has been shown to significantly increase employment probabilities, particularly among welfare recipients (Bastiaanssen et al., 2020).

In this light, trip suppression can be seen as one of the mechanisms through which transport poverty may emerge or intensify. Transport poverty is increasingly understood as a situation in which people struggle to access essential activities due to limited transport options, high travel costs, or personal constraints. In the Netherlands, an estimated 113,000 to 270,000 households face a combination of low income and high fuel costs, placing them at increased risk of transport poverty (Dalla Longa et al., 2024).

Rather than being a single issue, transport poverty is typically described as a combination of related challenges (Lucas et al., 2016), including:

- transport affordability: being unable to afford transport costs,
- mobility poverty: having limited access to motorized transport,
- accessibility poverty: experiencing difficulties in reaching key destinations.

Taken together, these dimensions point to a broader understanding of transport poverty as the difficulty or inability to access activity locations due to inadequate transport options (both in objective terms and as perceived by individuals) combined with socio-demographic and spatial conditions, and personal capabilities. As a result, people effected by transport poverty may participate less in social and economic life, which in turn negatively effects their quality of life (Jorritsma et al., 2018).

Car-reducing measures can potentially amplify these challenges when alternatives to the car are not sufficiently accessible, affordable, or reliable. This is especially the case for people who depend heavily on car use in their daily lives. Transport poverty also tends to effect certain groups more than others (Dorantes & Murauskaite-Bull, 2023). These differences are shaped by factors such as income, age, gender, employment and housing situation, health or disability, and migration background. Spatial patterns also play a role, as vulnerable groups are often concentrated in large urban areas or in regions facing population decline (Jorritsma et al., 2018).

Although transport poverty is not the primary focus of this study, it remains an important aspect to consider. Research shows that policies and analyses tend to lead to better outcomes when the needs of vulnerable groups are explicitly taken into account, even when transport poverty itself is not the central objective (Dorantes & Murauskaite-Bull, 2023).

2.4. Differences across population groups and equity impacts

While the societal benefits of reducing car use are well established, as discussed in Section 2.2, many studies pay limited attention to how the impacts of these measures are distributed across society and experienced by individual travellers (Mouratidis, 2026). This highlights the importance of explicitly considering equity when evaluating car-reducing measures.

From an equity perspective, assessing whether a transport system is fair requires identifying which groups are most likely to be disadvantaged and understanding how they respond to changes in accessibility (Martens et al., 2019). As discussed in Section 2.3, behavioural responses such as modal shift,

rerouting, and the risk of transport poverty are strongly influenced by socio-demographic characteristics. Consequently, different population groups may experience and respond to car-reducing measures in fundamentally different ways.

To understand these differences, equity analyses often consider a wide range of interrelated socio-demographic factors. These include individual characteristics such as income, gender, age, ethnicity, disability, and nationality (Cludius et al., 2024), as well as household and contextual variables such as household composition, car availability, and place of residence (Di Ciommo & Shiftan, 2017). In addition, particular attention is frequently given to vulnerable groups, including children, older adults, single-parent households, low-skilled workers, ethnic minorities, and people with physical or mental impairments (Martens et al., 2019).

Among these factors, income plays a particularly important role. Income directly influences people's travel opportunities and is closely related to other determinants of accessibility, such as car ownership (Dargay, 2001). Car ownership is especially relevant in cases of involuntary carlessness, where the absence of a car can substantially limit access to daily activities (Brown, 2017). These challenges are often reinforced by spatial patterns. Lower-wage employment, for example, is more commonly located in peripheral areas such as industrial zones, whereas higher-income jobs tend to cluster in more accessible urban locations. This spatial mismatch can further exacerbate accessibility inequalities (Bastiaanssen et al., 2025).

Demographic characteristics such as age and gender also influence vulnerability to transport disadvantage. Older adults, particularly those experiencing declining mobility, often reduce both the number and length of their trips, making them more vulnerable to transport poverty (Schmöcker et al., 2005). Young people may face disadvantages as well, especially those not enrolled in higher education and therefore lacking access to subsidised public transport options (Lucas et al., 2016). Gender further shapes these patterns. Women are generally more likely to experience transport-related disadvantages due to safety concerns and broader social barriers associated with accessing and using public transport (Roy et al., 2024). Although these challenges are most extensively documented in the Global South (Iqbal et al., 2020), evidence from developed countries also points to persistent gendered inequalities in transport systems (Balarezo et al., 2025).

Migration background can further contribute to accessibility inequalities (Awaworyi Churchill, 2020). In the Dutch context, individuals with a migration background have been associated with lower levels of both car ownership and bicycle use, potentially increasing their vulnerability to transport disadvantage (Harms, 2006). Together, these findings demonstrate that accessibility outcomes are shaped by a combination of socio-demographic characteristics rather than by any single factor in isolation.

Given the wide range of factors that may influence the equity impacts of car-reducing measures, it is necessary to make a selection for the analysis. Although no set of variables can fully capture all dimensions of transport equity, the literature suggests that the following factors are among the most relevant determinants of travel behaviour and accessibility outcomes:

- Income
- Car ownership
- Age
- Gender
- Migration background

However, as illustrated throughout this section, these characteristics are closely interconnected. Travel behaviour is rarely shaped by a single socio-demographic attribute, but rather by the interaction of multiple factors. Analysing each variable separately may therefore overlook important behavioural differences between travellers. To better capture this complexity, a persona-based analysis is a promising approach. By grouping individuals according to a combination of socio-demographic and mobility-related characteristics, personas provide a more holistic representation of travel behaviour and offer richer insights into how different population groups respond to car-reducing measures.

2.5. Methods for studying travel behaviour change

Methods used to study changes in travel behaviour can broadly be divided into qualitative and quantitative approaches. Qualitative methods such as interviews and focus groups aim to understand underlying motivations, perceptions, and decision-making processes (Clifton & Handy, 2003). Quantitative methods, by contrast, use numerical data and statistical or modelling techniques, including econometric analyses, panel studies, and choice models, to explain and predict behaviour as the outcome of structured decision processes (McFadden, 1977).

Given the focus of this research on behavioural responses to car-reducing measures, a quantitative approach is adopted. The central question is how travellers respond when road capacity is reduced and, in particular, where their car trips go. While surveys and panel studies provide valuable insights into observed behavioural changes, they require the effected individuals to be identified and surveyed. In the case of Hofplein, however, the travellers whose behaviour will change are not known beforehand. Capturing these system-wide responses therefore favours a modelling approach. This choice is further supported by the need identified in the literature for complementary methods beyond the predominantly survey- and panel-based evidence used to study travel behaviour change (Adamidis et al., 2025).

2.5.1. Transport modelling

Transport modelling is widely used to analyse the impacts of infrastructure and policy interventions before implementation. Because such projects are often costly and have long-lasting effects, policymakers rely on these models as decision-support tools. A transport model can be described as a simplified representation of reality that captures the key mechanisms of a transport system, with the aim of estimating how travel behaviour and overall system performance respond to different scenarios in a specified future year (Correia & Wee, 2023).

Within transport modelling, a fundamental distinction can be made between demand and assignment models. Demand models focus on explaining why and how people travel, including decisions such as destination choice, mode choice, and trip frequency. Assignment models, by contrast, analyse how travel is carried out within the transport network, focusing on route choice, travel times, and congestion patterns (Calvert et al., 2016).

As this research is primarily concerned with behavioural responses to car-reducing measures, demand models are the most relevant modelling approach due to their closer link to individual decision-making. Within this category, a further distinction can be made based on the level of behavioural detail. Aggregate models describe travel demand at the level of zones, focusing on average flows rather than explicitly modelling individual choices. Disaggregate models, in contrast, represent behaviour at the level of individuals or households and are typically based on random utility theory, allowing heterogeneity in preferences and constraints to be captured more explicitly. As a result, disaggregate approaches generally provide a more behaviourally realistic representation than models that group behaviour at the zonal level (Ortúzar & Willumsen, 2024).

2.5.2. History of transport models

The distinction between aggregate and disaggregate approaches reflects a broader evolution in transport demand modelling. Early models were largely aggregate and mathematical in nature, such as gravity models. These were followed by trip-based models that relied more heavily on observed data and later evolved to include tour-based representations in order to better capture behavioural patterns. This modelling paradigm is still widely applied in practice today, particularly in the form of the four-step model (Sivakumar, 2007). However, because travel demand is ultimately derived from the need to participate in activities, more recent developments have shifted towards activity-based models.

2.5.3. Activity-based models

Building on these developments, activity-based models offer a more behaviourally consistent representation of travel demand. Rather than modelling trips in isolation, they capture travel as part of a broader pattern of daily activities. This allows for a more realistic representation of how individuals organise their travel and adapt their behaviour.

As a result of this stronger behavioural foundation, activity-based models are particularly well suited to evaluating policy measures that effect not only route or mode choice, but also travel timing, destina-

tion choice, and overall activity patterns (Correia & Wee, 2023). However, their application in practice remains limited due to their complexity, high data requirements, and the substantial effort needed for development and calibration (Miller, 2023).

Despite these challenges, the richness of activity-based models is a key strength for this research. In particular, they provide detailed outputs on how travel-related benefits and disadvantages are distributed across different population groups, which supports equity analyses (Castiglione et al., 2015). This is directly aligned with the objectives of this thesis, which aims to examine how car-reducing measures effect travel behaviour differently across socio-demographic groups. For this reason, an activity-based modelling approach is considered most appropriate for addressing the research question.

2.6. Current state of activity-based modelling

Following the introduction of activity-based models in the previous section, this section provides a more detailed discussion of their conceptual foundations and current developments.
Activity-Based Modelling (ABM) is commonly defined as a subclass of agent-based models (Drchal et al., 2016). A key distinguishing feature of ABM lies in its explicit representation of the link between activities and travel demand. Whereas traditional trip-based models, such as the four-step model, treat trips as independent entities, activity-based approaches conceptualise travel as the outcome of a sequence of interrelated activities. This perspective allows for a more behaviourally grounded representation of travel decisions and enables a more comprehensive assessment of transport policies (McNally, 2000).

2.6.1. Prominent activity-based models

The core idea behind the ABM framework was introduced by Ben-Akiva et al. (1996). At its heart, the framework describes the different levels of decisions individuals make, as shown in Figure 2.1.

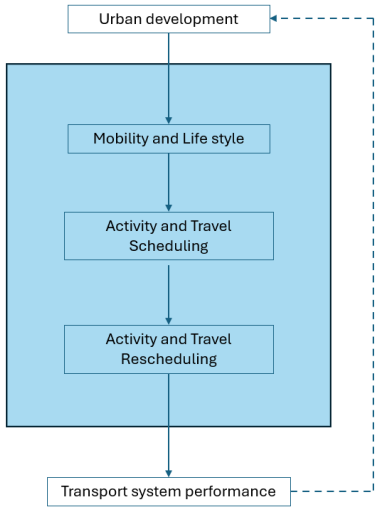


Figure 2.1: Base framework for activity-based models (Ben-Akiva et al., 1996)

Figure 2.1 gives a clear overview of how an ABM works. It starts with long-term mobility and lifestyle decisions, which are shaped by urban development, or more generally, where certain locations are. This includes choices such as what kind of job someone has and where it is located, where they live, and whether they have a driver's licence and/or access to a car.
The next level focuses on activity and travel scheduling. Here, individuals decide what they do on a day-to-day basis: where they travel, which mode they use, and when and how they make their trips. After that, travellers may still reschedule their plans in response to traffic conditions. Together, these decisions determine how the transport system ultimately performs.

While this description is quite straightforward, in reality, these decisions are not made strictly sequentially, as Figure 2.1 might suggest. Instead, there are important feedback loops between them. A good example is the way Ben-Akiva et al. (1996) describes the process of building a daily activity schedule,

shown in Figure 2.2. This essentially zooms in on the activity and travel scheduling decision-making process shown in the previous figure.
In this process, a traveller determines which activities to perform. They then typically organise these into a primary tour, often centred around a main activity such as work or school. Additional (secondary) tours may also be included. What is important here is that the arrows go both ways: the ease of making certain tours (accessibility) can actually influence which activities are chosen in the first place.

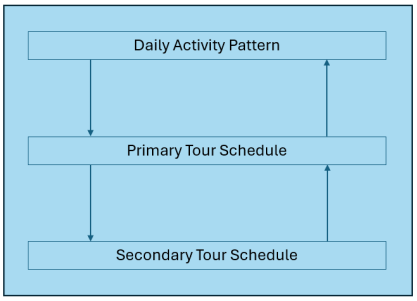


Figure 2.2: Feedback in scheduling (Ben-Akiva et al., 1996)

Since this foundation was established, many ABMs have been developed. These are commonly grouped into two broad categories: models based on Random Utility Maximization (RUM) and rule-based Computational Process Models (CPM) (Tajaddini et al., 2020). Some models, most notably MATSim (Horni et al., 2016), are difficult to place neatly within either category and are often treated as a separate agent-based approach.

RUM-based models represent behaviour by comparing different alternatives and assigning each a "score" based on factors such as travel time, cost, and personal characteristics. Choices are then made probabilistically, with higher-scoring options being more likely to be selected. ActivitySim (Galli et al., 2009) follows this approach by evaluating choices in a sequence of interconnected steps within a simulation framework, enabling relatively detailed decision-making. Similarly, CEMDAP (Bhat et al., 2004) adopts an econometric approach based on the same underlying principles, while FAMOS (Pendyala et al., 2005) extends this framework by incorporating constraints related to time and available resources. Although these models differ in their level of detail and implementation, they share the objective of estimating the likelihood of choices based on observed behaviour. Within this group, ActivitySim stands out due to its modular structure, which makes it relatively straightforward to adjust or extend individual components while maintaining a consistent overall framework.

In contrast, CPM-based models take a different perspective on decision-making. They model behaviour as a sequence of processes governed by predefined or learned rules. These rules determine how decisions are made in specific contexts and how different choices are linked over time. For example, ALBATROSS (Arentze & Timmermans, 2004) constructs daily schedules through a sequence of dependent decisions. FEATHERS (Bellemans et al., 2010) extends this line of research by allowing greater flexibility in updating model components, while ADAPTS (Auld & Mohammadian, 2012) focuses more explicitly on modelling the timing and ordering of decisions. However, CPM-based models typically require the explicit specification of decision rules, their structure, and their dependencies. This increases model complexity and calibration effort, which can make them less straightforward to adapt to new applications.

In summary, both RUM-based and CPM-based models describe how individuals choose between alternatives, but differ in how this process is structured. RUM-based models treat decisions as probabilistic choices based on utility, whereas CPM-based models represent decisions as part of a sequence of rule-based processes over time. While CPM approaches can capture decision-making in more detail, they are generally more complex to specify and calibrate. RUM-based models therefore offer a more viable balance, especially for large-scale applications. For this reason, ActivitySim is adopted in this thesis as the primary modelling framework to analyse behavioural responses to car-reducing measures. The following section provides a more detailed description of ActivitySim and its underlying structure.

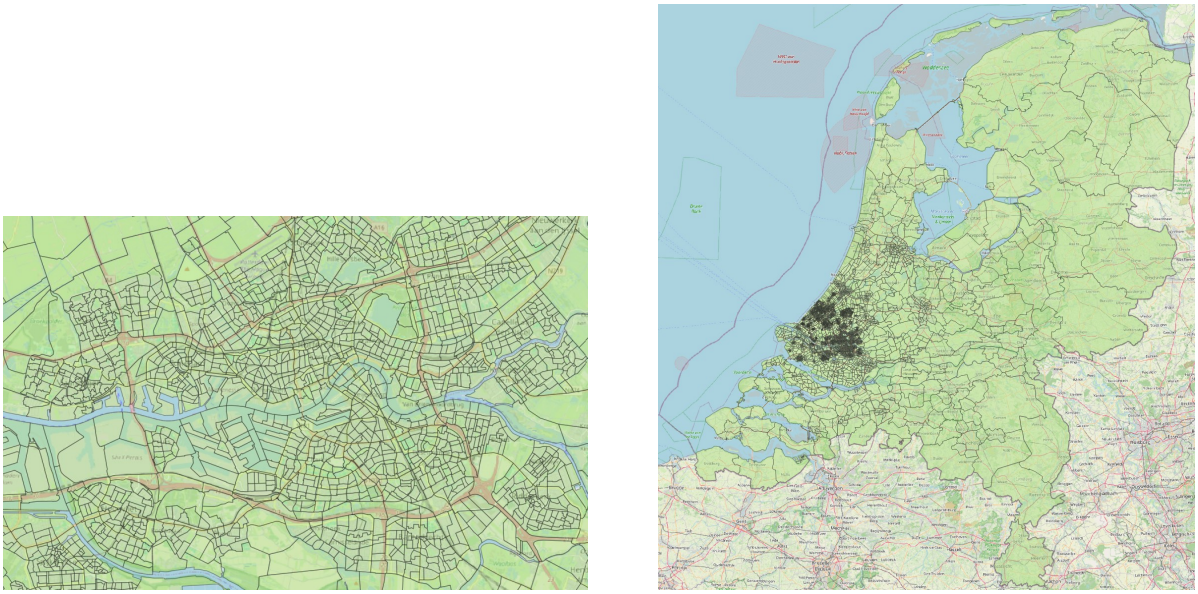
2.6.2. ActivitySim

ActivitySim (Galli et al., 2009) is an open-source, activity-based model that is adopted by multiple transportation agencies. As a RUM-based model, it represents individual decision-making through a series of connected discrete choice models. This allows daily activity and travel patterns to emerge from individual behaviour, rather than being imposed through aggregate assumptions.

The synthetic population used in ActivitySim is generated by combining population data with Iterative Proportional Fitting (IPF). This approach ensures that the distribution of socio-demographic attributes in the synthetic population matches the real world. In this study, the synthetic population represents the expected population of the MRDH region in the year 2030, as described by Snelder et al. (2021).

Travel behaviour in ActivitySim is represented using discrete choice models based on random utility maximization (RUM). As a result, behavioural choices are formulated using multinomial logit and probit models (Zhou et al., 2023). The utility function consists of an alternative specific constant, a linear combination of attributes that are specific to each alternative (such as travel time or cost), and a linear combination of attributes that are specific to the traveler. Most model components in ActivitySim are estimated using multinomial logit models, however, multinomial probit models are used for more complex choices, most notably trip mode choice (Zhou et al., 2023).
Trip mode choice is one of the more complex components in ActivitySim due to its explicit representation of multimodal travel options (Zhou et al., 2023). Unlike unimodal trips (where walking is typically used for access and egress), multimodal trips involve at least one additional access or egress mode. This structure enables the model to explicitly represent transfers and combinations of different transport modes.
This level of detail is particularly relevant for this study, as car-reducing measures may influence not only the choice of a main transport mode, but also how travellers combine different modes within a trip. ActivitySim's modelling framework makes it possible to capture whether and to what extent this occurs.

Within ActivitySim, the study area is subdivided into Traffic Analysis Zones (TAZs), which serve as the spatial units for modelling origin–destination flows. The spatial allocation of these TAZs is illustrated in Figure 2.3. Figure 2.3b presents the full set of TAZs distributed across the Netherlands, with a notable concentration in the MRDH region. A more detailed view of the TAZ structure within Rotterdam is shown in Figure 2.3a. Travel conditions between zones are represented using skim matrices. These matrices contain pre-computed generalized travel costs, travel times, and distances for each transport mode and are used as key inputs to the behavioural models.



(a) TAZs in Rotterdam

(b) All TAZs

Figure 2.3: Spatial allocation of the TAZs

ActivitySim relies on three main categories of input data, largely derived from the OViN (Onderzoek Verplaatsingen in Nederland), CBS microdata and the BGT (Basisregistratie Grootschalige Topografie) datasets. First, population data describes the socio-demographic characteristics of individuals and households. Second, land-use data captures the spatial distribution of activities within each TAZ, such as population, employment, and education. Third, level-of-service data represents travel times, costs, and distances between all TAZ pairs for each mode; this information forms the skim matrices used throughout the model.
Together, these data requirements make ActivitySim a data-intensive model, as its behavioural realism strongly depends on the availability and quality of the input data.

2.6.3. Applications of ActivitySim

ActivitySim has been applied in a variety of contexts, and these applications demonstrate its suitability for analysing changes in travel behaviour under a wide range of policy scenarios (My et al., 2024). In particular, these applications highlight the model's ability to capture heterogeneous responses to changes in both transport systems and land-use patterns.
At the same time, a notable limitation of ActivitySim is that accessibility is treated as static, as it is derived from pre-computed "skim" matrices, which represent travel times, costs, and distances between origin-destination pairs. As a result, the model does not explicitly capture dynamic traffic conditions, such as congestion formation or complex network interactions. This can limit its ability to fully represent feedback between travel demand and network performance.
To address this limitation, ActivitySim can be co-simulated with complementary models such as MATSim (Li et al., 2025). This integration enables a more realistic representation of congestion and network dynamics, improving the assessment of accessibility and the impacts of transport policies.

2.7. Conclusions from literature

This chapter has shown that car-reducing measures are increasingly justified by their potential to address the environmental, health, and societal impacts of car-dominated transport systems. Empirical evidence indicates that such interventions are generally effective in reducing car use, through traffic evaporation.
The literature identifies three main behavioural responses to these measures: modal shift, trip rerouting, and trip suppression. While modal shift is often a key policy objective, it is often limited without strong alternatives. Rerouting occurs but tends to remain modest, whereas trip suppression highlights the risk of reduced accessibility. Together, these patterns indicate that accessibility is a primary mechanism driving the behavioural impacts of car-reducing measures.
Importantly, these impacts are not uniform across the population. Differences in income, car ownership, age, gender and migration background shape how individuals are able to adapt. As a result, the effectiveness of car-reducing measures is closely linked to their equity impacts, as some groups may benefit while others face increased constraints or risks of transport disadvantage.

The literature therefore emphasises the need for a disaggregated and behaviourally detailed analysis. ABMs, such as ActivitySim, are particularly suitable for this purpose, as they capture individual decision-making processes and allow for the analysis of heterogeneous behavioural responses, accessibility changes, and interactions between activities and travel. When properly calibrated, these models are well suited to represent behavioural responses to transport interventions and to compare travel behaviour before and after implementation.
However, existing studies largely remain focused on aggregate outcomes and therefore provide limited insight into how individual behavioural responses differ across socio-demographic groups in the context of car-reducing measures. As a result, the extent to which these measures (such as the redesign of the Hofplein) lead to different adaptations in travel behaviour, and potentially unequal impacts, remains insufficiently understood.

3

Case study: Hofplein

This chapter describes the Hofplein case study. It first outlines the historical development of the area, followed by an overview of the current transport system. The chapter then discusses relevant urban policies that shape the intervention. In addition, the planned intervention at Hofplein is described, which forms the basis for the scenario analysis in this study. Finally, observed traffic intensities before and during the intervention are analysed to provide insight into its initial impacts.

3.1. History

Hofplein is one of the most recognisable squares in Rotterdam and occupies a central position in the city's transport network. Today, it is dominated by traffic, with more than 30,000 motor vehicles passing through the square each day, in addition to trams, cyclists, and pedestrians. In many ways, Hofplein reflects Rotterdam's broader reputation as one of the more car-oriented cities in the Netherlands.

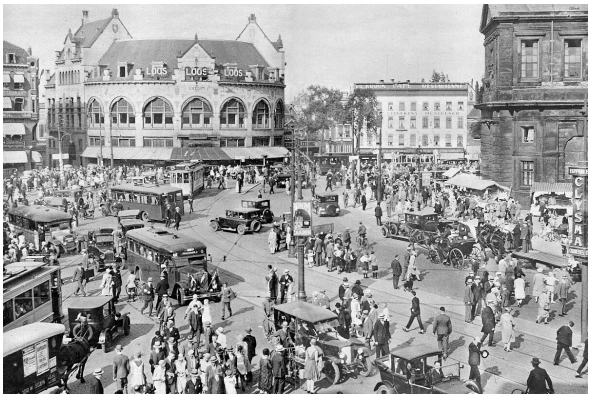
This dominant role of car traffic is not a coincidence, but the result of how the area has developed over time. To understand why Hofplein takes its current form, it is therefore necessary to look at its historical development, which is closely tied to the evolution of Rotterdam itself. The square takes its name from the Hofpoort, one of the former city gates that was demolished in 1833 (Engelfried, 2017), marking its origins as an access point to the historic city.

Building further on this early history, it becomes clear that Hofplein has changed significantly over time. Before the Second World War, Hofplein looked very different from today. It was a dense and lively space where pedestrians, trams, and other forms of traffic came together. Although the square was already busy, cars were not yet the dominant mode of transport. Based on historical images, it can be described as relatively car-light, with a strong presence of public transport and walking. At the same time, this mix of flows made the space complex and sometimes chaotic, especially during peak hours (Figure 3.1a). Even before the war, there were plans to reorganise the square to improve its functioning, but these were never realised.

The bombing of Rotterdam in May 1940 marked a clear turning point in the development of Hofplein. Large parts of the city were destroyed, including the area around the square. This created an opportunity not just for reconstruction, but for a fundamental rethinking of the urban layout. During this process, Hofplein was slightly relocated to the west (Blok, 2014), allowing planners to redesign it almost entirely from scratch.

The design that was implemented, completed in 1952 (Platform Wederopbouw Rotterdam, n.d.), reflects the dominant planning ideas of that time. Hofplein was transformed into a large roundabout, explicitly designed to accommodate increasing levels of car traffic. While the well-known fountain was introduced as a central element, the primary function of the space shifted towards facilitating traffic flow. Compared to the pre-war situation, this represents a clear break: a previously mixed and lively urban space was reorganised into a traffic-oriented intersection. This transformation aligns with broader post-war planning trends, in which many cities prioritised accessibility for cars, shaping the car-dominated

structure that is still visible at Hofplein today.



(a) Rush hour at the Hofplein (1932)



(b) Aerial photo of the Hofplein (1932)

Figure 3.1: Hofplein before World War II (Rotterdamkaart.nl, n.d.)



(a) Newly reconstructed Hofplein (1955) (SERC, n.d.)



(b) Current Hofplein design (1968) (VanToen.nl, n.d.)

Figure 3.2: Hofplein after World War II

This historical development helps explain the present-day character of Hofplein. While the square originally functioned as a multimodal urban space, the post-war reconstruction increasingly prioritised the accommodation of motorised traffic. The current dominance of car traffic is therefore not the result of a gradual or inevitable process, but of deliberate planning choices. Even the design of the square reflected these ambitions, with the centrally positioned fountain intended to establish Hofplein as a prominent urban landmark. In this sense, Hofplein embodies a broader period in urban planning during which traffic circulation and accessibility for cars became leading design principles.
The planned redesign represents a shift away from these priorities. Rather than functioning primarily as a traffic junction, Hofplein is intended to become a more balanced and human-centred urban space again.

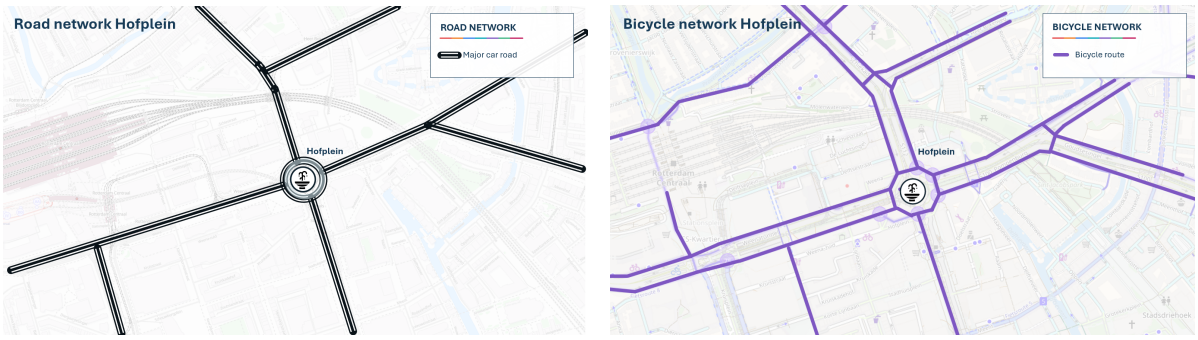
3.2. Transport system

As shown in the previous section, Hofplein has evolved into a central node within the urban transport network of Rotterdam. This section builds on that by examining how the square currently functions within this network across different transport modes. This is particularly relevant, as these modes rely on the same limited space and therefore directly interact and compete with one another. The backgrounds of the maps shown in this section are taken from OpenStreetMap.org (n.d.).

Roads and Active Mobility

The current transport system around Hofplein reflects the strong emphasis on car traffic. The square functions as a major intersection where several important roads meet, including the Coolsingel, Weena, Pompenburg, and Schiekade. As a result, it serves as a key connection within the road network of the city center. The design of the surrounding infrastructure reinforces this role, with street layouts aimed at handling large volumes of traffic and ensuring sufficient throughput of motor vehicles (Figure 3.3a).

For active modes, the infrastructure largely follows the structure of the car network. Separated bicycle paths are present along most of the main roads (Figure 3.3b), which results in relatively direct cycling connections. However, these routes remain closely tied to car-oriented corridors, which generally offer a less comfortable and attractive cycling environment.
For pedestrians, most streets are accessible, but the overall walking environment is less supportive. While it is possible to reach most destinations on foot, there are relatively few places that encourage staying or contribute to a high-quality public space. This reflects the fact that the area is primarily designed to accommodate motor vehicle traffic rather than to support active modes.



(a) Road network **(b)** Bicycle network

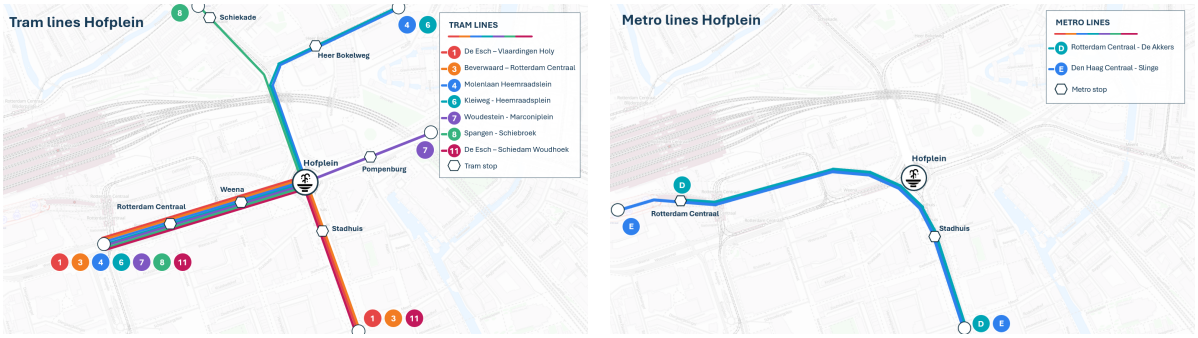
Figure 3.3: Car and bicycle infrastructure in proximity of Hofplein

Public transport

Public transport is also strongly present at Hofplein and can be understood by distinguishing between how different modes operate within the available space.

At street level, several tram lines pass directly through the square. Lines 1, 3, 4, 6, 7, 8, and 11 all approach from Rotterdam Central Station and cross Hofplein before continuing in different directions. As shown in Figure 3.4a, this makes the square an important node within the tram network, where multiple lines intersect and branch out across the city. The location of the stops further highlights the high level of accessibility by public transport in this area.

In contrast to the trams, the metro operates underground. Lines D and E pass beneath Hofplein, providing high-capacity connections across the city without competing for space at street level (Figure 3.4b). This separation allows the metro to function independently of the congestion and spatial constraints that hinder surface transport. Bus services are also present, such as line 38 between Schiedam Centrum and Crooswijk, although their role at this location is relatively limited compared to trams and metro.



(a) Tram network **(b)** Metro network

Figure 3.4: Public transport in proximity of Hofplein

Hofplein is also located close to Rotterdam Central Station, one of the busiest stations in the Netherlands, which served over 100,000 passengers per day in 2025 (NS, n.d.). However, a large share of these trips consists of longer-distance journeys and therefore does not directly translate into activity at the local scale of Hofplein.

Overall, Hofplein can be characterised as a location where multiple transport systems intersect, but with a clear dominance of car-oriented infrastructure. Different modes coexist within the same limited space, leading to direct competition between them. This makes Hofplein a suitable case for analysing how changes in the allocation of space, particularly those that reduce the role of cars, may influence travel behaviour and the functioning of the urban transport system.

3.3. Urban policy

With the historical development and the current transport system of Hofplein established, the next step is to look at the policy context in which the proposed intervention takes place. Understanding how the municipality of Rotterdam envisions the future of the city helps to place the Hofplein redesign into this wider context. This vision is outlined in the *Omgevingsvisie* (Municipality Rotterdam, 2021). This section therefore examines how the planned intervention at Hofplein fits within this vision.

A central concept within the *Omgevingsvisie* is “Green Growth”. In simple terms, this means that the city aims to continue growing, but in a way that improves sustainability and quality of life. Rather than focusing on a single goal, the municipality approaches this through different perspectives, aiming for a compact, productive, circular, inclusive, and healthy city (Figure 3.5). By combining these perspectives, the goal is to find more balanced solutions for urban development.



Figure 3.5: Green growth in Rotterdam (Municipality Rotterdam, 2021)

Many of these ambitions require changes in the way mobility is organised. For example, creating a compact and healthy city is difficult when a large share of urban space is dedicated to cars as they take up a lot of space and have negative effects on public health. The municipality therefore aims for a mobility transition, which can be understood as a shift in priorities between transport modes. In the

past, car traffic was typically given the most space, followed by public transport, and then active modes such as walking and cycling. In the new approach, this order is reversed, with more priority given to walking, cycling, and public transport (Figure 3.6).

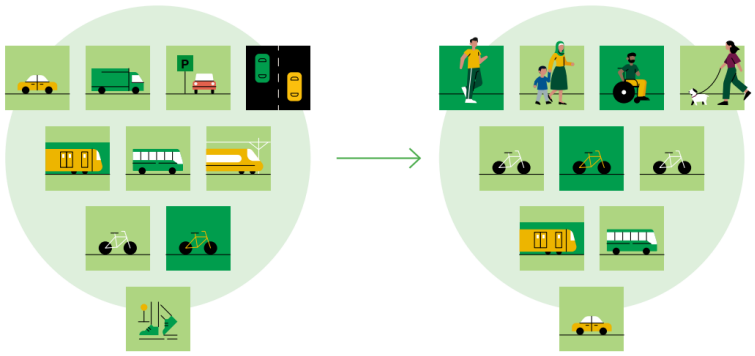


Figure 3.6: Mobility transition (Municipality Rotterdam, 2021)

These ideas are translated into concrete plans for the city centre, as illustrated in Figure 3.7. In this plan, the principles of Green Growth are applied spatially, with several areas designated for densification, particularly around locations such as Hofplein, while at the same time major car-oriented roads are reimagined as greener urban boulevards and intersections. The *Omgevingsvisie* states that by 2040 a connected network of these green boulevards and intersections should be realised, including key locations such as the Coolsingel and Hofplein (Municipality Rotterdam, 2021), showing that the Hofplein intervention is part of a broader transformation of the city centre rather than a stand-alone project.

In addition, Figure 3.7 identifies seven so-called “City Projects”, which are large-scale interventions aimed at improving the built environment, particularly in terms of liveability and quality of life. Hofplein is one of these seven projects (Municipality Rotterdam, n.d.-b; Stadmakerscongres, 2020), highlighting its importance within the overall plans of the municipality.

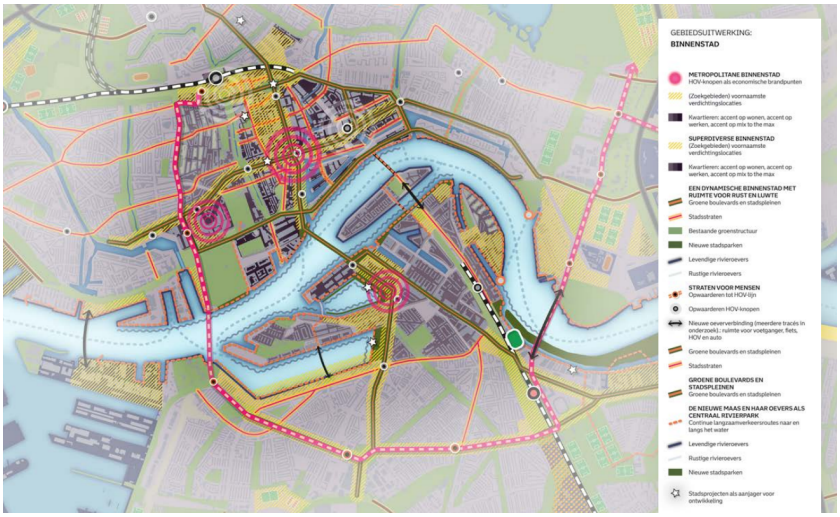


Figure 3.7: Area plan for the city center (Municipality Rotterdam, 2021)

3.4. Intervention

This section describes the Hofplein intervention. It discusses the planned physical changes to the square and the broader developments that accompany the transformation of the area. An overview of the redesign is shown in Figure 3.8.

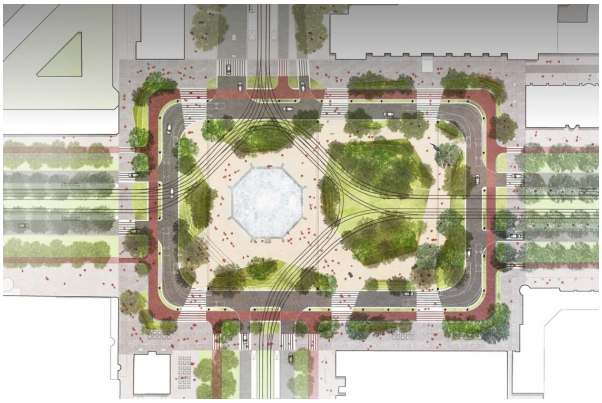


Figure 3.8: Hofplein Redesign (Juurlink+Geluk, 2020)

The intervention primarily involves a reallocation of space at Hofplein. The current layout, which is strongly oriented towards car traffic, is restructured to reduce space for cars and make room for other transport modes, greenery, and public space. As a result, the square shifts from mainly a traffic node to a more balanced urban space. These changes are driven by broader goals for the city. Reducing space for car traffic makes room for other functions and supports alternative transport modes, while the addition of greenery improves air quality, reduces heat stress, and makes the area more attractive to stay in.

The intervention is part of a broader set of measures in the city center. It is an integral part of the *Verkeerscirculatieplan* (VCP), which aims to reorganise traffic circulation by reducing car accessibility and improving conditions for walking, cycling, and public transport. Through changes in circulation patterns and the reallocation of street space, the VCP seeks to improve safety and overall liveability, while maintaining accessibility at the level of the wider network (Municipality Rotterdam, 2005).

New housing

The redesign of Hofplein takes place alongside substantial urban development in the surrounding area. Figure 3.9 illustrates how the redesigned square fits within these developments, with the orange buildings representing housing projects that are expected to be realised within the next five to ten years. According to the *Wonen in Rotterdam* website, which provides an overview of current and planned housing developments in the city (Municipality Rotterdam, n.d.-c), a total of 4,736 new dwellings are planned in the Hofplein area.

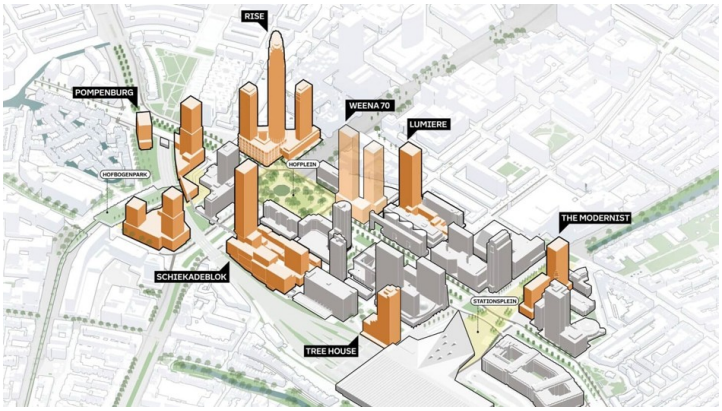


Figure 3.9: New dwellings surrounding Hofplein (Rotterdam Central District, 2023)

The combination of the spatial redesign and the planned housing development makes the intervention particularly relevant. The area will accommodate more residents in the coming years, while at the same time reducing the space available for car traffic. This increases the importance of alternative transport modes and creates a setting in which changes in travel behaviour can be expected.

Implementation
The intervention is being implemented in phases, with the planned phasing from June 2026 onwards shown in Figure 3.10. This approach ensures that the intersection remains accessible throughout construction. At the same time, car capacity is reduced early in the implementation process to a level that closely resembles the final design. As a result, road users are confronted with conditions similar to those of the completed project before construction is finished, allowing travel behaviour to gradually adapt. This also provides a unique opportunity to study behavioural responses under conditions that closely approximate the final situation. The implications of this are discussed further in the next section.

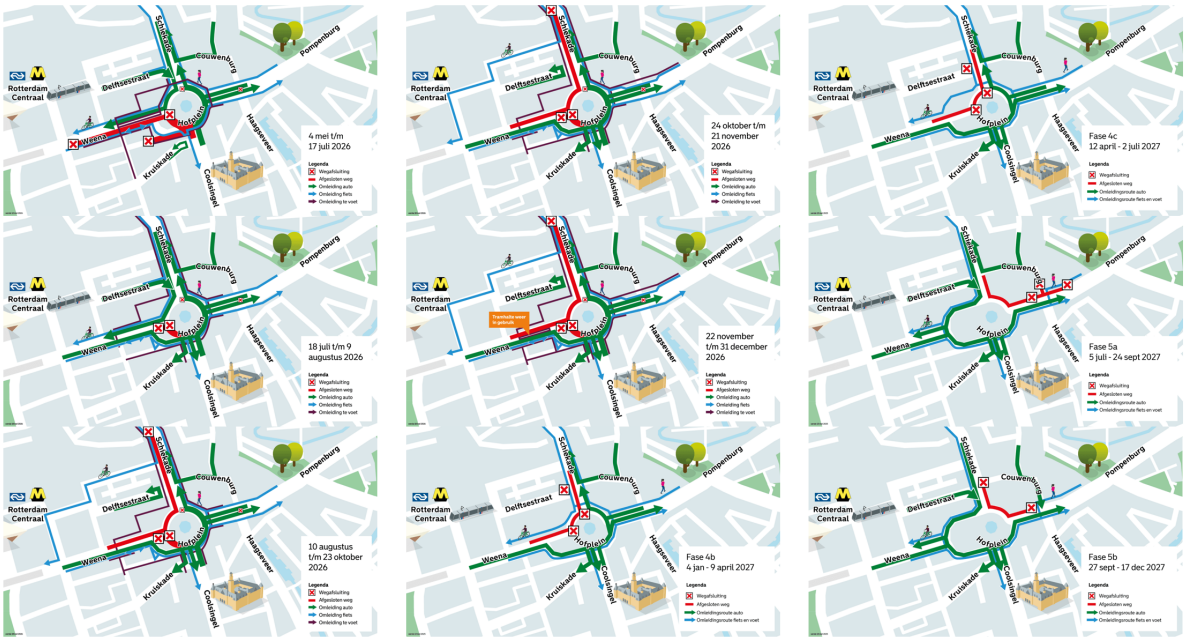


Figure 3.10: Phases of Hofplein intervention (Municipality Rotterdam, n.d.-a)

3.5. Traffic intensity

Before modelling the broader impacts of the Hofplein intervention, it is first useful to examine how traffic volumes actually changed following the early reduction in road capacity during the implementation phase. This section compares observed traffic counts before and during the intervention to quantify changes in the number of vehicles using the intersection. While changes in walking, cycling, and public transport use are also relevant, data on motor vehicle traffic are the most readily available and provide a direct indication of behavioural adaptation to the intervention. As such, motor vehicle traffic forms the primary focus of the analysis in this section.

Estimates of pre-intervention traffic volumes are available from several sources. In a letter from the *wethouder* of Rotterdam to the city council, the average traffic intensity at Hofplein is reported to be approximately 30,000 motor vehicles per day (Karremans, 2023). This estimate is broadly consistent with data from the Nationaal Dataportaal Wegverkeer (NDW), which indicates an average daily traffic intensity of 27,076 vehicles in January 2025 (NDW, n.d.). However, the NDW measurements are based on a limited number of counting locations and therefore provide only a partial picture of traffic flows at the intersection.

To obtain a more complete overview, traffic count data collected from the traffic signal installations (*Verkeersregelinstallaties*, VRIs) surrounding Hofplein were provided by the Municipality of Rotterdam. By combining data from all signalized approaches to the intersection, it is possible to capture the total

volume of motorized traffic entering Hofplein. The locations of the included VRIs are shown in Appendix H.

Table 3.1 presents the aggregated traffic intensity during the last week of January for the years 2024, 2025, and 2026. The results show a substantial decline in vehicle volumes during the intervention period in 2026. While traffic intensity decreases from 38,385 vehicles in 2024 to 31,819 vehicles in 2025, the largest reduction occurs in 2026, when the total intensity falls to 12,053 vehicles. This decrease coincides with the implementation of the Hofplein redesign and reflects the traffic situation expected under the final layout once the intervention has been fully completed.

Table 3.1: Total traffic intensity at Hofplein (motor vehicles per day)

Year	Intensity
2024	38,385
2025	31,819
2026	12,053

While the aggregate figures provide an overview of the overall reduction in traffic, it is also useful to examine changes by approach road. Figure 3.11 shows the traffic intensity for the four main directions leading into Hofplein. The largest reductions can be observed on Schiekade and Weena. This pattern is consistent with the phasing of the intervention shown in Figure 3.10, where these approaches are among the first sections effected by construction activities and network changes. As a result, a considerable share of traffic is either rerouted or no longer uses these corridors during the intervention period.

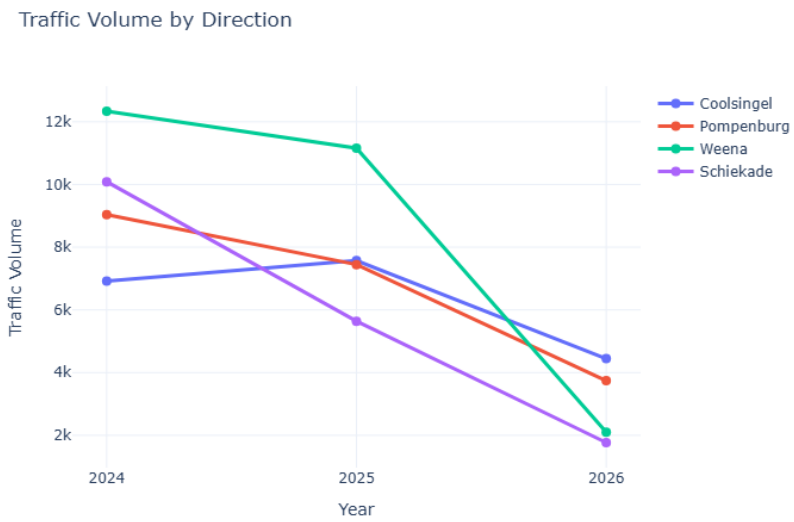


Figure 3.11: Traffic intensity at Hofplein per direction

The observed traffic counts provide a first indication of how traffic volumes responded to the reduction in road capacity at Hofplein. As the intervention was implemented, a substantial decline in motor vehicle traffic was observed at the intersection. These empirical observations provide an important point of departure for the methodology presented in the following chapter, where the effects of the intervention are analysed in more detail.

4

Methodology

The following research question is addressed in this chapter:

> *What is the most appropriate approach to analyse changes in aggregate travel behaviour resulting from car-reducing measures, and how can these changes in travel behaviour be disaggregated for different socio-demographic groups?*

Answering this question is not straightforward. Travellers who adjust their behaviour in response to a car-reducing measure are typically unknown beforehand and cannot easily be identified afterwards, as they can no longer be observed at the intervention location. As discussed in Section 2.5, survey- and panel-based methods are therefore limited in their ability to capture these behavioural responses. For this research, quantitative transport modelling provides a way to overcome these limitations. The literature review further identified activity-based transport models as particularly well suited to represent behavioural adaptation across population groups, leading to the selection of ActivitySim as the modelling framework for this study.

This chapter presents the methodology developed and applied in this study. Figure 4.1 provides an overview of the research workflow. The chapter first introduces the intervention scenarios and model inputs. Accessibility changes resulting from the Hofplein intervention are then estimated using the V-MRDH assignment model and incorporated into ActivitySim through scenario-specific skim matrices. The behavioural realism of the resulting model is subsequently evaluated through sensitivity analysis, travel-time elasticity analysis, and Bayesian calibration. Finally, the simulated behavioural responses are analysed at both the aggregate and persona level to examine how different socio-demographic groups respond to the intervention.

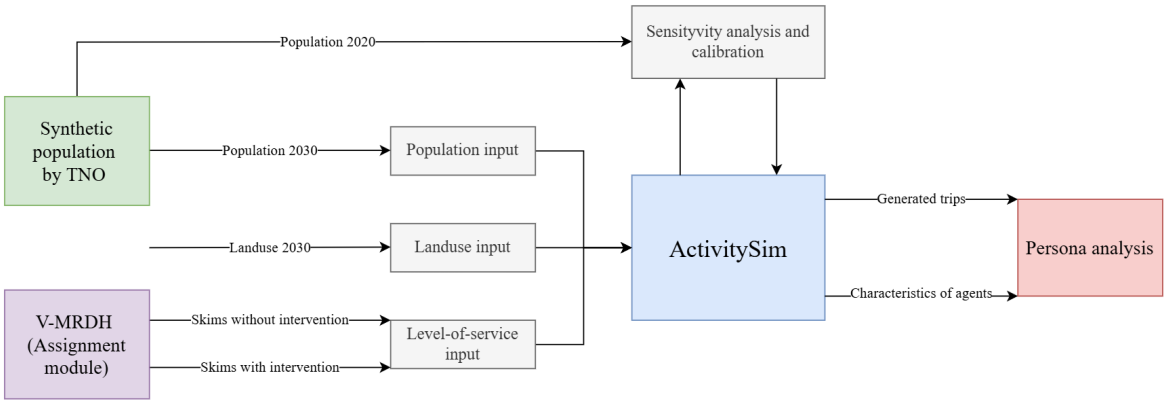


Figure 4.1: Methodology overview

4.1. Scenario definition

The first step in the methodology is to define the scenarios that form the basis of the comparison. To isolate the behavioural effects of the Hofplein intervention, all assumptions unrelated to the intervention are kept identical across scenarios.

Both scenarios represent the Rotterdam region in 2030 and therefore use the same population forecasts and land-use assumptions. The only difference between the scenarios is the transport accessibility resulting from changes to the road network. Consequently, any observed differences in travel behaviour can be attributed directly to the Hofplein intervention.

The baseline scenario represents the 2030 situation without the Hofplein intervention. Population growth and planned land-use developments are included, while the transport network remains unchanged.

The intervention scenario incorporates the redesigned Hofplein. The intervention substantially reduces road capacity by replacing the existing five-lane roundabout with a two-lane configuration. As a result, traffic volumes are expected to decrease from approximately 35,000 vehicles per day to around 15,000 vehicles per day (CROW, n.d.). These network changes effect travel times and accessibility throughout the transport system, which are subsequently reflected in the level-of-service inputs used by ActivitySim.

4.2. ActivitySim implementation

The general principles of activity-based modelling and the ActivitySim framework were introduced in Section 2.6. This section describes how ActivitySim is implemented in this research and how the Hofplein intervention is translated into behavioural responses.

Figure 4.2 provides a simplified overview of this process. The intervention first effects the transport network by reducing road capacity at Hofplein. These network changes are subsequently reflected in the assignment results as changes in travel times. The resulting accessibility changes are incorporated into ActivitySim through scenario-specific level-of-service inputs, influencing the utility of available travel alternatives. Changes in utility may ultimately lead travellers to adapt their behaviour through destination changes, rerouting, modal shift, or trip suppression.

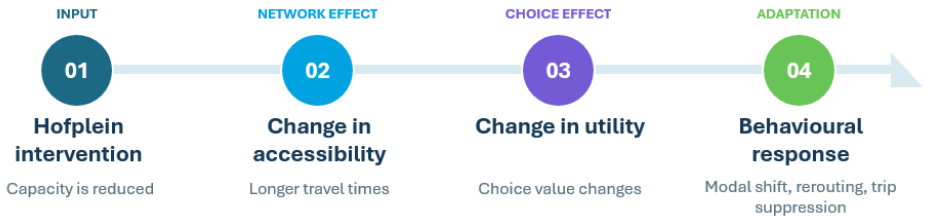


Figure 4.2: ActivitySim process

4.2.1. Model inputs

ActivitySim requires three key categories of input data: a synthetic population, land-use data, and level-of-service information. Together, these inputs define who travels, where activities are located, and how easily destinations can be reached. The synthetic population represents the travellers within the study area, the land-use data describe the distribution of opportunities, and the level-of-service data capture the transport conditions that connect them.

Synthetic population

ActivitySim requires a synthetic population that represents the characteristics and spatial distribution of residents within the study area. The synthetic population used in this research was developed in 2024 and builds upon earlier work by Snelder et al. (2021). It combines information from multiple data sources, including CBS microdata, ODiN survey data, land registry data, and electric vehicle registration data.

The resulting dataset represents the entire Dutch population and contains detailed information on household composition, residential location, socio-demographic characteristics, and vehicle ownership. Key attributes include person and household ID, residential zone, income, age, gender, education level, migration background, and vehicle ownership.

Since this study focuses on travel behaviour within the MRDH region, the national synthetic population was filtered to include only residents living within this area. Relevant attributes were subsequently mapped and reformatted to meet the input requirements of ActivitySim. This processed dataset forms the population used in both the baseline and intervention scenarios.

Land-use input
Land-use information represents the spatial distribution of households, employment opportunities, and activity locations throughout the MRDH region. The 2030 land-use dataset is applied consistently across all scenarios. Maintaining identical land-use assumptions ensures that any behavioural differences between scenarios can be attributed to changes in transport accessibility rather than changes in the spatial distribution of opportunities.

Level-of-service input
The level-of-service input consists of skim matrices containing travel times, distances, and travel costs between all origin-destination pairs within the MRDH region. These matrices describe the accessibility conditions experienced by travellers and form a key input to the behavioural models within ActivitySim.

Unlike the synthetic population and land-use data, the level-of-service inputs differ between scenarios. Separate skim matrices are generated from the V-MRDH assignment model for the baseline and intervention scenarios (see Section 4.3). Differences between these skims will be the basis for the changes in accessibility caused by the Hofplein redesign.

4.2.2. Utility functions

Changes in accessibility do not directly alter travel behaviour. Instead, they effect the attractiveness of the travel alternatives available to travellers within ActivitySim. This attractiveness is represented through utility functions, which form the basis of the mode choice models used throughout the framework.

ActivitySim is grounded in Random Utility Maximization (RUM) theory, which assumes that individuals choose the alternative that provides the highest utility. For mode choice, this decision process is commonly represented using a Multinomial Logit (MNL) model. The observed utility of transport mode i for traveller j is expressed as:

$$V_{i,j} = ASC_i + \sum_{k=1}^{K} \beta^T_{i,k,l} T_{i,k} + \beta^A_{i,l} A_{j,l} + \sum_{m=1}^{M} \beta^S_{i,m} S_{j,m}, \qquad \text{if } i \in C_j \tag{4.1}$$

where $V_{i,j}$ denotes the observed utility of mode i for traveller j, and C_j represents the set of alternatives available to that traveller. The variable l denotes the trip purpose associated with traveller j, such as commuting, shopping, or leisure. Since each trip is associated with a single purpose, l is treated as a given characteristic of the mode choice decision.

The utility consists of an alternative-specific constant (ASC_i), which captures the baseline preference for each mode that is not explained by the observed variables, and three explanatory components representing level-of-service conditions, activity type, and socio-demographic characteristics.

The first explanatory component,

$$\sum_{k=1}^{K} \beta^T_{i,k,l} T_{i,k},$$

represents the contribution of the level-of-service (LOS) attributes associated with transport mode i for activity type l. Here, k indexes the different LOS attributes, such as travel time and travel cost, represented by $T_{i,k}$. These attributes form the basis of the model, as travellers are generally most sensitive to the time, effort, and monetary costs associated with a trip (Deneke et al., 2024). The

coefficients $\beta^T_{i,k,l}$ determine how strongly travellers respond to each LOS attribute and allow these responses to vary by activity type. This reflects the observation that the importance of travel conditions depends on trip purpose. For example, travellers may be willing to tolerate longer travel times for commuting trips than for leisure activities.

The second component,

$$\beta^A_{i,l} A_{j,l},$$

captures the influence of activity type on mode choice. Here, $A_{j,l}$ indicates the activity type l associated with traveller j, while $\beta^A_{i,l}$ captures the extent to which that activity type influences the utility of transport mode i. Travel behaviour is closely linked to the activity a traveller intends to perform, as different activities impose different requirements and constraints. Including activity type therefore allows the model to represent systematic differences in mode preferences between trip purposes that cannot be explained by travel conditions alone. For example, commuting trips may favour different transport modes than shopping or leisure trips, even under similar travel conditions.

The final component,

$$\sum_{m=1}^{M} \beta^S_{i,m} S_{j,m},$$

accounts for socio-demographic differences between travellers. Here, m indexes the socio-demographic characteristics included in the model, $S_{j,m}$ represents the value of characteristic m for traveller j, and $\beta^S_{i,m}$ captures how that characteristic influences the utility of transport mode i. Individuals do not respond equally to the same travel conditions, as their travel choices are shaped by personal and household characteristics. Variables included in the model include age, income, gender, car ownership, and migration background, among others. These characteristics can all influence the attractiveness of different transport modes. Incorporating such variables allows the model to represent behavioural heterogeneity across the population and is particularly important for this research, which aims to analyse how different socio-demographic groups respond to a car-reducing intervention.

Within the RUM framework, travel behaviour is not assumed to be deterministic. Utility is therefore represented as the sum of an observed component and an unobserved random component:

$$U_{i,j} = V_{i,j} + \epsilon_{i,j} \tag{4.2}$$

where $\epsilon_{i,j}$ captures influences that are not explicitly represented in the model, such as individual preferences, imperfect information, or measurement errors. In the MNL formulation, these error terms are assumed to be independently and identically distributed according to a Gumbel distribution (Zhou et al., 2023).

The resulting utility is converted into a choice probability using the multinomial logit formulation:

$$P_{i,j} = \frac{\exp(V_{i,j})}{\sum_{i \in C_j} \exp(V_{i,j})} \tag{4.3}$$

where $P_{i,j}$ denotes the probability that traveller j selects mode i. Alternatives with higher utility are more likely to be chosen, although the stochastic component ensures that travel behaviour remains probabilistic rather than perfectly predictable.

4.3. Assignment model

As discussed in the previous section, the Hofplein intervention influences travel behaviour through changes in accessibility. To quantify these accessibility changes, the intervention must first be translated into changes in network performance. This is achieved using the V-MRDH assignment model (MRDH, n.d.-b), which is used to assign travel demand to the road network and generate the skim matrices that serve as input for ActivitySim.

Because ActivitySim is a transport demand model, it simulates behavioural decisions such as destination choice and mode choice, but it does not determine the travel conditions experienced by travellers. Instead, these conditions have to be generated by an assignment model. The assignment model therefore forms the link between the physical network intervention and ActivitySim.

Traffic assignment is performed in OmniTRANS using the travel demand matrices provided by the V-MRDH model. The static assignment process converts origin-destination demand into traffic flows on individual road links by determining how travellers distribute themselves across the available routes. Route choice is based primarily on travel time and other generalized travel costs. As traffic volumes increase, congestion develops, causing travel times to rise and making alternative routes more attractive. Through an iterative assignment procedure, traffic is repeatedly redistributed until a stable traffic pattern is reached in which travel demand, traffic flows, and network conditions are consistent.

To assess the accessibility impacts of the Hofplein redesign, separate assignment results were generated for the reference and intervention scenarios. The intervention was implemented by adjusting the capacities of the effected road links according to the values shown in Figure 4.3, based on the observed traffic intensity presented in Section 3.5.

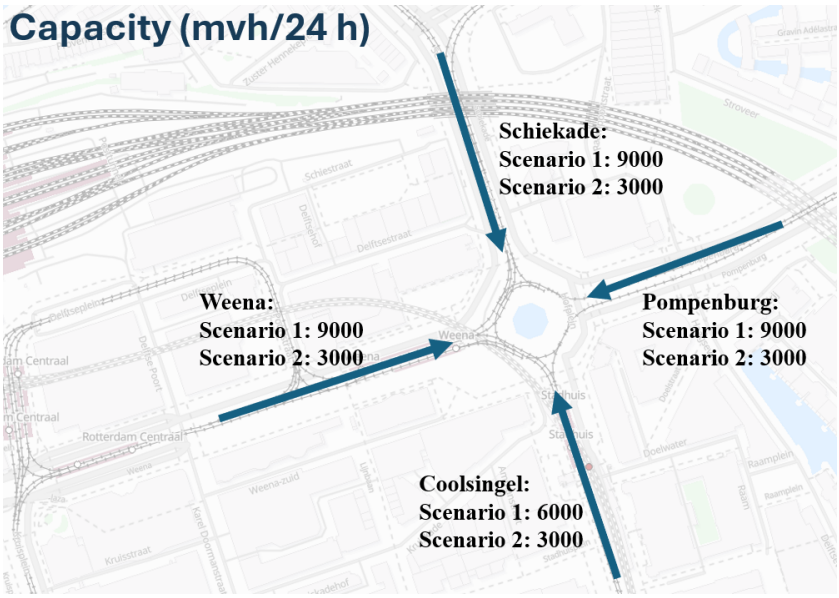


Figure 4.3: Road capacities (motor vehicles per day) used in the reference and Hofplein intervention scenarios.

Within the assignment procedure, freight traffic is assigned first, followed by passenger car traffic. This approach ensures that congestion generated by freight vehicles is taken into account when assigning passenger demand. The final assignment therefore reflects the combined effects of freight and passenger traffic on network performance and travel times. Once the assignment is done, the resulting network conditions are converted into skim matrices. These matrices contain travel times, distances, and travel costs between all origin-destination pairs in the MRDH region.

4.4. Model behaviour analysis

Before ActivitySim is applied to the Hofplein case study, it is necessary to assess whether the model produces sufficiently realistic behavioural responses. Although the model is based on established behavioural theory, the magnitude and direction of these responses depend on the parameters used in the underlying choice models. The model is therefore evaluated and calibrated before it is used to analyse the intervention scenarios.

Two complementary concepts are used to evaluate the model's behaviour: sensitivity and elasticity. Sensitivity examines how model outcomes change when model parameters are varied, whereas elasticity examines how model outcomes respond to changes in external inputs, such as travel time. Together, these provide insight into both the internal behaviour of the model and the plausibility of its response to changes in travel conditions.

Based on this distinction, the model behaviour analysis consists of three consecutive steps. First, a sensitivity analysis identifies which behavioural parameters have the greatest influence on the model outputs. Second, a travel time elasticity analysis evaluates whether car use responds plausibly to an increase in car travel time and whether the resulting reduction in car trips is accompanied by shifts towards other modes. Finally, Bayesian calibration is used to improve the model's ability to reproduce observed modal shares while maintaining realistic behavioural responses.

For these analyses, a population representing the year 2020 is used, allowing the simulated travel patterns to be compared with recent observed mobility data. However, running ActivitySim is computationally demanding, particularly because both the sensitivity analysis and calibration require the model to be executed repeatedly. To keep these analyses computationally feasible while retaining a representative population, a random sample of 10,000 households is used throughout the model behaviour analysis.

4.4.1. Sensitivity analysis

As the model contains a large number of parameters, it is important to identify which model parameters have the greatest influence on the simulation outcomes. To achieve this, a sensitivity analysis is performed as a first step to understand the models behaviour.

Sensitivity analysis provides a systematic approach for quantifying how variations in model parameters effect model outputs (Saltelli et al., 2000). In this study, the Morris screening method (Morris, 1991) is applied using the `SALib` Python package (Iwanaga et al., 2022) to identify the most influential parameters prior to model calibration and scenario analysis.

The Morris method is a global sensitivity analysis technique based on a One-at-a-Time design. Parameters are varied sequentially across the parameter space, while the remaining parameters are held constant during each individual step. The effect of each parameter change on the model output is measured through an elementary effect.

In this study, the model outputs of interest are the modal shares. The elementary effect of parameter β_p on the modal share of mode i is expressed as:

$$EE_{ip} = \frac{\Delta MS_i}{\Delta \beta_p} \tag{4.4}$$

where ΔMS_i is the change in the modal share of mode i, and $\Delta \beta_p$ is the applied change in parameter β_p. Because each parameter is evaluated at multiple locations in the parameter space, several elementary effects are obtained for each parameter.

The overall importance of parameter β_p is measured using the mean of the absolute elementary effects, commonly denoted by μ_p^* (Iooss & Lemaître, 2014):

$$\mu_p^* = \frac{1}{r} \sum_{q=1}^{r} \left| EE_p^{(q)} \right| \tag{4.5}$$

where r is the number of elementary effects calculated for parameter β_p, and $EE_p^{(q)}$ is the elementary effect obtained during evaluation q. A larger value of μ_p^* indicates that changes in the parameter have a stronger overall influence on the model output.

The standard deviation of the elementary effects, denoted by σ_p, provides information on the consistency of this influence:

$$\sigma_p = \sqrt{\frac{1}{r}\sum_{q=1}^{r}\left(EE_p^{(q)} - \mu_j\right)^2} \tag{4.6}$$

A high value of σ_p indicates that the effect of the parameter varies across the parameter space. This may point to non-linear behaviour or interactions with other parameters. Together, μ_p^* and σ_p provide insight into both the overall importance of a parameter and the complexity of its influence on model outcomes.

The sensitivity analysis focuses on the parameters of the mode choice utility functions introduced in Section 4.2.2. To distinguish between the different components while limiting the computational burden, three separate Morris analyses are performed. This is because the number of required simulations increases with the number of input variables, following $N = R(k+1)$ (Morris, 1991), where R is the number of trajectories and k the number of input parameters. In this research, $R = 4$ is used to limit the number of required ActivitySim runs.

The first analysis considers the alternative-specific constants and travel time coefficients, capturing baseline mode preferences and sensitivity to travel time. The second analysis evaluates the activity-specific mode choice parameters. The third analysis focuses on socio-demographic parameters associated with characteristics such as age and income. Together, the three analyses provide insight into the relative influence of mode preferences, travel time, activity purpose, and traveller characteristics on the simulated modal shares.

The sensitivity analysis identifies which parameters have the greatest influence on the model outputs. However, parameter influence alone does not indicate whether the corresponding behavioural responses are realistic. The next step therefore evaluates how the model responds to a controlled change in car travel time.

4.4.2. Travel time elasticity analysis

The travel time elasticity analysis examines whether ActivitySim responds plausibly when travel conditions change. This is particularly important for the Hofplein case study because the intervention is expected to influence travel behaviour primarily by changing car accessibility and travel times.

Elasticity is an economic concept that quantifies the responsiveness of demand to changes in a given variable. In the context of travel time elasticity, it expresses the percentage change in demand resulting from a 1% change in travel time (Litman, 2004). In this study, the reference model run is compared with a test scenario in which car travel times are increased by 10%. The resulting change in the number of trips made by each transport mode is used to calculate the corresponding elasticity:

$$E_i = \frac{\Delta Trips_i\,(\%)}{\Delta TT_{\text{car}}\,(\%)} \tag{4.7}$$

where E_i is the elasticity of demand for mode i, $\Delta Trips_i$ is the percentage change in the number of trips made by that mode, and ΔTT_{car} is the percentage change in car travel time.

Two types of elasticity are considered. The first is the direct, or own, elasticity of car demand. This elasticity measures the percentage change in car trips resulting from an increase in car travel time. A negative value is expected because travelling by car becomes less attractive as car travel times increase. The direct elasticity therefore indicates whether car demand is sufficiently responsive to deteriorating car accessibility.

The second type is the cross-elasticity of the alternative modes. Cross-elasticities measure how the number of trips made by public transport, bicycle, e-bike, and walking changes when car travel time increases. A reduction in car trips does not necessarily imply that these trips are transferred directly to another mode. Travellers may also select different destinations, reorganise their activity schedules, or decide not to make a trip. The cross-elasticities are therefore used to examine the extent to which ActivitySim captures modal substitution following a deterioration in car accessibility.

The calculated elasticities are compared with values reported in the literature. According to Smit et al. (2021), car travel time elasticities generally range from approximately -0.15 to -0.50. This range is used as a benchmark for evaluating the direct response of car demand. The Dutch *Handboek Elasticiteiten* (Hofman, 2024) is additionally used as a reference for the expected responses of alternative modes to changes in car travel time.

3.1.7. Elasticiteiten aantal reizen alle motieven samen

Reizen - Alle motieven	Autobestuurder	Autopassagier	Trein	BTM	Fiets Totaal	**Totaal**
Reistijden Auto	**-0,17**	**-0,27**	0,22	0,14	0,15	-0,02

Figure 4.4: Reference values for travel time elasticities in the Netherlands (Hofman, 2024).

The calculated elasticities are compared with values reported in the literature, with particular attention to the distinction between direct and cross-elasticities. Obtaining a plausible direct elasticity for car demand is relatively straightforward, as it captures the direct response of car use to changes in car travel time. Cross-elasticities are more complex, as behavioural responses can be distributed across several adjustment mechanisms. Assessing both therefore provides a more complete understanding of how realistically the model responds to changes in travel conditions. Together, the sensitivity and elasticity analyses provide the basis for the subsequent calibration.

4.4.3. Bayesian calibration

The final step of the model behaviour analysis is to calibrate ActivitySim so that it reproduces both observed travel patterns and realistic responses to changes in accessibility. Focusing only on modal shares could produce a model that matches current travel behaviour but responds unrealistically to interventions. On the other hand, focusing only on elasticities could give plausible behavioural responses while failing to reproduce the observed modal distribution. Both aspects are therefore included in the calibration.

This optimisation problem is difficult to solve manually. ActivitySim consists of many interacting behavioural models, meaning that changes in a single parameter can propagate through multiple travel decisions and influence model outputs in complex ways. Consequently, while the effects of a parameter set can be observed through a model run, the underlying relationship between parameter values and outputs cannot be described analytically. For calibration purposes, ActivitySim can therefore be treated as a black-box function, with the model parameters serving as inputs and the resulting modal shares and elasticities as outputs. Furthermore, each evaluation requires a complete ActivitySim simulation, making exhaustive exploration of the parameter space impractical.

Bayesian optimization is therefore used to calibrate the model. The method is specifically designed for expensive black-box optimisation problems and can identify promising parameter combinations with relatively few model evaluations (Agriesti et al., 2023; Schultz et al., 2022). Rather than searching the parameter space exhaustively, it uses the results of previous simulations to guide the selection of new parameter combinations, improving calibration efficiency.

The calibration focuses on parameters that directly influence mode choice: the alternative-specific constants, travel time coefficients, and activity-specific mode choice parameters. Parameters related to destination choice and logsum propagation are excluded from the Bayesian optimization, as they primarily effect how changes in accessibility propagate through the modelling framework. Their influence is therefore examined separately through the elasticity analysis and subsequent model experiments.

Calibration targets for modal share are derived from CBS mobility statistics (CBS, 2026). The targets

are based on travel behaviour observed in 2019, which serves as a reference year for the synthetic population representing 2020 conditions. The year 2019 was selected to avoid distortions associated with the COVID-19 pandemic and the resulting travel restrictions. The resulting modal share targets are presented in Figure 4.5.

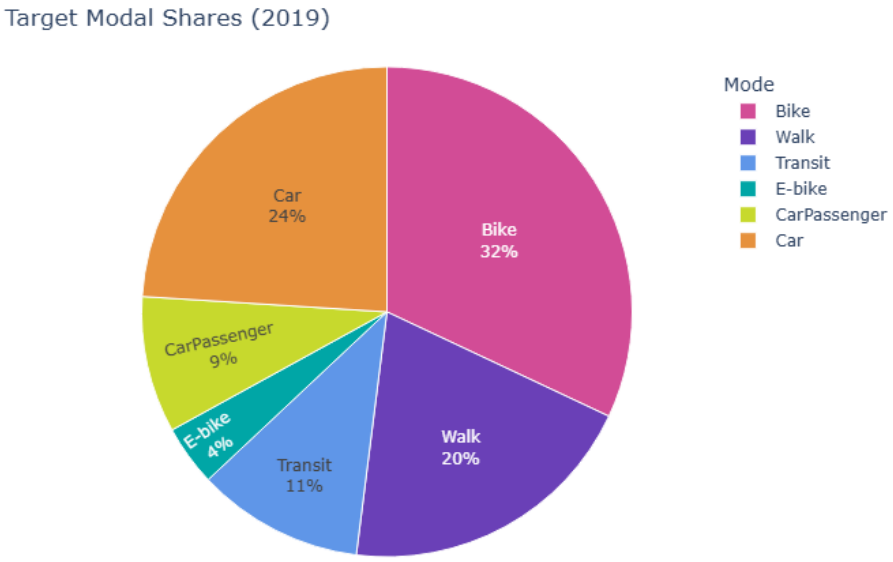


Figure 4.5: Target modal shares used in the calibration (CBS, 2026).

In addition to the modal share targets, the calibration includes target travel time elasticities obtained from the literature (Figure 4.4). The objective is to minimise the difference between the simulated and target modal shares while simultaneously minimising the difference between the simulated and target elasticities. This prevents the optimization from improving one aspect of model performance at the expense of the other.

The objective unction for the calibration is defined as:

$$\min \left[\sum_{i=1}^{m} (MS_i - MS_{i,\text{target}})^2 + \sum_{i=1}^{m} (E_i - E_{i,\text{target}})^2 \right] \tag{4.8}$$

where MS_i presents the simulated modal share of mode i, and $MS_{i,\text{target}}$ is its corresponding target value. While, E_i is the simulated travel time elasticity of mode i, and $E_{i,\text{target}}$ is the corresponding literature-based target. The modal share and elasticity components are weighted equally.

The optimization is implemented using the `gp_minimize` function from the `scikit-optimize` package (Head et al., 2018). This function performs Bayesian optimization using a Gaussian Process as its surrogate model, which approximates the relationship between the parameter values and the objective function (Agriesti et al., 2023).

The calibration starts by testing a range of parameter combinations within the predefined search space. For each combination, ActivitySim is executed and the resulting modal shares and travel time elasticities are compared with the calibration targets. The difference between the simulated and target values is quantified using the objective function.

After evaluating these initial parameter combinations, Bayesian optimization uses the results to determine which parameter values should be tested next. Rather than searching the parameter space

randomly, the algorithm learns from previous surrogate model runs and gradually focuses on combinations that are expected to improve the calibration. At the same time, it continues to test less explored regions of the parameter space to avoid overlooking potentially better solutions.

The optimization is conducted within predefined parameter bounds. For the travel time coefficients and activity-specific mode choice parameters, values can vary between zero and twice their original value. This allows substantial changes in behavioural sensitivity while ensuring that the direction of the effect remains consistent with the underlying model specification.
For the alternative-specific constants, wider bounds are applied, ranging from minus twice to plus twice the original parameter value. These constants capture the attractiveness of each mode that is not explained by the observed variables. Allowing both positive and negative adjustments provides the flexibility required to align the simulated modal shares with the calibration targets.

Because a full ActivitySim run is required for every evaluation, the optimization is limited to sixty model runs. The procedure is terminated earlier if consecutive iterations no longer produce meaningful improvements in the objective function.

Together, the sensitivity analysis, elasticity analysis, and Bayesian calibration provide a structured process for improving confidence in the model's behavioural responses. The sensitivity analysis establishes which parameters matter, the elasticity analysis evaluates whether the model reacts plausibly to accessibility changes, and the Bayesian calibration identifies parameter values that reproduce both observed modal shares and literature-based elasticities. Following this evaluation and calibration process, the model is applied to the Hofplein scenarios. The next section describes how the resulting outputs are selected and analysed.

4.5. Output analysis

After calibration, the ActivitySim model is applied to evaluate the effects of the Hofplein intervention. Although the model simulates travel behaviour across the entire MRDH region, Hofplein represents a highly localised network change. Analysing all trips within the region would therefore dilute many of the intervention effects. To focus the analysis on travellers who are most likely to be effected, a subset of relevant origin-destination (OD) pairs is identified.

Ideally, these trips would be selected using a selected-link analysis from the assignment model. However, due to limitations in the implementation of the selected-link functionality, the resulting outputs were not considered sufficiently reliable for this purpose. An alternative geographic approach is therefore adopted.

Relevant OD pairs are identified by drawing straight lines between the centroids of all origin and destination zones. OD pairs for which these lines intersect the Hofplein area, including a buffer of 100 meters, are classified as relevant to the analysis. Although these lines do not represent actual travel routes, they provide a practical approximation of trips that are likely to pass through or be effected by the Hofplein corridor. The selected OD pairs form the basis for the subsequent analysis.

First, aggregate indicators such as modal shares and average trips per person are examined to assess the overall behavioural impact of the intervention.

Second, the analysis focuses on people who were using the car at Hofplein before the intervention. These are defined as individuals who make at least one car trip within the selected OD pairs in the baseline scenario. Tracking these travellers across scenarios makes it possible to investigate how existing car users adapt their travel behaviour when accessibility conditions change.

To further distinguish between these behavioural responses, car trips are compared between the baseline and intervention scenarios. Car trips that are present in the baseline but no longer occur in the intervention scenario are identified as lost car trips. The number of these lost trips is compared with the overall reduction in car trips observed at the Hofplein in Section 3.5. The difference represents car trips that are still made by car but no longer belong to the selected OD pairs. These trips therefore indicate either rerouting around Hofplein or a change in destination. In this way, the analysis distinguishes between reductions in car use and adaptations in where or how car trips are made.

To assess whether these responses differ across the population, the results are further segmented

by socio-demographic characteristics, including age, income, gender, migration background, and car ownership. This enables the identification of potential distributional effects across different population groups.

Socio-demographic characteristics, however, provide only one perspective on differences in travel behaviour. The following section therefore extends the analysis by examining how the behavioural responses relate to broader differences in mobility-based personas.

4.6. Persona analysis

The final stage of the methodology examines how behavioural responses to the Hofplein intervention differ across socio-demographic population groups. To support this analysis, the synthetic population generated by ActivitySim is classified using a persona analysis.

Personas are representative archetypes that capture common characteristics, lifestyles, and behavioural patterns within specific population segments. They provide a structured way to interpret differences in travel behaviour and communicate model outcomes in a more intuitive manner. However, meaningful personas should be grounded in empirical evidence rather than arbitrary assumptions (Gaiser et al., 2006). To ensure validity, personas are ideally developed using a combination of qualitative and quantitative methods (Rasca et al., 2023; Salminen et al., 2020).

Rather than developing a new set of personas specifically for this research, this study adopts the existing persona framework developed by the Netherlands Institute for Transport Policy Analysis (KiM) (Hamersma & Huang, 2026). These personas are based on extensive empirical research and provide a consistent way to segment the Dutch population into groups with distinct socio-demographic characteristics, mobility preferences, and travel patterns.

The ten KiM personas used in this study are illustrated in Figure 4.6. A detailed description of each persona, including its defining characteristics and mobility behaviour, is provided in Appendix E. The personas range from multimodal young travellers and car enthusiasts to environmentally conscious travellers and older adults with varying mobility needs, thereby capturing the diversity of travel behaviour within the Dutch population.

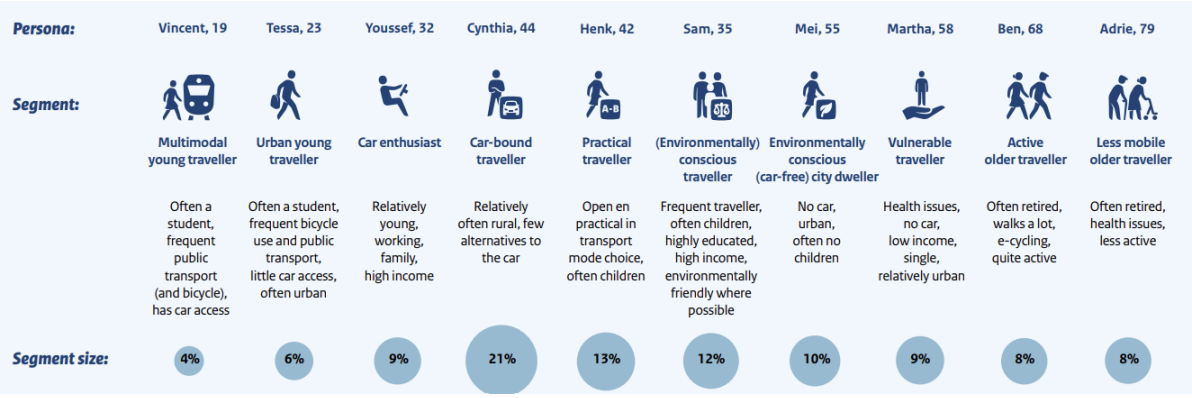


Figure 4.6: KiM personas (Hamersma & Huang, 2026)

4.6.1. Persona assignment

To enable persona-based analyses, a probabilistic assignment is used to map the synthetic ActivitySim population to the ten KiM personas. The objective is to determine which persona best matches each synthetic individual based on both socio-demographic characteristics and simulated travel behaviour.

The persona assignment combines demographic and mobility characteristics for each individual. Demographic attributes are obtained from the synthetic population and include age group, gender, student and employment status, car ownership, level of urbanisation, education level, household income, household composition, and migration background. These attributes are converted into categorical classes corresponding to those used in the KiM framework. Mobility characteristics are derived from

the trips simulated by ActivitySim and indicate whether an individual used car, bicycle, e-bike, public transport, or walking at least once during the simulated day.

These characteristics are compared with two probability tables derived from the KiM personas. One table describes the distribution of demographic characteristics within each persona, while the other describes their mode-use frequencies. As the latter are reported as days per year, they are converted into daily probabilities by dividing them by 365.

Bayes' theorem is used to combine the observed demographic and mobility characteristics with the overall distribution of personas in the population. In its general form, Bayes' theorem estimates the probability of an agent belonging to a persona as:

$$P(p \mid D, M) = \frac{P(D, M \mid p)\, P(p)}{P(D, M)} \tag{4.9}$$

where p denotes a persona, D the observed demographic characteristics, and M the observed mobility characteristics. The term $P(p)$ represents the prior probability of a persona based on the population shares reported by KiM.

In principle, applying Bayes' theorem requires estimation of the joint likelihood $P(D, M \mid p)$, which represents the probability of observing a specific combination of demographic and mobility characteristics given a persona. In practice, estimating this joint probability would require detailed information on all possible combinations of characteristics, which is not available from the KiM report.

To address this limitation, a Naive Bayes classifier is used. Whereas Bayes' theorem itself makes no assumptions regarding relationships between variables, Naive Bayes assumes that the observed characteristics are conditionally independent given the persona. Under this assumption, the joint likelihood can be decomposed into individual likelihood terms:

$$P(D, M \mid p) = \prod_{i=1}^{n} P(D_i \mid p) \prod_{j=1}^{m} P(M_j \mid p) \tag{4.10}$$

Substituting this expression into Bayes' theorem yields:

$$P(p \mid D, M) \propto P(p) \prod_{i=1}^{n} P(D_i \mid p) \prod_{j=1}^{m} P(M_j \mid p) \tag{4.11}$$

where D_i represents an observed demographic characteristic and M_j represents an observed mobility characteristic. The symbol $\propto$ indicates that the right-hand side is proportional to the posterior probability, after which the probabilities are normalised so that they sum to one across all personas.

In practical terms, a persona receives a higher probability when both the demographic characteristics and travel behaviour of an individual are typical for that persona. For example, a young student who frequently uses bicycles and public transport will generally receive a higher probability for personas such as Vincent or Tessa.

Rather than assigning each individual to the persona with the highest probability, the final persona is randomly sampled from the estimated probability distribution. This allows the assignment to reflect uncertainty in cases where multiple personas have similar probabilities and avoids creating artificially distinct groups based on small differences in estimated likelihoods.

Finally, the assigned persona is attached to both the synthetic individuals and their trips. This enables subsequent analyses of accessibility changes, modal shifts, and behavioural adaptations at the persona level. The persona-based segmentation therefore complements the socio-demographic analysis by providing a broader behavioural perspective on how different groups of travellers respond to the Hofplein intervention.

5

Model Behaviour Analysis and Calibration

The following research question is addressed in this chapter:

> *To what extent does the selected approach reproduce realistic travel behaviour, and how can its behavioural performance be improved through calibration?*

The research question is addressed in this chapter through a series of analyses that evaluate the behavioural performance of the ActivitySim model and calibrate the model parameters that will be used in the Hofplein case study. First, a sensitivity analysis identifies the parameters that have the greatest influence on mode-choice outcomes, followed by a travel time elasticity analysis to assess whether the model responds realistically to changes in travel times. The parameters are subsequently calibrated using Bayesian Optimization, after which the behavioural performance of the model is re-evaluated. Together, these analyses establish the final parameter set used in the remainder of this study.

5.1. Sample population

All analyses presented in this chapter were performed using a random sample of 10 000 households from the MRDH region. The full ActivitySim model requires approximately 50 minutes per simulation run, while simulations using the reduced population require approximately 8 minutes. Given that the analyses in this chapter require many dozens up to even hundreds of model evaluations in total, using the full population would have resulted in prohibitively long computation times.

To assess whether the reduced population provides a representative approximation of the full study area, key model outputs are compared between the sample and full populations. The comparison focuses on modal shares and vehicle kilometres travelled (VKT) per capita, as summarised in Table 6.2.

Table 5.1: Comparison between the full and sampled MRDH populations

Indicator	Full population	Sample	Difference
Car (%)	17.5	17.8	+0.30
Car passenger (%)	5.07	5.11	+0.04
Bike (%)	33.2	33.1	-0.10
E-bike (%)	5.77	5.63	-0.14
Walk (%)	26.2	26.2	0.00
Public transport (%)	12.2	12.1	-0.10
VKT per capita	11.335	11.606	+0.271

The differences between the sampled and full populations are found to be sufficiently small for the purposes of model development and calibration. The sampled population therefore provides a computationally efficient representation of the study area while preserving the key behavioural characteristics of the full model.

5.2. Sensitivity analysis

The sensitivity analysis was conducted to identify which mode-choice parameters have the greatest influence on simulated modal shares, as described in Section 4.4.1. Three separate Morris analyses were performed for alternative-specific constants (ASC) and travel time, activity-specific parameters, and socio-demographic parameters, with four trajectories used in each analysis. Parameter are evaluated using the Morris importance indicator μ^*, where higher values indicate a stronger influence on model outputs.The main findings are presented in this section, while the complete sensitivity analysis results for all transport modes can be found in Appendix B.

Figure 5.1 presents the results for the travel time and ASC parameters. The car ASC is the most influential parameter, followed by the bicycle travel time coefficient, the public transport ASC, and the travel time coefficients for car and public transport. The ten most influential parameters and their corresponding μ^* values are shown alongside the figure.

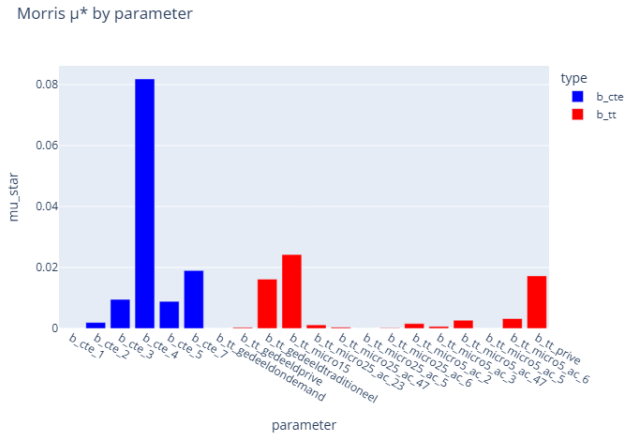


Figure 5.1: Morris μ^* values for parameters effecting car modal share.

Rank	Parameter	μ^*
1	ASC_{car}	0.08186
2	$\beta_{tt,bike}$	0.02425
3	ASC_{PT}	0.01899
4	$\beta_{tt,car}$	0.01726
5	$\beta_{tt,PT}$	0.01618
6	ASC_{ebike}	0.00953
7	$ASC_{carpassenger}$	0.00887
8	$\beta_{tt,walk_ac6}$	0.00321
9	$\beta_{tt,walk_ac47}$	0.00269
10	ASC_{bike}	0.00196

Table 5.2: Most influential parameters for car modal share

Figure 5.2 shows the sensitivity results for the activity-specific parameters. The car ASC remains the most influential parameter, while the remaining top-ranked coefficients are associated with specific activity-purpose combinations. Their influence is considerably smaller than that of the car ASC.

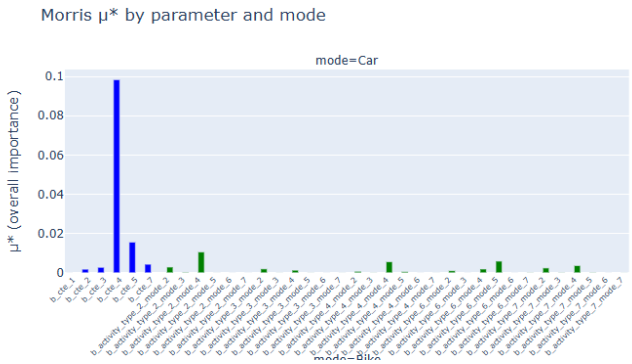


Figure 5.2: Morris μ^* values for parameters effecting car modal share.

Rank	Parameter	μ^*
1	ASC_{car}	0.09836
2	$ASC_{carpassenger}$	0.01556
3	$\beta_{activity-2,car}$	0.01054
4	$\beta_{activity-6,carpassenger}$	0.00588
5	$\beta_{activity-4,car}$	0.00558
6	ASC_{PT}	0.00430
7	$\beta_{activity-7,car}$	0.00363
8	$\beta_{activity-2,bike}$	0.00287
9	ASC_{ebike}	0.00273
10	$\beta_{activity-7,bike}$	0.00241

Table 5.3: Most influential parameters for car modal share

The socio-demographic sensitivity results are presented in Figure 5.3. Parameters related to car ownership are the most influential within this group, followed by coefficients associated with gender, income, age, and migration background.

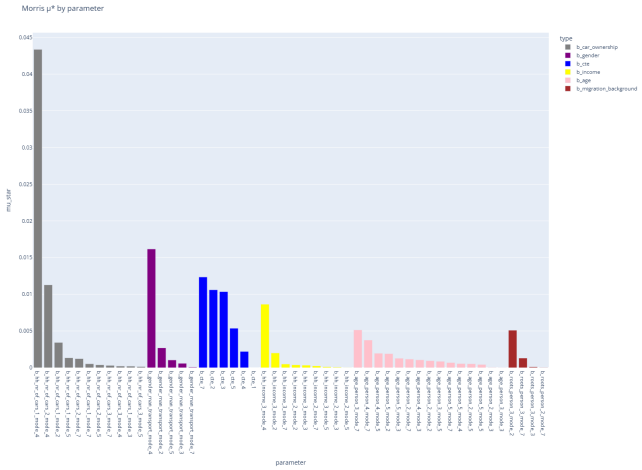


Figure 5.3: Morris μ^* values for parameters effecting car modal share.

Rank	Parameter	μ^*
1	$\beta_{carownership-1,car}$	0.04336
2	$\beta_{male,car}$	0.01616
3	ASC_{PT}	0.01234
4	$\beta_{carownership-2,car}$	0.01128
5	ASC_{bike}	0.01060
6	ASC_{ebike}	0.01035
7	$\beta_{high-income,car}$	0.00863
8	$ASC_{carpassenger}$	0.00536
9	$\beta_{age18-25,PT}$	0.00513
10	$\beta_{non-western,bike}$	0.00509

Table 5.4: Most influential parameters for car modal share

Comparing the three analyses shows that ASC and travel time parameters generally have a stronger influence on modal shares than activity-specific and socio-demographic parameters. At the same time, the results show that the influence of travel time remains relatively small compared with the ASCs. For the car modal share, for example, the ASC is more than four times as influential as the travel time coefficient according to the Morris μ^* indicator. This raises the question of whether the model responds sufficiently to changes in travel time, rather than being predominantly driven by the baseline attractiveness captured by the ASCs. The elasticity analysis in the next section therefore examines this responsiveness directly, with the findings subsequently informing the calibration process.

5.3. Travel-time elasticity analysis

The travel time elasticity analysis described in Section 4.4.2 is presented in detail in this section. The purpose of this analysis is to determine whether the model responds realistically when car travel becomes less attractive. Since the Hofplein intervention primarily effects travel behaviour through increases in car travel time, it is essential that the model not only reduces car use, but also reproduces realistic shifts towards alternative transport modes.

5.3.1. Baseline elasticities

The elasticities presented in this section are based on the previously existing version of the model. The model parameters were estimated using ODiN data. During the estimation process, several adjustments were made to increase the responsiveness of the model to changes in travel conditions. In particular, mode-specific values of time (VoT) were introduced and the travel time coefficient for car travel was increased, because the original estimates did not produce realistic levels of sensitivity to car travel time. These modifications formed part of the model estimation process and were therefore already included in the baseline model before any of the analyses discussed in this chapter were carried out.

Using this parameter set, car travel times were increased by 10% and the resulting elasticities were calculated. Table 5.5 shows the resulting direct and cross-elasticities.

Table 5.5: Elasticities of the original model after a 10% increase in car travel time.

Mode	Model	Literature	Difference
Car	-0.2506	-0.17	-0.0806
Car Passenger	0.0325	-0.27	+0.3025
Bike	0.0253	0.15	-0.1247
E-bike	0.0479	0.15	-0.0521
Walk	0.0105	0.05	-0.0395
Public transport	-0.0093	0.20	-0.2093

The direct elasticity of car demand is within the range reported in the literature. A 10% increase in car travel time leads to a reduction in car trips of approximately 2.5%, corresponding to an elasticity of -0.25. This suggests that travellers in the model are reasonably sensitive to changes in car travel time.

The cross-elasticities paint a different picture. While bicycle, e-bike, walking and car passenger trips all increase when car travel times rise, these increases are much smaller than expected based on the literature. The bicycle elasticity, for example, is only 0.03 compared to a reference value of 0.15, while walking increases by just 0.01 compared to an expected value of 0.05. The largest discrepancy is found for public transport. Rather than increasing in response to higher car travel times, public transport demand slightly decreases, resulting in a negative elasticity of -0.01 where a positive elasticity of around 0.20 would be expected.

While cross-elasticities indicate the response of individual modes, they do not show what happens to the car trips that disappear when travel times increase. To gain further insight into the behavioural response of the model, the concept of a *recovery rate* is introduced. The recovery rate measures the share of reduced car trips that reappear as trips by other modes. A high recovery rate indicates strong modal substitution, whereas a low recovery rate suggests that most of the reduced car trips are simply suppressed rather than transferred to alternative modes.

Table 5.18 presents the recovery rate for the original model. A 10% increase in car travel time results in approximately 37,000 fewer trips by car drivers and car passengers combined. Of these lost trips, only around 10,800 are recovered by other transport modes, corresponding to a recovery rate of 28.8%. The remaining 71.2% of trips disappear entirely.

Table 5.6: Recovery of reduced car-mode trips after a 10% increase in car travel time.

Category	**Trips**	**Share of reduced car-mode trips**
Reduced car-mode trips	37,422	
Recovered by other modes	10,795	28.8%
Suppressed trips	26,627	71.2%

These results confirm the findings from the cross-elasticity analysis. Although the model reduces car travel when car travel times increase, only a relatively small share of the lost trips is transferred to alternative modes. Instead, most trips are suppressed. Since the Hofplein intervention aims not only to reduce car use but also to encourage a shift towards more sustainable travel modes, this low recovery rate indicates that the model underestimates modal substitution.

The remainder of this section investigates potential causes of these weak cross-elasticities and low recovery rates and evaluates a range of modifications aimed at improving the responsiveness of alternative modes while maintaining realistic levels of car travel time sensitivity.

5.3.2. Improving cross-elasticities

The initial elasticity analysis showed that the model responds realistically to increases in car travel time in terms of reducing car use, but that the resulting shift towards alternative modes is much weaker than expected. Since ActivitySim consists of multiple interacting choice models, the source of these low

cross-elasticities is not immediately clear. A series of targeted tests was therefore performed to identify which model components influence modal substitution behaviour.

Mode choice parameters

Because cross-elasticities describe travellers switching between transport modes, the mode choice model was the first place investigated.

travel time coefficient

A first hypothesis was that the calibrated car travel time coefficient was still not sensitive enough to encourage substantial mode shifts. To test this, the coefficient was varied across an extremely wide range.

Table 5.7: Sensitivity to the car travel time coefficient

Mode	Bike	Car	Car Pass.	E-bike	PT	Walk
$b_{tt,prive} = -0.005$	0.053	-0.110	-0.084	-0.009	0.005	-0.002
$b_{tt,prive} = -0.5$	0.047	-1.380	-0.057	-0.032	0.013	0.028

The results show that the car elasticity changes dramatically, from -0.11 to -1.38, indicating that the coefficient strongly controls the responsiveness of car demand. However, the cross-elasticities of competing modes remain relatively small. Even when car travel becomes much less attractive, the increases in bicycle and public transport demand remain limited. This suggests that the travel time coefficient mainly effects trip suppression rather than modal substitution.

Activity-specific parameters

A second hypothesis was that the weak cross-elasticities might be concentrated within particular trip purposes. To investigate this, all activity-specific mode choice coefficients were removed.

Table 5.8: All activity-type coefficients removed

Mode	Bike	Car	Car Pass.	E-bike	PT	Walk
Elasticity	0.062	-0.282	0.039	-0.039	0.044	0.040

Removing the activity effects has only a modest impact on the results. Bicycle and public transport elasticities increase slightly, but remain well below the reference values from the literature. This indicates that the low cross-elasticities are not driven by a particular activity type.

Value of Time

Because the model uses mode-specific values of time, a third hypothesis was that travellers place too little importance on travel time relative to monetary costs. To test this, the value of time for car travel was adjusted.

Table 5.9: Car value-of-time test

Mode	Bike	Car	Car Pass.	E-bike	PT	Walk
Car VOT = 0.05	0.0439	-0.1932	-0.0620	-0.1082	0.0135	0.0106

The effect of this modification is limited. While the direct elasticity of car demand changes slightly, the cross-elasticities remain small. The results therefore suggest that the low modal substitution rates cannot be explained by the value-of-time specification alone.

Generalised Cost Specification

ActivitySim includes an option to increase the weight of car travel time within the generalised cost calculation. Since this directly effects the perceived attractiveness of car travel, it was expected to strengthen modal responses.

Table 5.10: Generalised cost sensitivity tests

Scenario	Bike	Car	Car Pass.	E-bike	PT	Walk
Car TT sensitivity $\times 5$	0.1228	-0.8966	-0.0241	0.0271	0.0706	0.0509
Car TT = 3.0, car cost = 0.5, PT TT = 0.5	0.1010	-0.5955	0.0635	0.0026	0.0745	0.0658

These tests produce noticeably stronger responses. The bicycle elasticity increases to approximately 0.10–0.12, while public transport reaches values around 0.07. However, the direct elasticity of car demand also becomes much larger. Although all modal responses increase, the balance between modal substitution and trip suppression remains largely unchanged. The model becomes more responsive overall, but does not fundamentally solve the cross-elasticity problem.

Alternative-Specific Constants

The previous analyses showed that adjusting individual coefficients can influence model responsiveness, but does not fully explain the weak cross-elasticities. A final hypothesis was therefore that the utilities of the available transport modes are too far apart. If car utility decreases while competing modes remain substantially less attractive, travellers have little incentive to switch modes.

To investigate this, the utilities of the available modes were analysed at the trip level. The results indicated that cycling was often already considerably more attractive than car travel, while public transport remained insufficiently competitive. This suggests that the issue is not only sensitivity to travel time, but also the relative attractiveness of the available modes. To reduce these differences, the bicycle and public transport alternative-specific constants were adjusted, bringing the utility distributions closer together.

The impact of these changes is shown in Table 5.11. While the improvements are modest, cross-elasticities increase for several modes, indicating that reducing the gap between mode utilities can contribute to stronger modal substitution.

Table 5.11: Utility centering

Mode	Bike	Car	Car Pass.	E-bike	PT	Walk
Elasticity	0.0721	-0.1772	-0.0423	-0.0145	0.0141	0.0451

These results suggest that part of the cross-elasticity problem originates from the relative positioning of the utilities rather than from travel time sensitivity alone. When the utilities of competing modes are brought closer together, travellers are more likely to switch modes when car travel becomes less attractive.

Destination Choice Parameters

The second set of tests focused on destination choice. A possible explanation for the low cross-elasticities is that travellers respond to increased car travel times by choosing different destinations rather than changing transport modes. This hypothesis was motivated by early model runs, which showed increases in some short-distance car trips after car travel times were increased. This suggests that travellers may compensate for higher travel times by selecting closer destinations, allowing them to continue travelling by car instead of switching to alternative modes.

Destination Choice Sensitivity

To investigate this, the sensitivity of the destination choice model was strongly reduced by scaling the destination choice parameters to 10% of their original values. If destination substitution is responsible for the low cross-elasticities, reducing the ability of travellers to adjust their destinations should force a larger share of the response to occur through mode choice.

Table 5.12: Destination choice nuclear test

Mode	Bike	Car	Car Pass.	E-bike	PT	Walk
Elasticity	0.038	-0.206	0.055	-0.077	0.024	-0.003

The test alters several elasticities, particularly for car passenger and public transport trips. However, the changes are not large enough to explain the weak cross-elasticities observed in the original model. Destination choice therefore influences the results, but does not appear to be the primary cause of the problem.

Logsum Propagation
A final hypothesis was that accessibility feedback through the logsum variables weakens the propagation of travel time changes through the model system. To investigate this, the influence of logsums was reduced to 10% of their orginial value.

Table 5.13: Logsum propagation test

Mode	Bike	Car	Car Pass.	E-bike	PT	Walk
Elasticity	0.039	-0.158	0.047	-0.022	0.058	0.007

The results show somewhat stronger public transport responses and a weaker car elasticity, but the overall changes remain moderate. Similar to the destination choice test, logsum propagation contributes to the observed elasticities but does not fully explain the low level of modal substitution.

Taken together, these experiments suggest that the weak cross-elasticities cannot be attributed to a single parameter or model component. While several modifications effect the elasticities, none of the tests independently produces a realistic level of modal substitution. Instead, the results indicate that the cross-elasticity problem emerges from the combined interaction of multiple model components, requiring a combination of adjustments rather than a single targeted change.

5.3.3. Updated elasticities

The previous experiments showed that no single parameter was responsible for the low cross-elasticities. Instead, the results suggested that several parts of the model contributed to the problem. Based on these findings, a combination of adjustments was implemented. The most important changes were a reduction in the sensitivity to distant destinations, a reduction in the influence of logsums in the destination choice and scheduling models, and adjustments to the alternative-specific constants (ASCs) to bring the utilities of competing modes closer together. The full set of modified parameters can be found in Appendix C.

After applying these changes, the travel time elasticity analysis was repeated. Table 5.17 compares the elasticities of the original and modified models with the literature values used as references.

Table 5.14: Comparison of travel time elasticities with literature values.

Mode	**Original model**	**Modified model**	**Literature**
Car	-0.2506	-0.2208	-0.17
Car Passenger	0.0325	-0.3656	-0.27
Bike	0.0253	0.0834	0.15
E-bike	0.0479	0.0976	0.10
Walk	0.0105	0.0777	0.05
Public transport	-0.0093	0.0323	0.20

The updated model shows a clear improvement in modal substitution behaviour. While the direct elasticity of car demand remains within the expected range, the cross-elasticities increase for all sustainable

transport modes. The strongest improvements are observed for cycling and walking. The bicycle elasticity increases from 0.03 to 0.08, while the walking elasticity increases from 0.01 to 0.08. The e-bike elasticity also increases to 0.10, closely matching the literature value. Public transport remains less responsive than expected, but the elasticity changes from slightly negative to positive, indicating that increases in car travel time now lead to a measurable increase in public transport use.

Although some differences with the literature remain, the modified model produces a more plausible distribution of travellers across transport modes when car travel becomes less attractive. To better understand this shift, the recovery rate was evaluated again.

Table 5.15: Recovery of reduced car-mode trips after a 10% increase in car travel time.

Category	**Trips**	**Share of reduced car-mode trips**
Original model		
Reduced car-mode trips	37,422	
Recovered by other modes	10,795	28.8%
Suppressed trips	26,627	71.2%
Modified model		
Reduced car-mode trips	69,548	
Recovered by other modes	42,118	60.6%
Suppressed trips	27,430	39.4%

The recovery rate confirms the improvements observed in the elasticity analysis. In the original model, only 28.8% of the reduced car trips reappeared in other transport modes, while 71.2% were suppressed. After the modifications, the share of recovered trips increases to 60.6%. This means that most of the reduction in car travel is now absorbed by alternative modes rather than resulting in cancelled or avoided trips.

Overall, the results indicate that the implemented changes substantially improved the behavioural realism of the model. While some elasticities, particularly for public transport, remain below the values reported in the literature, the model now produces a considerably stronger modal shift in response to increased car travel times. The resulting parameter set therefore provides a more suitable starting point for calibration, serving as the basis for the Bayesian optimization process described in the next section.

5.4. Bayesian calibration

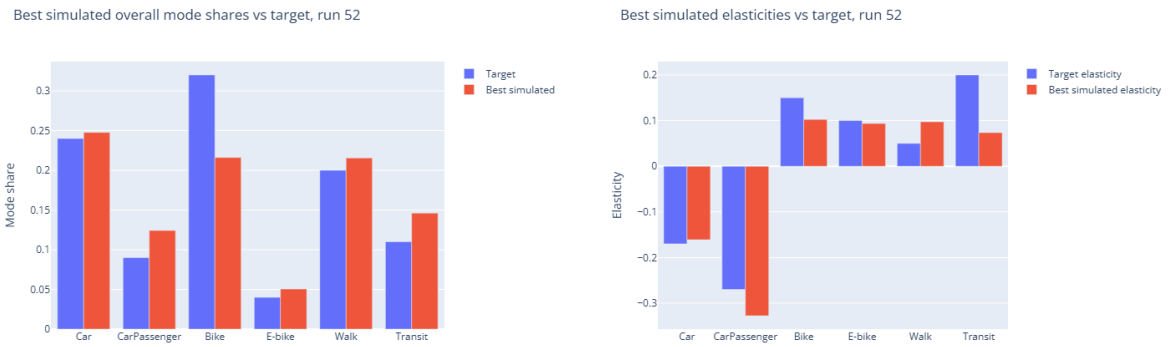
Using the parameter ranges identified in the sensitivity analysis, the Bayesian optimization process described in Section 4.4.3 explored a large number of parameter combinations. The results revealed a clear trade-off between reproducing observed modal shares and matching the elasticity targets derived from the literature. Parameter sets with very low modal share errors often produced relatively weak responses to changes in travel times, whereas solutions with a stronger elasticity fit generally achieved a less accurate modal split. The optimization therefore aimed to identify a parameter set that balanced both objectives.

Table 5.16: Best-performing calibration runs identified during Bayesian optimization.

Run	Modal share error	Elasticity error	Objective value
52	0.0137	0.0240	0.0376
58	0.0218	0.0400	0.0618
42	0.0461	0.0205	0.0666
41	0.0350	0.0363	0.0713
12	0.0090	0.0626	0.0716

Table 5.16 presents the best-performing solutions identified during the optimization process. The results show that similar overall performance can be achieved through different combinations of modal share and elasticity accuracy. Run 42 achieved the lowest elasticity error, while Run 12 achieved the lowest modal share error. Run 52 provided the best overall balance between both objectives and obtained the lowest objective value of all optimization runs. This parameter set was therefore selected as the final calibration result.

Figure 5.4 compares the selected calibration result with the target modal shares and elasticity values. The calibrated model reproduces the overall modal split reasonably well while also improving the behavioural response to travel time changes compared with the initial model specification. The direct car elasticity closely matches the literature benchmark, while the bicycle and e-bike elasticities move substantially closer to their target values.



(a) Modal share comparison

(b) Elasticity comparison

Figure 5.4: Comparison of the selected calibration result (Run 52) and the target values.

The optimization results also indicate that some elasticity targets were easier to reproduce than others. Across many of the high-performing solutions, the direct car elasticity and the bicycle and e-bike cross-elasticities converged towards their target values. For the selected calibration, the car elasticity closely matches the benchmark value, while the e-bike elasticity is nearly identical to its target.

Public transport proved more difficult to calibrate. Although the optimization improved the public transport elasticity, it remained below the target value in nearly all competitive solutions. This indicates that increases in car travel time generate a weaker shift towards public transport than suggested by the literature. At the same time, walking elasticities frequently exceeded their benchmark values, implying that part of the demand response is captured by active modes instead.

Similar patterns are visible in the modal share results. Bicycle use remained below the observed target values in many solutions, while car passenger, walking, and public transport often captured a larger share of demand. As these discrepancies persist across a wide range of parameter combinations, they likely reflect broader interactions within the model structure rather than the effect of a single parameter.

Based on the optimization results, Run 52 was selected as the final calibrated model. This solution achieved the lowest objective value across all 60 optimization runs and therefore provides the best overall balance between modal share accuracy and behavioural realism. The calibrated parameter values and their deviations from the original model specification are presented in Appendix D.

To provide additional insight into the calibration process, Appendix D also includes the evolution of the objective function, modal share error, and elasticity error across all optimization runs.

Overall, the calibration substantially improved the behavioural performance of the model. While some discrepancies with the literature remain, particularly for public transport and bicycle demand, the calibrated model reproduces observed travel patterns reasonably well and yields more realistic responses to changes in travel conditions. As such, it provides a suitable basis for evaluating the effects of the Hofplein intervention in the subsequent chapters.

5.5. Evaluation of the calibrated model

This section presents the calibrated model and evaluates the extent to which the calibration improved its behavioural realism. Figure 5.5 compares the target and calibrated modal shares. The results show a close match between the observed and simulated modal split, demonstrating that the calibrated model provides a realistic representation of aggregate travel behaviour within the study area.

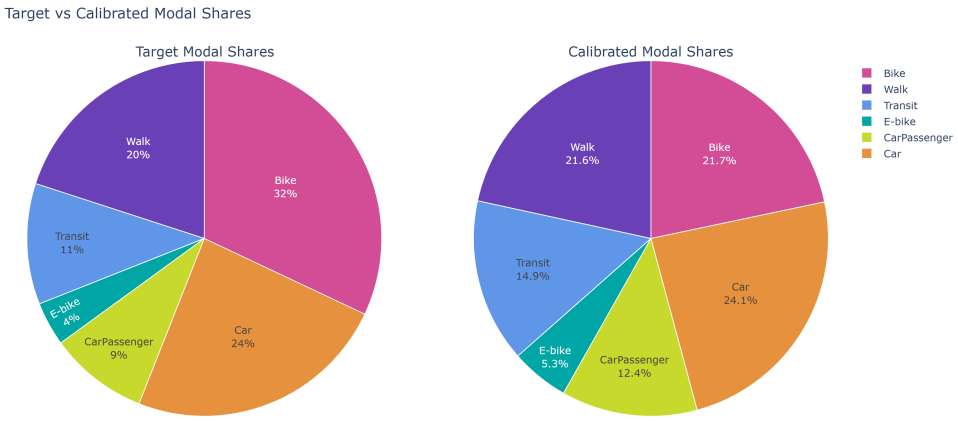


Figure 5.5: Observed and calibrated modal shares.

While matching aggregate modal shares is an important calibration objective, a realistic model should also respond plausibly to policy interventions. For this reason, the travel time elasticity experiment was repeated using the calibrated parameter set. Table 5.17 compares the resulting elasticity values with those obtained from the original and modified models, as well as with values reported in the literature.

Table 5.17: Comparison of travel time elasticities with literature values.

Mode	Original model	Modified model	Calibrated model	Literature
Car	-0.2506	-0.2208	-0.1812	-0.17
Car Passenger	0.0325	-0.3656	-0.3481	-0.27
Bike	0.0253	0.0834	0.1108	0.15
E-bike	0.0479	0.0976	0.1310	0.15
Walk	0.0105	0.0777	0.0930	0.05
Public transport	-0.0093	0.0323	0.0349	0.20

The calibrated model produces a substantially more realistic elasticity pattern than the original model. The direct elasticity for car travel remains close to the literature value, while the positive cross-elasticities for bicycle, e-bike and walking increase considerably. This indicates that increases in car travel time are more likely to result in modal substitution towards active transport modes. Although the public transport elasticity remains lower than reported in the literature, its response is directionally consistent and stronger than in the original model.

To further assess the behavioural realism of the model, the recovery rate of reduced car-mode trips was analysed. This metric evaluates whether trips that are no longer made by car are transferred to alternative modes or disappear entirely from the travel pattern. The results are presented in Table 5.18.

Table 5.18: Recovery of reduced car-mode trips after a 10% increase in car travel time.

Category	Trips	Share of reduced car-mode trips
Original model		
Reduced car-mode trips	37,422	
Recovered by other modes	10,795	28.8%
Suppressed trips	26,627	71.2%
Modified model		
Reduced car-mode trips	69,548	
Recovered by other modes	42,118	60.6%
Suppressed trips	27,430	39.4%
Calibrated model		
Reduced car-mode trips	76,736	
Recovered by other modes	51,222	66.8%
Suppressed trips	25,514	33.2%

The recovery-rate analysis reinforces the conclusions drawn from the elasticity evaluation. In the original model, the majority of reduced car trips disappeared entirely, indicating limited modal substitution. Following the model modifications and subsequent calibration, the proportion of trips recovered by alternative modes increased substantially, rising from 28.8% to 66.8%. This suggests that travellers are increasingly represented as switching modes rather than cancelling trips when car travel becomes less attractive.

Overall, the calibration procedure achieved its primary objective of improving the behavioural realism of the model. The calibrated model reproduces observed modal shares, responds more realistically to changes in car travel times, and exhibits substantially stronger modal substitution effects than the original model. Although some discrepancies remain, particularly for public transport and car-passenger travel, the results indicate that the calibrated model provides a credible basis for analysing the impacts of the Hofplein intervention and other car-reducing policy measures in the following chapters.

6

Results

The following research questions are addressed in this chapter:

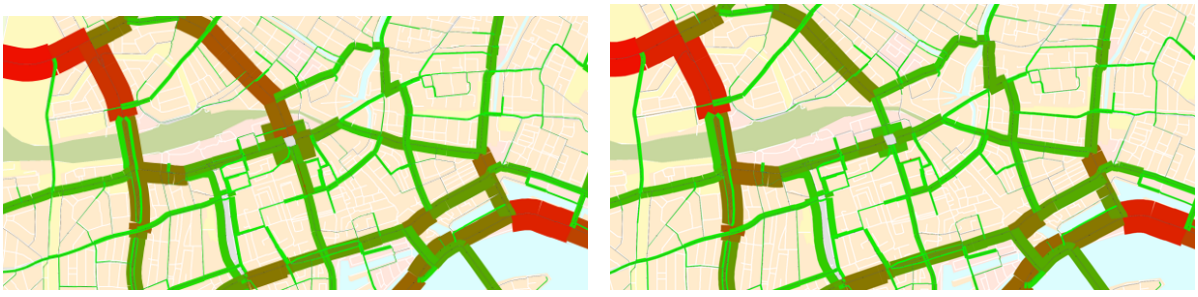
> *How does the Hofplein redesign effect travel behaviour in terms of mode choice, route choice, and trip generation, including the decision to forgo trips?*
>
> *Which traveller personas are most sensitive to the Hofplein intervention and how do they adapt their travel behaviour?*

The approach used to address these research questions is presented in the sections below.

This chapter evaluates the impacts of the Hofplein intervention on travel behaviour and accessibility. First, the traffic assignment results are presented to quantify changes in travel times and accessibility resulting from the network redesign. Next, modal shares are compared between the reference and intervention scenarios at both the MRDH and Hofplein scales. The underlying behavioural responses are then examined by distinguishing between modal shift, rerouting, and trip elimination. Finally, a persona-based analysis is conducted to identify which traveller types are most effected by the intervention and how they adapt their travel behaviour.

6.1. Traffic Assignment

The traffic assignment described in Section 4.3 was carried out in OmniTRANS for both the reference and Hofplein intervention scenarios. The capacity reductions implemented around Hofplein were applied to the network, after which traffic flows and travel times were assigned iteratively until equilibrium was reached. Figure 6.1 presents the resulting network conditions in the vicinity of Hofplein for both scenarios.



(a) Pre-intervention **(b)** Post-intervention

Figure 6.1: Traffic assignment results in the vicinity of Hofplein.

Table 6.1 shows that the overall impact on travel times remains limited at the regional scale. The mean absolute increase in travel time is 2.56 minutes, while the median increase is 1.74 minutes, indicating

that most OD pairs experience relatively small changes. Although some OD relations are effected more substantially, these represent a small share of all trips. Overall, the results suggest that the effects of the Hofplein intervention are highly localized and become diluted when averaged across the entire MRDH study area.

Table 6.1: Additional travel time due to capacity reduction

Metric	Value
Mean absolute difference (min)	2.56
Median absolute difference (min)	1.74

Figure 6.2 illustrates the distribution of travel time differences between both assignment scenarios. The distribution is strongly concentrated around zero, indicating that most OD pairs experience little or no change in travel time. This outcome is expected, as the Hofplein redesign represents a highly localized intervention while the simulations are performed for the entire MRDH region. Consequently, the effects on regional travel conditions are diluted when considering more than 60 million OD relations, many of which are located far from the intervention area.

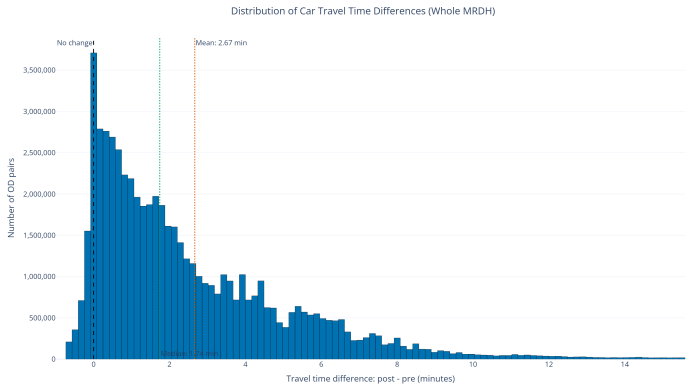


Figure 6.2: Distribution of travel time differences between the reference and intervention scenarios.

The updated skim matrices were subsequently used to recalculate accessibility indicators in ActivitySim. Figure 6.3 shows the percentage change in accessibility resulting from the intervention. Similar to the travel time results, accessibility impacts are generally limited at the scale of the MRDH region. Most zones experience only minor changes, reflecting the relatively small spatial extent of the intervention compared to the size of the regional transport network.

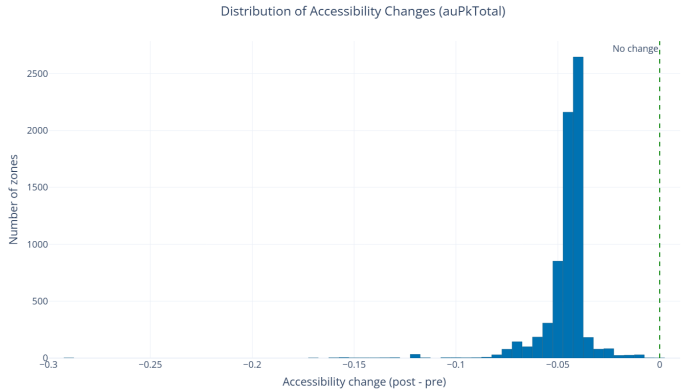


Figure 6.3: Distribution of percentage changes in accessibility between the reference and intervention scenarios.

It should be noted that the reported impacts are likely conservative. The analysis started from the post-intervention network and demand situation, after which the reference scenario was reconstructed by removing the Hofplein intervention. To compensate for demand that had already adjusted to the post-intervention network conditions, additional travel-time penalties were manually applied around Hofplein. these penalties were intended to approximate the higher levels of congestion that would have been present under the original network configuration.

Because the regional effects of the Hofplein intervention are relatively small when averaged across the entire MRDH region, a more targeted analysis is required. A selected-link analysis was initially performed to identify OD pairs whose routes pass through the Hofplein corridor. However, the resulting outputs were not considered sufficiently reliable for further analysis, as they identified fewer effected OD pairs than expected and were not clearly concentrated around the intervention area.

To ensure that the analysis focused on travellers most likely to be influenced by the intervention, the geographic filtering approach described in Section 4.5 is adopted instead. This approach provides a more robust basis for examining local accessibility and behavioural impacts while avoiding the dilution of effects that occurs when considering the full set of OD pairs across the MRDH region.

6.2. Output analysis

The traffic assignment results presented in the previous section demonstrate that the effects of the Hofplein intervention are highly local. Although travel-time changes can be observed throughout the MRDH region, these impacts become small when averaged over the more than 60 million OD pairs contained in the full skim matrix.

To better capture the local effects of the intervention, the remainder of the analysis focuses on the subset of Hofplein OD pairs. These OD pairs represent trips that traverse the Hofplein corridor and are therefore most likely to be effected by the network changes. Unless stated otherwise, all subsequent ActivitySim results are based on this filtered subset rather than the complete MRDH population.

Before analysing the intervention effects, it is useful to compare the travel behaviour of the Hofplein travellers with that of the wider MRDH population. Because the selected OD pairs are concentrated around central Rotterdam, they represent a more urban context with shorter travel distances and better public transport accessibility than many other parts of the MRDH area.

Table 6.2: Modal shares comparison between the entire MRDH region and the Hofplein intervention area

Indicator	Full population (%)	Hofplein area (%)	Difference (%)
Car	21.20	20.80	-1.89
Car passenger	9.46	9.25	-2.22
Bike	18.50	17.00	-8.11
E-bike	9.88	9.78	-1.01
Walk	23.90	17.40	-27.20
Public transport	17.10	25.80	+50.88

Table 6.2 compares the modal shares of the complete MRDH population and the Hofplein selected-link OD pairs. The overall distributions are broadly similar, indicating that the selected subset remains reasonably representative of the regional population. However, notable differences are visible for public transport and walking. Public transport accounts for a substantially larger share of trips within the Hofplein area (+50.9%), reflecting the strong public transport accessibility of central Rotterdam. In contrast, walking represents a smaller share than the regional average. The shares of car use, car passenger trips, cycling, and e-cycling differ only modestly from the MRDH-wide values.

These differences provide important context for interpreting the intervention results. Since the selected-link travellers already exhibit a relatively high reliance on public transport and a slightly lower dependence on private vehicles, their behavioural responses to changes in road-network conditions may differ from those observed at the regional level. The following sections therefore examine the impacts

of the Hofplein intervention on travel behaviour, accessibility, and mode choice within this subset of directly effected travellers.

6.3. Behavioural Response

Section 3.5 showed that observed daily traffic volumes through Hofplein decreased from 38,385 vehicles in the reference situation to 12,053 vehicles after the intervention. This reduction raises an important question: where did these 26,332 vehicles go and how did travellers respond to the loss of road capacity?

To answer this question, the behavioural responses of travellers effected by the intervention were analysed. Figure 6.4 traces the destination of trips that were previously made by car but are no longer observed as car trips in the intervention scenario. Of the 26,332 lost Hofplein trips, 13,640 are explained by either modal shift or trip elimination, while the remaining 12,690 trips are associated with travellers who rerouted or selected alternative destinations.

The results indicate that for the 13,640 lost car trips, trip elimination is a common response, accounting for 6,315 trips (46.3%). Modal shift represents the remaining behavioural changes, with 2,498 trips shifting to walking (18.3%), 1,864 to cycling (13.7%), 1,718 to e-bike (12.6%), and 1,245 to public transport (9.1%).

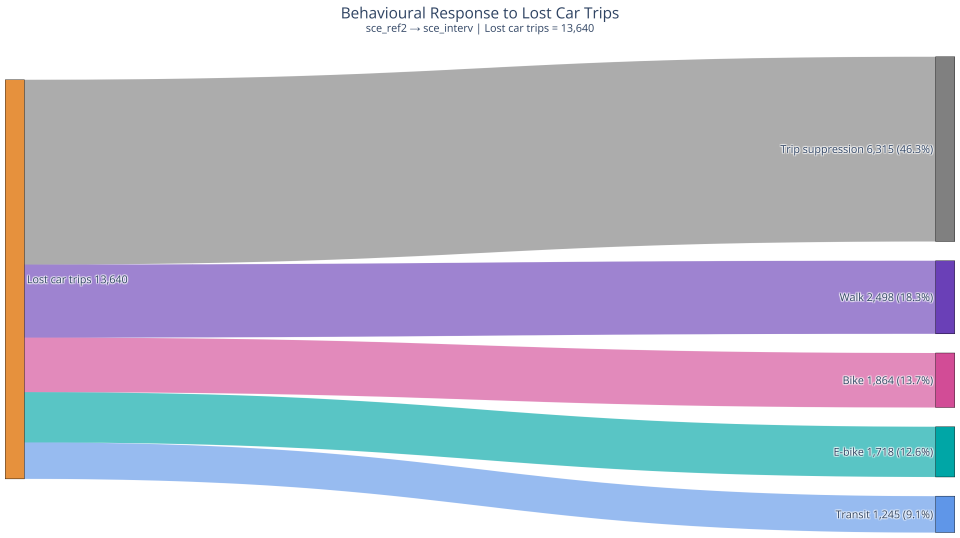


Figure 6.4: Behavioural response of lost car trips.

Figure 6.5 shows which trip purposes contribute most to the reduction in car travel. The largest reductions are observed for home- and work-related trips, with 3,673 and 3,592 fewer car trips respectively. Substantial reductions are also found for escort (2,026), shopping (1,936), and at-work trips (1,651). Together, these categories account for the majority of lost car trips.

The distribution of lost car trips across multiple trip purposes indicates that the effects of the Hofplein intervention are not limited to selected trip purposes. Instead, changes in car use occur across a broad range of daily activities, suggesting that travellers adapt in different ways depending on the purpose of the trip.

The remainder of this section examines these behavioural mechanisms in greater detail, focusing on modal shift, rerouting, and trip elimination.

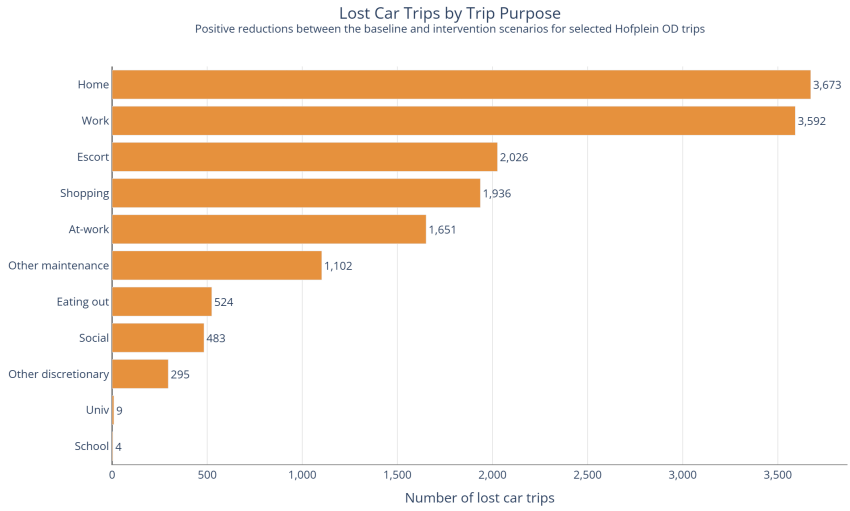


Figure 6.5: Lost car trips by trip purpose.

6.3.1. Modal Shift

The modal shift analysis focuses on trips that pass through the Hofplein corridor, where the intervention directly effects travel conditions. Figure 6.6 compares the modal shares of these trips in the baseline and intervention scenarios. Following the reduction in road capacity, the share of car trips decreases from 20.8% to 14.0%, indicating that a portion of travellers chooses alternative modes rather than continuing to drive through the area.

The reduction in car use is accompanied by increases across several sustainable modes. Public transport grows from 25.8% to 29.6%, walking from 17.4% to 20.0%, cycling from 17.0% to 19.4%, and e-bike use from 9.8% to 11.4%. These results suggest that the intervention encourages a shift away from private car use towards public and active transport for trips that interact with the Hofplein corridor.

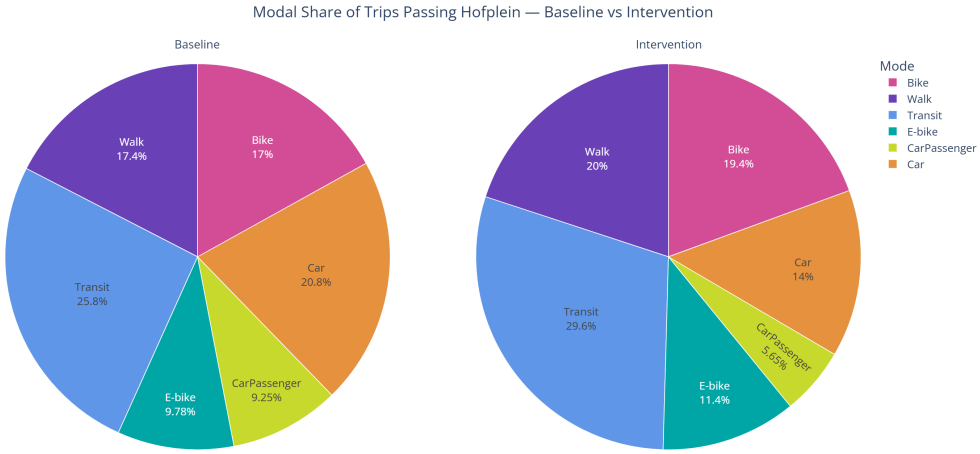


Figure 6.6: Modal share of trips passing through the Hofplein corridor in the baseline and intervention scenarios.

To better understand how existing car users adapt, a separate analysis was conducted for individuals who made at least one car trip within a Hofplein selected-link OD pair in the baseline scenario. Tracking these same travellers in the intervention scenario provides insight into whether they continue driving or switch to alternative modes.

Figure 6.7 shows that car use remains dominant within this group, but declines substantially from 79.3% to 63.2%. The displaced car trips are primarily redistributed to public transport, cycling, e-biking, and walking. Public transport increases from 5.1% to 9.0%, cycling from 3.8% to 8.8%, e-bike use from 3.6% to 8.4%, and walking from 4.4% to 7.2%.

These results demonstrate that even among travellers who initially relied on the car to travel through the Hofplein area, a considerable share adapts by switching mode when car travel becomes less attractive. At the same time, the majority of travellers continue to travel by car, indicating that not all users have equally viable alternatives available.

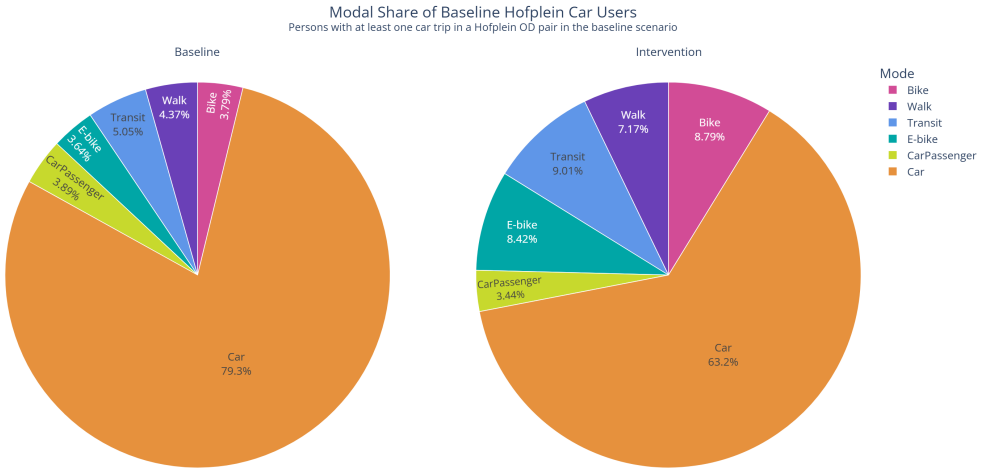


Figure 6.7: Modal share comparison for baseline Hofplein car users.

6.3.2. Rerouting

Not all travellers respond to the Hofplein intervention by changing transport mode. As shown in the previous section, a substantial share of effected travellers continues to travel by car. For these travellers, adaptation primarily occurs through changes in route choice. Approximately 50% of baseline Hofplein car users remain car travellers in the intervention scenario while no longer using the effected corridor, indicating rerouting behaviour within the network.

Additional evidence can be obtained from the distribution of trip distances shown in Table 6.3. While the overall changes are modest, a consistent reduction can be observed for longer-distance trips. The largest decreases occur for trips between 15 and 30 km (-0.8%) and trips longer than 30 km (-1.1%), whereas shorter trips remain largely unchanged.

The combination of these findings suggests that travellers have multiple adaptation strategies in response to the intervention. A considerable share continues travelling by car but selects alternative routes to avoid the reduced-capacity corridor. At the same time, the slight reduction in longer-distance trips indicates that some travellers may also adjust their destination choices, resulting in shorter travel distances. Consequently, the observed reduction in traffic through the Hofplein corridor cannot be attributed solely to modal shift, but also reflects behavioural adaptations within the car-travelling population.

Table 6.3: Trip distance distribution before and after the Hofplein intervention

Distance Group	Ref. Trips	Scenario Trips	Abs. Change	% Change
0–5 km	530,929	531,516	587	0.11%
5–10 km	471,183	470,838	-345	-0.07%
10–15 km	249,450	248,748	-702	-0.28%
15–30 km	403,686	400,350	-3,336	-0.83%
30+ km	340,342	336,521	-3,821	-1.12%

6.3.3. Trip Elimination

The final behavioural response considered is trip elimination. Trip elimination occurs when a trip present in the baseline scenario no longer appears in the intervention scenario. Within ActivitySim, this can result from changes in activity participation or tour generation decisions that make a trip less attractive under the updated travel conditions.

As illustrated in Figure 6.4, 6,315 baseline car trips are neither transferred to another transport mode nor observed elsewhere within the analysed travel set. These trips can therefore be classified as eliminated trips. Compared to modal shift and rerouting, trip elimination represents the smallest behavioural response category.

The magnitude of trip elimination is also expected to vary across population groups. Differences in factors such as age, employment status, household composition, and access to transport alternatives may influence an individual's ability to adapt to changing travel conditions. The following section therefore examines the socio-demographic characteristics associated with the observed behavioural responses.

6.4. Persona analysis

As described in the methodology, synthetic individuals were assigned to one of the ten KiM mobility personas using a combination of socio-demographic characteristics and simulated travel behaviour. This persona classification enables behavioural responses to the Hofplein intervention to be analysed for broader population segments rather than only for individual demographic variables.

Initial inspection of the results indicates that behavioural responses are not evenly distributed across the population. Differences in modal shift, rerouting, and trip elimination can be observed between groups with different socio-demographic characteristics, suggesting that travellers do not all have the same capacity or willingness to adapt to changing travel conditions. To provide additional insight into these differences, modal shift outcomes disaggregated by socio-demographic characteristics are included in Appendix F. The persona-based analysis presented in the following sections builds upon these socio-demographic patterns by examining how broader mobility lifestyles respond to the intervention.

6.4.1. Persona assignment

This section examines the outcomes of the persona assignment and assesses its validity within the synthetic population. The assignment builds on differences that already exist within the synthetic ActivitySim population.

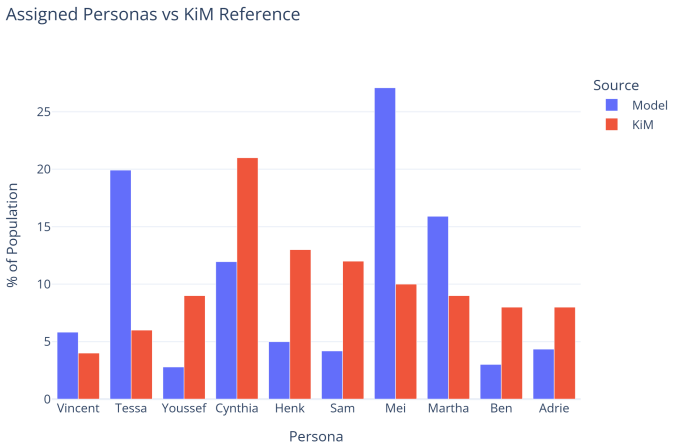


Figure 6.8: Distribution of assigned personas compared with the KiM reference distribution.

Figure 6.8 compares the distribution of assigned personas in the synthetic population with the reference distribution reported by KiM. While several personas are over- or underrepresented relative to the national reference values, all personas are represented in the model population. The observed

differences are likely related to the relatively urban character of the MRDH study area compared to the national population used in the KiM segmentation. As a result, more urban-oriented personas, such as Mei and Tessa, are assigned more frequently, whereas personas that are more strongly associated with less urban and car-dependent lifestyles such as Cynthia are represented less often.

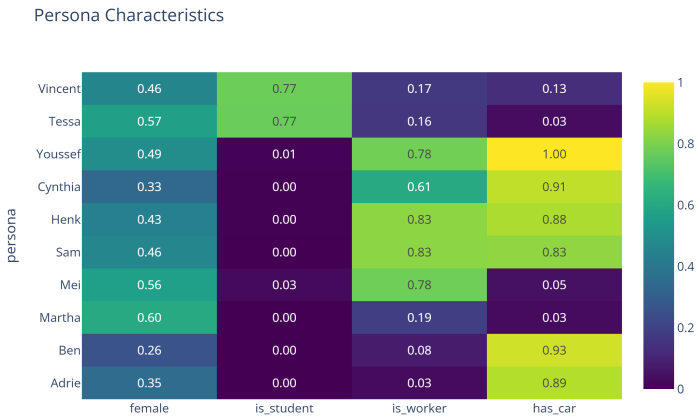


Figure 6.9: Average socio-demographic characteristics of individuals assigned to each persona.

Figure 6.9 presents selected socio-demographic characteristics of the assigned personas as an additional validation of the assignment procedure. These characteristics closely resemble the defining attributes of the corresponding KiM personas presented in Appendix E. Clear distinctions can be observed between personas in terms of student status, employment, car ownership, and gender composition. For example, Vincent and Tessa contain relatively high shares of students, while Youssef, Henk, Sam, and Mei are predominantly workers. Car ownership also varies substantially, ranging from very low shares for student-oriented personas to almost universal ownership for personas such as Youssef, Cynthia, Henk, Ben, and Adrie. The similarity between the assigned personas and the original KiM persona profiles indicates that the assignment procedure successfully reproduces the key socio-demographic characteristics associated with each persona.

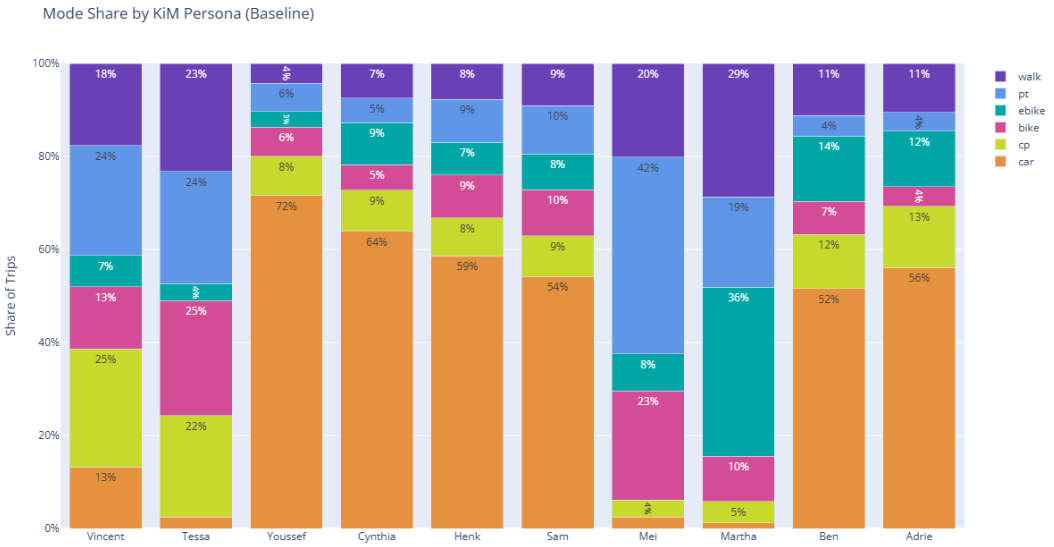


Figure 6.10: Baseline modal shares per persona.

Figure 6.10 presents the baseline modal shares for each persona. The assigned personas exhibit distinct travel behaviour, ranging from highly car-oriented profiles such as Youssef, Cynthia, Henk, and Adrie to more multimodal personas such as Vincent, Tessa, Mei, and Martha. In particular, Vincent and Tessa make relatively frequent use of cycling and public transport, while Mei and Martha are characterised by very low levels of car use and comparatively high shares of public transport, walking, and e-bike trips. The differences in modal shares demonstrate that the assigned personas represent clearly distinguishable behavioural groups within the synthetic population.

Although the persona assignment is partly informed by simulated travel behaviour, the resulting segments are not defined solely by mode choice. Instead, they represent broader combinations of socio-demographic and behavioural characteristics. This allows the impacts of the Hofplein intervention to be analysed at the level of meaningful population groups rather than individual demographic variables alone.

6.4.2. Persona behavioural response

This section examines how the Hofplein intervention effects the travel behaviour of the different personas identified in the last section. By comparing modal shares before and after the intervention, it becomes possible to assess whether certain population segments are more responsive to the reduction in road capacity than others.

Figure 6.11 compares the modal shares of each persona between the baseline and intervention scenarios. The results show that the overall direction of change is largely consistent across personas, with a reduction in car use accompanied by increases in public transport, cycling, e-bike use, and walking. However, the magnitude of these changes differs considerably between personas. The largest modal shifts are observed among the predominantly car-oriented personas, including Cynthia, Henk, Sam, Ben, and Adrie. In contrast, personas such as Vincent, Tessa, Mei, and Martha exhibit relatively limited changes, reflecting their already low levels of car use in the baseline scenario.

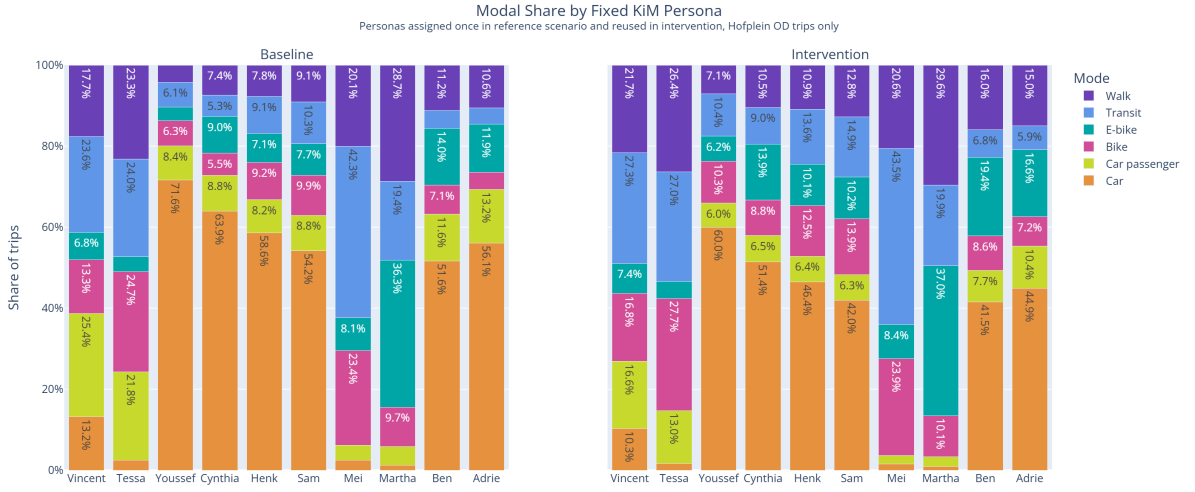


Figure 6.11: Baseline and intervention modal shares by persona.

To further examine the underlying behavioural adaptations, persona-specific Sankey diagrams are provided in Appendix G. These visualisations illustrate the movement of travellers between transport modes for each persona and provide additional insight into how the observed modal share changes emerge from individual behavioural responses.

In addition to modal shifts, the intervention also results in a number of eliminated car trips. Figure 6.12 presents the distribution of these lost car trips across the personas. The reduction in car travel is concentrated among a relatively small number of population segments. Cynthia accounts for the largest

share of lost car trips (41.9%), followed by Henk (17.9%) and Youssef (13.8%). Together, these three personas account for more than 70% of all lost car trips. In contrast, Vincent, Tessa, Mei, and Martha contribute only marginally, reflecting their comparatively limited reliance on car travel in the baseline scenario.

The concentration of lost car trips among a limited number of personas suggests that the impacts of the Hofplein intervention are not distributed evenly across the population. Instead, the reduction in car accessibility primarily effects personas that are relatively car-dependent. The implications of this uneven distribution are explored further in the discussion chapter of this thesis.

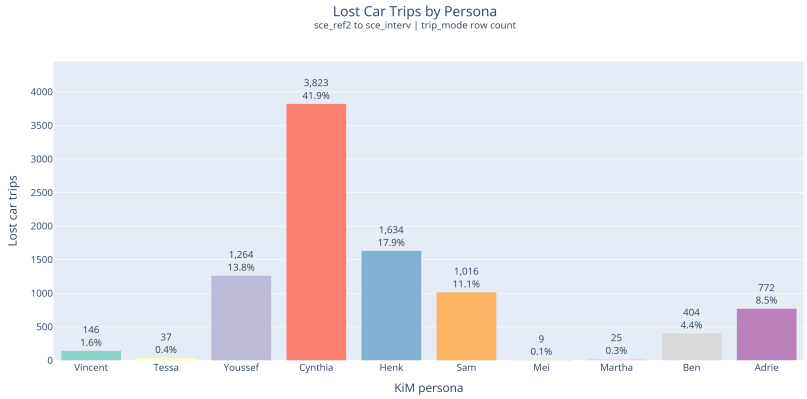


Figure 6.12: Lost car trips by persona.

7

Discussion

This chapter discusses the main findings of the study and reflects on their broader implications. It first interprets the observed behavioural responses and differences between traveller groups, before considering the assumptions and limitations of the modelling approach. The chapter then discusses the implications for car-reducing measures, society and policy, and activity-based transport modelling. Finally, recommendations for future research are presented.

Interpreting the results

The results show that the Hofplein intervention influences travel behaviour through multiple adaptation mechanisms. Although the intervention is geographically concentrated and therefore produces only limited impacts at the scale of the MRDH region, the effects are substantially stronger within the Hofplein analysis area, where the car modal share decreases from 20.8% to 14.0%. This indicates that reducing car accessibility can meaningfully alter the travel behaviour of those directly exposed to the intervention.

Further insight into these behavioural responses can be obtained by combining observed traffic counts with the activity-based modelling results. Observed traffic volumes passing through Hofplein decrease from approximately 38,385 vehicles per day in the reference situation to 12,053 vehicles during the intervention in 2026, representing a reduction of 26,332 vehicle movements. These observed volumes and the modelled trips differ in nature and cannot be compared directly. The traffic counts describe the overall real-world change in vehicle movements at Hofplein, whereas the activity-based model provides insight into the behavioural mechanisms that may underlie this reduction. Within the model, 13,640 lost car trips are explained by either modal shift or trip elimination, while other travellers adapt through rerouting or destination changes.

Trip elimination accounts for 6,315 trips, representing nearly half of all explained behavioural changes. The remaining reduction in car trips is primarily associated with shifts towards walking, cycling and e-bike use, with a smaller contribution from public transport. These findings suggest that travellers respond to reduced car accessibility through a combination of adaptations rather than through a single mechanism. Rerouting, destination changes, modal shift and trip suppression all contribute to the reduction in car traffic, highlighting the flexibility of travel behaviour when accessibility conditions change.

The calibration results are important when interpreting the reliability of these findings. The sensitivity analysis showed that a relatively small number of mode-choice parameters exert a strong influence on model outcomes, while the calibration process demonstrated that modest parameter adjustments can noticeably effect predicted behaviour. Calibration improved agreement with observed modal shares and travel-time elasticities, increasing confidence that the model responds plausibly to changes in travel conditions. At the same time, the influence of the calibrated parameters means that the precise magnitudes reported in this study remain subject to some uncertainty. Greater confidence can therefore be placed in the overall behavioural patterns than in the exact number of trips associated with each response mechanism.

The persona analysis demonstrates that behavioural responses are not evenly distributed across the population. Clear differences exist between personas in both their socio-demographic characteristics and baseline travel behaviour. Personas such as Cynthia, Henk, Youssef, Ben and Adrie exhibit relatively high levels of car ownership and car use, whereas Vincent, Tessa, Mei and Martha rely more strongly on public transport, cycling, walking and e-bike travel.

These differences become particularly important once the intervention is introduced. Cynthia, Henk and Youssef account for more than 70% of all eliminated car trips despite representing a substantially smaller share of the population. This pattern suggests that behavioural adaptation is strongly influenced by existing travel behaviour, which is consistent with the utility-based choice framework underlying ActivitySim. For car-oriented personas, the car provides the highest utility for a large share of their daily trips, making them more dependent on car accessibility across their activity patterns. Travellers who already use a mixture of transport modes have more trips for which viable alternatives are available and therefore require less behavioural adjustment when car accessibility changes.

The findings should also be considered within the broader context of Rotterdam's city-centre redevelopment. The Hofplein intervention is analysed here as a stand-alone measure, allowing the effects of reduced car accessibility to be studied separately. In practice, however, the redesign forms part of a wider urban transformation that includes substantial investments in public space and the planned construction of approximately 10,000 new homes. These developments are not explicitly represented in the model, but they are likely to increase the number of travellers effected by the intervention and may also improve the attractiveness of sustainable transport modes. The long-term impacts of the wider redevelopment programme could therefore extend beyond the effects identified for the Hofplein redesign alone.

Assumptions and limitations

Several assumptions and limitations should be considered when interpreting the findings. These concern the scope of the analysis, the representation of behavioural heterogeneity, the calibration of the model, and the interaction between travel demand and traffic assignment.

Reflection on the scope

The scope defined in Chapter 1 appears to be broadly consistent with the objectives of this study. The selected behavioural responses, namely route choice, modal shift and trip suppression, capture the most direct ways in which travellers can adapt to reductions in car accessibility and are therefore well suited for analysing the impacts of a car-reducing intervention.

The analysis of differences between population groups is subject to greater uncertainty. While the study initially aimed to assess impacts across socio-demographic categories such as age and income, the final persona analysis relies on behavioural personas that combine a broad range of demographic, mobility and attitudinal characteristics. This provides a richer representation of behavioural heterogeneity than individual socio-demographic variables alone, but also makes it more difficult to isolate the influence of specific characteristics. Consequently, the estimated behavioural responses are likely to be more robust than conclusions regarding the precise impacts on individual socio-demographic groups.

Behavioural assumptions and persona assignment

The persona assignment procedure is based on a probabilistic Naive Bayes approach. This method assumes that the observed characteristics used for classification are conditionally independent given a persona. In reality, many demographic and mobility characteristics are correlated, meaning that this assumption is unlikely to hold perfectly. Nevertheless, the approach provides a transparent and computationally efficient method for assigning synthetic individuals to personas and was considered sufficiently accurate for the purposes of this study.

The KiM personas themselves were not specifically developed for evaluating car-reducing measures in Rotterdam. Their main advantage is that they are grounded in extensive empirical research and therefore provide a robust behavioural framework. However, because they were designed to describe travel behaviour within the Dutch population as a whole, some characteristics relevant to the Hofplein case study may not be fully captured.

In addition, the socio-demographic parameters used in ActivitySim were assumed to provide a realistic

representation of behavioural heterogeneity. Although these parameters influence activity and mode-choice behaviour, they were not systematically validated against empirical evidence or previous studies. The plausibility of these effects therefore depends largely on the underlying model specification.

Calibration and behavioural realism
The calibrated model does not perfectly reproduce all target modal shares and travel-time elasticity values. Although Bayesian calibration substantially improves model performance relative to the starting parameter set, exact agreement was not achieved within the available calibration budget of 60 model evaluations. This reflects both the computational constraints of calibrating large-scale activity-based models and the complexity of the behavioural interactions represented within ActivitySim.

Furthermore, the calibration targets themselves contain uncertainty. The travel-time elasticity values were derived from the Dutch National Model System (LMS), which is itself a transport model rather than an observed dataset. Because LMS uses a different modelling framework and is not activity-based, discrepancies between the target elasticities and ActivitySim's behaviour may partly reflect differences between modelling approaches rather than actual behavioural inaccuracies.

Traffic assignment and route-choice representation
An important limitation concerns the treatment of route choice. Due to the absence of a feedback mechanism between demand and assignment, route adaptation cannot be observed directly. Travellers who change routes are captured implicitly through changes in network travel times, but the model cannot determine precisely how many travellers reroute or which alternative routes are selected. A tighter integration between activity generation, mode choice and network assignment would allow route-choice responses to be quantified more explicitly.

Finally, traffic assignment was performed using the V-MRDH model, for which the available network representation already incorporated elements of the redesigned Hofplein configuration. Consequently, travel demand patterns in the higher-capacity scenario may already partially reflect behavioural adaptations associated with the intervention, meaning that the baseline scenario does not fully represent pre-intervention conditions. To partly compensate for these differences in local congestion levels, additional travel-time penalties were manually applied around Hofplein to create a more realistic representation of the expected accessibility impacts. Nevertheless, the analysed scenarios are likely to provide a conservative estimate of the intervention's effects. If a separate representation of the original Hofplein configuration and its corresponding travel demand had been available, larger changes in travel behaviour, accessibility and traffic patterns might have been observed.

Implications for car-reducing measures

While the Hofplein intervention represents a specific case study, the behavioural patterns identified in this research are likely relevant for many cities pursuing policies aimed at reducing car use and improving urban liveability.

A first insight is that the impacts of car-reducing measures are not distributed evenly across the population. Although the overall behavioural effects remain relatively modest, certain traveller groups experience substantially larger changes. In particular, the strongest responses occur among travellers with a high dependence on private car use. Importantly, these travellers are often not residents of the city centre itself, but are more likely to live in suburban or regional areas and rely on the car to access employment, services and other opportunities within the city. As a result, measures implemented within urban centres may have their largest behavioural consequences for travellers entering the city rather than for those living within it.

The results further show that reducing car accessibility does not necessarily lead to a proportional shift towards sustainable modes. While some travellers adapt through rerouting or modal shift, a substantial share of car trips disappears altogether, suggesting that the available alternatives are not always sufficiently attractive or able to provide a comparable level of accessibility.

A key policy lesson therefore emerges. Car-reducing measures can contribute to improved liveability, lower traffic volumes and a more efficient use of urban space, but their effectiveness depends on more than restricting car travel alone. Reductions in car accessibility should be accompanied by attractive alternatives that enable travellers to adapt without sacrificing access to opportunities. Investments in

regional public transport, park-and-ride facilities and integrated multimodal travel chains may therefore be just as important as the restrictions themselves, particularly for travellers accessing the city from surrounding municipalities.

Implications for society and policy

The findings also contribute to the broader discussion on the societal consequences of car-reducing policies. Across Europe, cities are increasingly reallocating road space to improve public space, reduce emissions and create healthier urban environments. The results do not challenge these ambitions, but demonstrate that the benefits and burdens of such policies are not always experienced equally.

From a societal perspective, interventions such as the Hofplein redevelopment can generate substantial benefits through reduced traffic volumes, improved environmental quality and enhanced public space. At the same time, the results suggest that a relatively small group of car-dependent travellers experiences a disproportionate share of the negative impacts. It is important to note that these impacts do not necessarily imply a complete loss of access to activities. Many travellers adapt by changing destinations, modes, routes or activity schedules rather than abandoning participation altogether. Nevertheless, such adaptations may still involve reductions in convenience, flexibility or accessibility.

This raises an important question of equity: even when the overall societal balance is positive, how should policymakers respond when particular groups bear a larger share of the costs than others?

Many of the travellers most effected by the intervention rely heavily on the car and have relatively few practical alternatives available. For these travellers, the car is often not merely a preferred option, but an important means of maintaining access to opportunities. If society benefits from reduced congestion, emissions and improved urban quality, there is a strong argument that complementary measures should also be considered for those who experience the greatest accessibility losses.

This finding relates to the concept of transport poverty, which highlights how limited transport options can restrict participation in society. Although the results do not suggest that the Hofplein redevelopment directly causes transport poverty, they indicate that car-reducing measures may increase accessibility challenges for travellers who are already relatively dependent on the car. Policies that improve liveability for one group can therefore simultaneously reduce accessibility for another.

More broadly, the findings highlight that the desirability of car-reducing policies depends not only on the benefits they generate, but also on how those benefits and costs are distributed across society. Determining where this balance lies is ultimately a normative policy choice. However, the results suggest that policy evaluation should move beyond aggregate indicators such as traffic volumes or emissions and explicitly consider who benefits, who bears the costs, and whether these trade-offs are regarded as acceptable. The success of car-reducing policies should therefore be assessed not only by the extent to which they reduce car use, but also by their implications for accessibility and the distribution of impacts across different groups of travellers.

Implications for activity-based modelling

Beyond the policy implications, this study also demonstrates the value of activity-based transport models for evaluating car-reducing measures and their distributional consequences. A major advantage of ActivitySim is its ability to represent travel behaviour at the level of individual travellers rather than aggregate trip flows. Travel decisions emerge from interactions between socio-demographic characteristics, household structures, activity participation and accessibility conditions, allowing the model to capture behavioural mechanisms that are difficult to represent in more aggregate modelling approaches.

This capability becomes particularly valuable when evaluating interventions whose impacts differ across population groups. Aggregate indicators such as traffic volumes and modal shares provide an overview of overall system performance, but reveal little about who is effected and why. The persona analysis illustrates this clearly. While the aggregate behavioural effects of the intervention appear relatively modest, substantial differences emerge between traveller groups. Many of the distributional insights discussed in this chapter would therefore have remained hidden in a conventional aggregate analysis.

Such capabilities are becoming increasingly important as transport planning expands beyond questions

of efficiency and capacity towards broader concerns related to accessibility, equity and behavioural adaptation. Activity-based models provide a framework for understanding not only whether behaviour changes, but also which travellers are effected, how they respond and what mechanisms drive those responses.

At the same time, the study highlights one of the major practical challenges of activity-based modelling: calibration. Although the calibrated model reproduced observed behaviour more accurately than the initial model, simultaneously matching modal shares and travel-time elasticities proved difficult. The study therefore demonstrates both the strengths and challenges of activity-based modelling. Its richer behavioural representation provides valuable insight into the distributional consequences of transport interventions, but this additional realism comes at the cost of increased model complexity and calibration effort.

Recommendations for future research

This study provides an initial exploration of how car-reducing measures influence travel behaviour within an activity-based modelling framework. Several opportunities exist to extend and strengthen the analysis.

First, future research could focus on more extensive empirical validation of behavioural responses. While this study compared simulated changes in car travel with observed traffic intensities, validation opportunities for other modes were limited. Additional data sources, such as public transport passenger data, bicycle and pedestrian counts, shared-mobility usage, travel surveys and mobile-device data, could provide a more comprehensive assessment of model performance.

Second, future work could investigate behavioural responses at a more detailed activity level. While this study provided an initial exploration of activity-level adaptation, the analysis could not be empirically validated. Further research could examine which activities are most likely to be cancelled, relocated, rescheduled or combined, and which trip purposes are most likely to shift to alternative modes. This would help distinguish between activity loss and activity reorganisation, as a reduction in trips does not necessarily imply reduced participation in activities.

Third, persona-based approaches could be further developed. The personas used in this study were based on the national KiM segmentation framework and proved useful for identifying heterogeneous responses. However, personas specifically designed around car dependency, accessibility and mobility transitions, or tailored to the Rotterdam region, may provide additional insight. Comparing persona-based results with analyses based directly on socio-demographic variables could further clarify which outcomes are associated with broader behavioural profiles and which are linked to characteristics such as income, car ownership or residential location.

Fourth, future elasticity analyses could be extended beyond car travel time to include travel costs, parking costs, public transport travel time and fares. This would provide a broader understanding of behavioural sensitivity to different policy instruments and help identify which combinations of measures are most likely to produce the intended responses.

Fifth, stronger integration between ActivitySim and V-MRDH could improve the representation of interactions between travel demand and network conditions. Additional feedback iterations between demand modelling and traffic assignment would allow behavioural choices and congestion levels to influence one another, resulting in a more consistent equilibrium between simulated demand and network performance. Such an approach would also provide greater insight into rerouting behaviour by allowing route choices to adapt more explicitly to changes in network conditions.

Sixth, future studies could explicitly incorporate the planned housing development in the Hofplein area. The construction of new housing is expected to increase travel demand and may amplify the effects of reduced car accessibility over time. A useful extension would be to develop a future scenario that combines the redesigned Hofplein with the planned residential development. Within ActivitySim, this could be implemented by expanding the synthetic population to reflect the expected increase in residents and associated travel demand. Such a scenario would provide insight into how a growing population adapts to reduced car accessibility and whether sustainable transport alternatives are able to accommodate the resulting increase in demand.

Seventh, future research could examine the economic impacts of car-reducing measures on businesses. The results of this study suggest that the strongest behavioural responses occur among travellers who are most dependent on car use. An interesting extension would therefore be to investigate small businesses with high levels of car dependency, such as plumbers, painters and other service-oriented occupations that rely on transporting tools and materials between multiple locations. Examining how reduced car accessibility effects their operations, costs and accessibility could provide a broader understanding of the economic implications of car-reducing policies alongside their mobility and environmental effects.

Finally, future evaluations could consider packages of interventions rather than individual projects in isolation. Since the Hofplein redevelopment forms part of a broader transformation of Rotterdam's city centre, behavioural responses may depend on complementary measures elsewhere in the transport system. Evaluating combinations of measures, such as reduced road capacity, parking restrictions, public transport improvements, cycling infrastructure and park-and-ride facilities, would provide a more realistic assessment of long-term behavioural adaptation.

Main takeaway

The central lesson from this study is that the impacts of car-reducing measures cannot be fully understood through aggregate changes in traffic volumes or modal shares alone. While the overall behavioural response to the Hofplein intervention is relatively modest, substantial differences emerge between traveller groups. Car-dependent travellers account for most behavioural adaptation, whereas travellers who already rely on a mix of transport modes are effected to a much smaller extent. The results also show that adaptation occurs through multiple mechanisms, including modal shift, rerouting and trip suppression.

Although this study focuses on Hofplein, these insights are relevant for many cities pursuing similar transitions towards more sustainable and people-oriented urban environments. The findings suggest that the effectiveness and distributional impacts of car-reducing measures depend strongly on existing travel patterns and the availability of attractive alternatives. Understanding who is effected, how travellers adapt, and which groups face the greatest barriers to adaptation is therefore essential for designing effective and equitable transport policies.

More broadly, this research demonstrates the value of activity-based modelling for analysing behavioural adaptation to transport interventions. By capturing heterogeneity between travellers and the mechanisms underlying behavioural change, such models can support more informed decision-making as cities seek to balance accessibility, liveability and sustainability objectives.

8

Conclusions

This thesis examined the effects of car-reducing measures on travel behaviour using the Hofplein redesign in Rotterdam as a case study. By combining an activity-based transport model with a calibrated behavioural model, it was possible to analyse not only aggregate travel responses, but also differences between socio-demographic groups represented by traveller personas. This chapter answers the research questions and concludes with the main conclusion.

Research Question 1

What is the most appropriate approach to analyse changes in aggregate travel behaviour resulting from car-reducing measures, and how can these changes in travel behaviour be split out for different socio-demographic groups?

The findings show that travel behaviour responses to car-reducing measures are best analysed using behavioural transport models that explicitly represent traveller decision-making. Traditional four-step transport models are useful for estimating changes in traffic volumes and network performance, but they provide only limited insight into the behavioural mechanisms underlying these changes. In particular, they do not explicitly represent individual socio-demographic characteristics.

Activity-based models offer a more suitable framework because they simulate travel decisions at the level of individual persons and households. This makes it possible to analyse behavioural responses such as mode shift, route choice adaptation, and trip cancellation while simultaneously considering traveller characteristics.

To examine impacts across socio-demographic groups, a persona-based segmentation approach was applied. Personas were assigned to synthetic individuals based on demographic and behavioural attributes, enabling model outputs to be disaggregated into meaningful traveller groups. This combination of activity-based modelling and persona segmentation provides a promising approach for evaluating both the behavioural and distributional impacts of car-reducing measures.

Research Question 2

To what extent does the selected approach reproduce realistic travel behaviour, and how can its behavioural performance be improved through calibration?

The analyses presented in this chapter showed that the ActivitySim model reproduces several important aspects of travel behaviour reasonably well, including overall modal shares and the direct response of car travel demand to changes in travel time. However, the initial model exhibited limited behavioural realism in terms of modal substitution. When car travel times increased, a large share of reduced car trips was suppressed rather than shifted to alternative transport modes, resulting in cross-elasticities that were generally lower than values reported in the literature.

The sensitivity analysis identified travel time coefficients and alternative-specific constants as the most

influential parameters effecting modal share outcomes. Subsequent elasticity experiments demonstrated that the weak cross-elasticities could not be explained by a single parameter or model component. Instead, they resulted from the combined influence of mode choice utilities, destination choice sensitivity, and accessibility feedback mechanisms throughout the model system.

To improve behavioural realism, a series of targeted modifications was implemented, including adjustments to alternative-specific constants, reductions in destination choice sensitivity, and a lower influence of logsum feedback. These changes substantially improved modal substitution behaviour, increasing cross-elasticities for sustainable transport modes and raising the share of reduced car trips recovered by alternative modes from 28.8% to 60.6%.

Building on these improvements, Bayesian Optimization was applied to calibrate the most influential model parameters. This process identified a parameter set that achieved a balanced trade-off between reproducing observed modal shares and matching travel time elasticity targets. The resulting calibrated model reproduces observed travel behaviour more realistically and responds more plausibly to changes in travel conditions. Although some discrepancies remain, particularly regarding the responsiveness of public transport demand, the calibrated model provides a sufficiently realistic basis for evaluating the impacts of the Hofplein intervention.

Research Question 3

How does the Hofplein redesign effect travel behaviour in terms of mode choice, route choice, and trip generation, including the decision to forgo trips?

The results show that the Hofplein redesign effects travel behaviour through a combination of modal shift, rerouting, and trip suppression rather than through a single adaptation mechanism. While the intervention reduces car accessibility in and around the Hofplein corridor, travellers respond in different ways depending on the available alternatives and the characteristics of their trips.

Figure 8.1 illustrates the behavioural response of travellers who no longer use the car after the intervention. Of the 13,640 lost car trips, 46.3% are eliminated entirely, indicating that a substantial share of travellers choose to forgo travel rather than switch to another mode. Among the trips that remain, walking captures the largest share (18.3%), followed by cycling (13.7%), e-bike use (12.6%), and public transport (9.1%). These results demonstrate that a significant proportion of displaced car travel is absorbed by more sustainable transport modes.

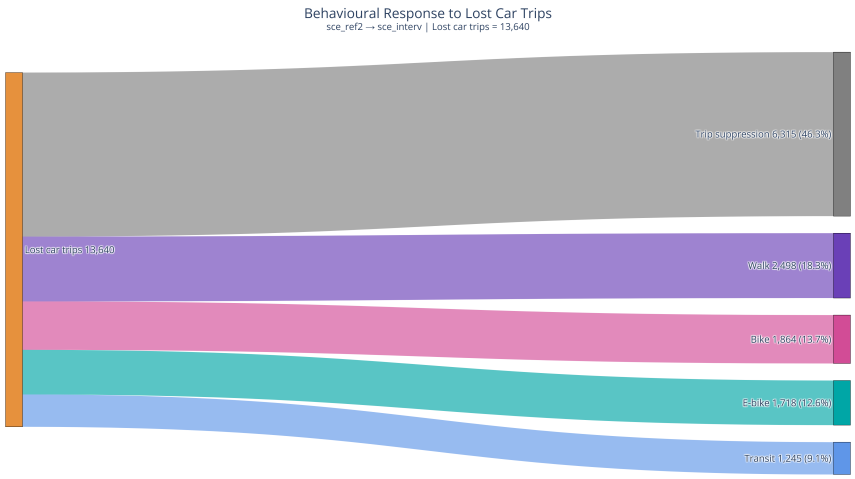


Figure 8.1: Behavioural response of lost car trips.

The analysis also showed that not all behavioural adaptation occurs through mode choice. Approximately 30% of baseline Hofplein car users continue travelling by car while avoiding the effected corri-

dor, demonstrating that route adaptation plays an important role in the overall response. In addition, longer-distance trips were found to decline slightly more than shorter-distance trips, suggesting that some travellers also adjust destination choices when confronted with higher travel costs.

Overall, the findings indicate that the Hofplein redesign reduces traffic volumes through a combination of modal shift, rerouting, destination adjustment, and trip suppression. Rather than simply displacing traffic elsewhere on the network, the intervention triggers a broader behavioural adaptation process in which travellers reconsider how, where, and even whether they travel.

Research Question 4

Which population groups are most sensitive to the Hofplein intervention and how do they adapt their travel behaviour?

The persona analysis showed that the effects of the Hofplein intervention are distributed unevenly across the population. While most personas responded in similar ways, namely through reduced car use and increased use of walking, cycling, e-bikes, and public transport, the magnitude of these changes differed considerably between groups.

The strongest responses were observed among the more car-oriented personas, including Cynthia, Henk, Sam, Ben, and Adrie. These groups experienced the largest reductions in car use and accounted for most of the lost car trips. In contrast, personas such as Vincent, Tessa, Mei, and Martha showed relatively limited changes, largely because they already relied less on the car and more on alternative modes before the intervention.

Figure 8.2 illustrates these differences. Personas with a stronger dependence on car travel have both more opportunity and greater necessity to adapt when car accessibility is reduced, whereas already multimodal personas are effected to a lesser extent.

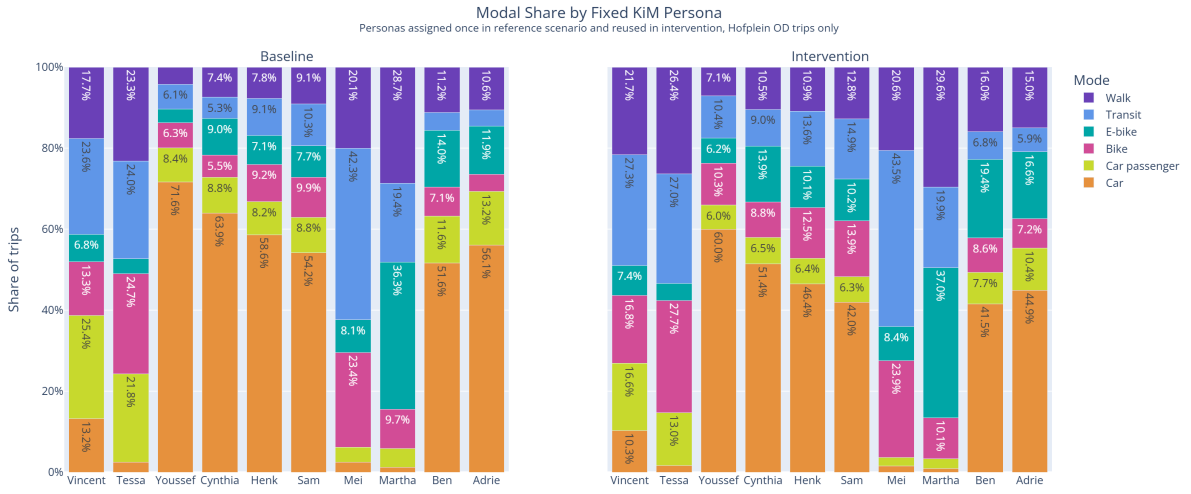


Figure 8.2: Baseline and intervention modal shares by persona.

The analysis further shows that the effects are concentrated among a relatively small number of personas. Cynthia accounted for the largest share of lost car trips, followed by Henk and Youssef. Together, these personas represented more than 70% of all eliminated car trips.

Overall, the results indicate that socio-demographic and behavioural characteristics strongly influence how they adapt after the Hofplein intervention. Understanding these differences provides valuable insight into the effectiveness and impacts of car-reducing measures and highlights the importance of considering heterogeneous behavioural responses when evaluating urban transport policies.

Main Research Question

What are the effects of car-reducing measures on travel behaviour across different socio-demographic groups?

The results of this thesis show that reducing car accessibility influences travel behaviour through multiple adaptation mechanisms. Following the Hofplein intervention, travellers responded through modal shift, rerouting and trip suppression.

A central finding is that these effects are distributed unevenly across the population. The largest behavioural changes were observed among car-oriented personas such as Cynthia, Henk, Sam, Ben, and Adrie, whereas already multimodal personas such as Vincent, Tessa, Mei, and Martha experienced comparatively small changes. Travellers who relied most heavily on the car generally faced the greatest reductions in accessibility and, as a result, exhibited the strongest behavioural responses. The impacts of car-reducing measures therefore depend not only on the characteristics of the intervention itself, but also on the travel preferences, opportunities, and constraints of the travellers effected.

Perhaps the most important lesson from this research is methodological. The study demonstrates that reproducing observed modal shares alone is not sufficient when transport models are used for policy evaluation. A model may match observed travel patterns while still responding unrealistically to changes in travel conditions. By incorporating travel-time elasticities into the calibration process, the ActivitySim model was able to reproduce more plausible behavioural responses to policy interventions. This highlights that behavioural realism is essential if transport models are to provide credible estimates of policy impacts.

The combination of activity-based modelling and persona segmentation proved particularly valuable in this regard. One of the key strengths of activity-based models is their ability to represent decision-making at the level of individual travellers rather than population averages. This makes them especially suited to evaluating car-reducing measures, whose impacts are often experienced very differently across society. By linking simulated travellers to personas, the analysis was able to identify not only whether car use decreased, but also how travellers adapted and which groups experienced the largest accessibility impacts. Such insights cannot be obtained from traditional aggregate modelling approaches and demonstrate the added value of activity-based models for analysing both behavioural responses and distributional effects.

Overall, the findings indicate that socio-demographic and behavioural characteristics strongly influence both the magnitude and nature of behavioural adaptation. More broadly, this thesis demonstrates that activity-based transport models can be used not only to estimate the effectiveness of transport interventions, but also to understand who is effected, how they adapt, and how impacts are distributed across the population. These insights can support the design of transport policies that reduce car dependency while maintaining accessibility for a diverse range of travellers.

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A

Academic paper

Calibrating an Activity-Based Model for Both Observed Travel Patterns and Behavioural Responses

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***Abstract*—Activity-based models (ABMs) provide a detailed representation of travel behaviour, but calibration often focuses on reproducing observed travel patterns rather than validating whether behavioural responses are realistic. This paper presents a workflow combining sensitivity analysis, travel-time elasticity analysis, and Bayesian optimization to incorporate behavioural validation into ABM calibration.**

The approach is applied to the Rotterdam region. The original model produced realistic direct car travel-time elasticities, but cross-elasticities were too low compared with literature benchmarks, resulting in limited modal substitution and excessive trip suppression. Sensitivity analysis and targeted model experiments were used to identify influential model components, after which Bayesian optimization was performed using modal-share and elasticity targets. The calibrated model produced improved direct and cross-elasticities, while maintaining a realistic aggregate modal split.

The main contribution is a calibration approach that uses Bayesian optimization to explicitly incorporate elasticity validation alongside observed travel patterns. This enables ABMs to be calibrated not only to reproduce observed travel behaviour, but also to produce realistic behavioural responses to changing transport conditions.

***Index Terms*—Activity-based modelling, Model calibration, Bayesian optimization, Transport modelling**

I. Introduction

Transport models play an important role in understanding what may happen when changes are made to the transport system. They allow policy measures to be explored before implementation and can reveal consequences that may otherwise be difficult to anticipate (Nes & Jong, 2020). The usefulness of these models, however, ultimately depends on how well they represent the behaviour of the people they represent. A model can describe current travel patterns well, yet still react unexpectedly when the conditions under which people travel begin to change.

This challenge becomes increasingly important as transport models become more behaviourally detailed. Activity-based models (ABMs) have emerged as a promising approach because they represent travel as part of people's daily activities. Instead of treating trips as isolated movements, they model how decisions about activities, destinations, transport modes are connected. This brings transport modelling closer to how travel decisions are made in reality and provides greater depth for studying the consequences of transport policies. At the same time, this detail comes at a cost: the large number of interacting behavioural components makes these models computationally heavy and difficult to calibrate (Miller, 2023).

This raises an important question when such a model is used for policy analysis: *To what extent do activity-based models reproduce realistic travel behaviour, and how can its behavioural performance be improved through calibration?* Calibration should not simply result in a model that reproduces the situation it was calibrated to. It should also provide confidence that the behavioural mechanisms within the model respond plausibly when travellers are confronted with new conditions. Achieving this is particularly challenging in activity-based models (Habtemariam & Lee, 2026), where a change in one part of the model can propagate through several interconnected decisions.

This paper presents a structured process for analysing and calibrating the behavioural performance of an activity-based transport model. Rather than treating calibration as a single step of fitting model outcomes to observations, the proposed approach first examines how and why the model responds to changing conditions and uses this understanding to guide the subsequent calibration. The aim is to arrive at a model that not only represents observed travel behaviour, but also produces credible behavioural responses to changing transport conditions.

The model is applied to the redesign of Hofplein in Rotterdam to examine travel behaviour in response to car-reducing measures. Beyond their overall effects on travel behaviour, such measures may effect population groups differently depending on how they travel and respond to changes in car accessibility. Activity-based models provide the level of detail needed to examine these differences. Within this broader application, this paper focuses on establishing and calibrating the behavioural performance of the model.

II. Literature review

Transport models provide a simplified representation of travel behaviour and the transport system (Correia & Wee, 2023), allowing infrastructure and policy measures to be evaluated before they are implemented. A distinction can broadly be made between transport demand models, which represent why, where, when, and how people travel, and traffic assignment

models, which represent how the resulting trips move through the transport network and how this effects routes, travel times, and congestion (Calvert et al., 2016). This paper focuses on the calibration of activity-based models (ABMs), a form of transport demand modelling in which travel behaviour is represented at the level of individual travellers and their daily activities.

Transport demand models have become increasingly detailed in the way they represent this behaviour. Traditional approaches, such as the four-step model, primarily represent travel as aggregated flows between zones (Sivakumar, 2007). In contrary, disaggregate models describe decisions at the level of individual travellers or households, allowing differences in their characteristics and behaviour to be represented (Ortúzar & Willumsen, 2024). ABMs extend this approach by recognising that travel generally results from the need or desire to participate in activities, such as working, studying, shopping, or visiting others (McNally, 2000). Travel is therefore represented as part of an individual's daily activity pattern rather than as a collection of independent trips.

This representation is particularly promising for policy evaluation because changes in the transport system can influence several connected decisions. Travellers may change their mode or destination, reschedule activities, or reorganise parts of their daily pattern (Correia & Wee, 2023). Moreover, because these decisions are simulated for individual travellers, ABMs can represent differences in responses between population groups (Castiglione et al., 2015). They can therefore provide insight not only into the overall effects of a transport intervention, but also into how these effects are distributed across the population.

The behavioural detail of ABMs also makes them difficult to calibrate. ABMs often consist of connected choice models whose parameters determine how travellers respond to different conditions and alternatives. Calibration adjusts these parameters so that simulated behaviour better reflects observed behaviour. However, parameters can influence multiple model outcomes, while evaluating new parameter combinations requires additional model runs. Exploring large parameter spaces can therefore quickly become computationally demanding (Agriesti et al., 2023).

A. Calibration of activity-based models

This computational challenge has motivated the use of more efficient methods for exploring the parameter space. Rather than evaluating all possible parameter combinations, these methods use information from earlier model evaluations to guide the search towards promising regions of the parameter space. One approach that is particularly suited to activity-based models is Bayesian optimization.

Although the behavioural mechanisms of an ABM are known, the relationship between behavioural parameter values and resulting model outcomes is often highly complex and cannot be described analytically (Schultz et al., 2022). The model can therefore be treated as a computationally expensive black-box function, where parameter combinations are evaluated based on the resulting outputs. Bayesian optimization is well suited to this setting because it can efficiently identify promising parameter values while limiting the number of costly model evaluations. Bayesian optimization uses a computationally inexpensive *surrogate model* to approximate the relationship between parameter values and model performance (Schultz et al., 2022). After each model evaluation, the surrogate model is updated and used to determine which parameter combination should be evaluated next. As a result, the search progressively focuses on promising regions of the parameter space while balancing exploration of uncertain areas with exploitation of known good solutions.

Recent applications demonstrate its potential for calibrating activity-based models. Schultz et al. (2022) used a Gaussian Process surrogate model to calibrate behavioural parameters and highlighted the value of identifying influential parameters before optimization. Agriesti et al. (2023) extended this approach to a substantially larger problem involving hundreds of behavioural parameters, demonstrating its applicability to high-dimensional calibration problems.

Beyond computational efficiency, calibration must also account for interactions between model components and calibration targets. Le et al. (2025) shows that improving one model outcome can influence the performance of others and therefore argues that multiple calibration objectives should be considered together. This is particularly important because a good fit to observed outcomes does not necessarily imply that the behavioural responses underlying these outcomes are plausible. For policy evaluation, the model should also respond realistically when the conditions influencing travel behaviour change.

These findings motivate a calibration process in which model behaviour is examined before parameter optimization. Sensitivity analysis can first identify which parameters have the greatest influence on model outcomes, while behavioural responses to changing travel conditions can be evaluated separately for their plausibility. These findings can then guide the selection and optimization of parameters. Calibration is thereby treated not only as finding a parameter set that improves model fit, but as a process of understanding and improving the behaviour that produces that fit.

B. ActivitySim

The ABM considered in this research is ActivitySim (Galli et al., 2009), an open-source modelling framework that simulates travel behaviour through a sequence of connected choice models. Rather than modelling trips independently, ActivitySim represents decisions about activities and travel at the level of individual travellers and households. These decisions depend on personal and household characteristics, the spatial distribution of activities, and the available travel alternatives.

ActivitySim combines several sources of information to represent these choices (Zhou et al., 2023). A synthetic population, as described by Snelder et al. (2021), represents the

individuals and households within the study area, while land-use data represents the spatial distribution of opportunities such as employment and education. Level-of-service conditions between zones are represented through *skim* matrices, which contain attributes such as travel times, costs, and distances for different modes. These attributes enter the choice models and effect the relative attractiveness of the available alternatives. Changes in transport conditions can therefore propagate through the connected choice models and result in changes in simulated travel behaviour.

ActivitySim illustrates the calibration challenges identified in the literature: its connected choice models mean that parameters can influence multiple outcomes, while reproducing observed travel patterns does not necessarily ensure plausible responses to changing transport conditions. At the same time, the computational demands of ABMs limit how extensively parameter combinations can be explored. The calibration process developed in this research therefore combines sensitivity analysis to identify influential parameters, travel-time elasticity analysis to assess the plausibility of model responses, and Bayesian optimization to efficiently identify suitable parameter values. Together, these steps aim to improve both model fit and the behaviour underlying that fit.

III. Methodology

Building on the calibration challenges identified in the literature, the proposed process evaluates both the influence of ActivitySim's behavioural parameters and the plausibility of the responses they produce before optimizing their values. To understand how these parameters effect model behaviour, it is first necessary to consider how ActivitySim translates changes in transport conditions into individual choices.

ActivitySim represents travel behaviour through a sequence of discrete choice models. Changes in transport conditions effecteffect the level-of-service attributes of available alternatives, thereby influencing their relative attractiveness and resulting travel choices, including mode, destination, activity timing, and trip frequency.

The underlying choices are based on Random Utility Maximization, in which a traveller is assumed to select the alternative with the highest utility. For mode choice, the utility is defined as:

$$V_{i,j} = ASC_i + \sum_{k=1}^{K} \beta^T_{i,k,l} T_{i,k} + \beta^A_{i,l} A_{j,l} + \sum_{m=1}^{M} \beta^S_{i,m} S_{j,m}, \quad (1)$$

where $V_{i,j}$ is the observed utility that traveller j associates with mode i. The utility consists of four components. First, ASC_i is the alternative-specific constant, which captures the general preference for mode i that is not explained by the other variables. Second, $T_{i,k}$ represents level-of-service attribute k for mode i, such as travel time, cost, or distance. Its effect may differ by mode, attribute, and activity purpose l_j, as represented by β^T_{i,k,l_j}. Third, A_{j,l_j} represents the activity purpose of traveller j, with β^A_{i,l_j} capturing how the attractiveness of a mode differs between purposes. Finally, $S_{j,m}$ represents socio-demographic characteristic m of traveller j, such as income, age, or car ownership. The corresponding $\beta^S_{i,j,m}$ parameters determine how these characteristics influence the utility of each mode. The observed utilities are combined with a Gumbel-distributed random error term (Zhou et al., 2023) to represent unobserved factors influencing each choice. The resulting utilities are then converted into choice probabilities using a multinomial logit model:

$$P_{i,j} = \frac{\exp(V_{i,j})}{\sum_{h \in C_j} \exp(V_{h,j})}, \quad (2)$$

where C_j is the set of modes available to traveller j. The parameters in these utility functions therefore determine both the choices produced in the reference situation and how those choices respond when transport conditions change. The calibration process evaluates these two aspects through the three steps introduced in the literature review: sensitivity analysis determines which parameters have the greatest influence on model outcomes, travel-time elasticity analysis evaluates the plausibility of the resulting behavioural responses, and Bayesian optimization uses these insights to calibrate the selected parameters.

All three analyses are performed using a random sample of 10,000 households from the synthetic 2020 population. This reduces the computational burden from 50 to approximately 8 minutes per run, as the sensitivity analysis and Bayesian optimization require many dozens to hundreds of repeated ActivitySim runs.

The model uses an existing set of parameters estimated from observed travel data from Onderweg in Nederland (ODiN). These estimated parameters form the base parameter set that is subsequently evaluated and adjusted in the calibration process described in this study.

A. Sensitivity analysis

The first step identifies which mode-choice parameters meaningfully influence simulated modal shares. Here, *sensitivity* refers to the extent to which a model output changes when a parameter is varied. A global sensitivity analysis is conducted using the Morris screening method (Morris, 1991), implemented through the `SALib` Python package (Iwanaga et al., 2022). The method varies each parameter at different locations in the parameter space and records its effect on the model output.

For parameter β_p and the modal share of mode i, an elementary effect is expressed as:

$$EE_{ip} = \frac{\Delta MS_i}{\Delta \beta_p}, \quad (3)$$

where ΔMS_i is the resulting change in modal share and $\Delta\beta_q$ is the applied parameter change, defined relative to the specified range of parameter q. Overall parameter influence is evaluated using the mean absolute elementary effect:

$$\mu^*_p = \frac{1}{r} \sum_{q=1}^{r} \left| EE^{(q)}_p \right|, \quad (4)$$

where r is the number of elementary effects calculated for parameter p. A larger μ_p^* indicates a stronger overall influence on the model output. The standard deviation σ_p describes the variation in these elementary effects across the parameter space, with higher values indicating possible non-linear effects or interactions with other parameters.

Three separate Morris analyses are performed, each including the alternative-specific constants (ASCs) alongside (1) travel-time coefficients, (2) activity-specific mode-choice parameters, and (3) socio-demographic parameters. Separating these groups limits the computational burden, since the required number of model runs increases with the number of parameters according to $N = R(k+1)$, where R is the number of trajectories and k is the number of input parameters (Morris, 1991). This research uses $R = 4$ trajectories. Although relatively low, this limits the number of required ActivitySim runs while providing an initial screening of parameter influence.

B. Travel-time elasticity analysis

Sensitivity analysis establishes which parameters influence model outcomes, but not whether the behaviour produced by the model is plausible. The second step therefore evaluates how strongly simulated travel demand responds to a change in travel conditions. This response is expressed through *elasticity*, which measures the percentage change in travel demand resulting from a percentage change in a travel attribute.

To evaluate the response to increased car travel time, the reference model is compared with a scenario in which all car travel times are increased by 10%. For each mode i, the resulting elasticity is calculated as:

$$E_i = \frac{\Delta Trips_i\,(\%)}{\Delta TT_{\text{car}}\,(\%)}, \tag{5}$$

where $\Delta Trips_i$ is the percentage change in trips by mode i and ΔTT_{car} is the percentage change in car travel time. The *direct elasticity* describes the response of car demand to the increase in car travel time and is therefore expected to be negative. *Cross-elasticities* describe the resulting changes in demand for public transport, cycling, e-bike, and walking.

In ActivitySim, however, a reduction in car trips does not necessarily result in an equivalent increase in trips by other modes. Travellers can also change destinations, reschedule activities, or suppress trips. Direct and cross-elasticities are therefore evaluated together to assess the overall behavioural response. The resulting elasticities are compared with literature benchmarks, including a direct car travel-time elasticity of approximately -0.15 to -0.50 (Smit et al., 2021) and the Dutch reference values reported in Table I.

TABLE I: Travel-time elasticity for a 10% increase in car travel time, based on Hofman (2024)

	Car	Car passenger	Train	BTM	Bike	Total
Elasticity	-0,17	-0,27	0,22	0,14	0,15	-0,02

C. Bayesian calibration

The preceding analyses identify which parameters most strongly influence model outcomes and assess whether the model responds plausibly to changes in travel conditions. Building on these insights, the final step calibrates the model using Bayesian optimization. The objective is to identify parameter values that improve both the representation of observed travel behaviour and the plausibility of simulated behavioural responses. To achieve this, calibration targets are defined for both observed modal shares and travel-time elasticities. Including both targets reduces the risk of obtaining a parameter set that reproduces observed travel patterns while responding unrealistically to changes in travel conditions, or vice versa.

The calibration focuses on the alternative-specific constants, travel-time coefficients, and activity-specific mode-choice parameters identified as influential in the preceding analyses. Parameters related to destination choice and logsum propagation are excluded from the optimization, as they primarily effect how accessibility changes propagate through the model. Their role is instead evaluated through the elasticity analysis and subsequent model experiments.

TABLE II: Modal shares in Zuid-Holland in 2019, based on CBS (2026)

	Car	Car passenger	Bike	E-bike	Walk	Public transport
%	24	9	32	4	20	11

Observed modal-share targets are derived from 2019 CBS mobility statistics for Zuid-Holland (CBS, 2026) and are shown in Table II. Zuid-Holland is used as the reference region because the Hofplein case study is located within this province and no more detailed local data source on observed travel behaviour was available. Although the synthetic population represents 2020, 2019 is used as the reference year to avoid distortions in travel behaviour caused by COVID-19 restrictions. Travel-time elasticity targets are obtained from the literature. Both targets are combined into a single objective function that is minimized during calibration:

$$\min_{\boldsymbol{\beta}} \left[\sum_{i=1}^{m} \left(MS_i(\boldsymbol{\beta}) - MS_{i,\text{target}} \right)^2 + \sum_{i=1}^{m} \left(E_i(\boldsymbol{\beta}) - E_{i,\text{target}} \right)^2 \right] \tag{6}$$

where $\boldsymbol{\beta}$ is the calibrated parameter set, MS_i is the simulated modal share of mode i, and E_i is its simulated travel-time elasticity. Both components receive equal weight, encouraging the optimization to improve both the representation of existing travel patterns and behavioural responses.

The optimization is implemented using the `gp_minimize` function from the `scikit-optimize` package (Head et al., 2018). A Gaussian Process is used as the surrogate model. After each ActivitySim evaluation, the surrogate model is updated and used to select the next parameter combination by

balancing exploitation of promising regions with exploration of uncertain parts of the parameter space.

Travel-time coefficients and activity-specific parameters are allowed to vary between zero and twice their original values. These bounds permit substantial changes in behavioural sensitivity while preserving the direction of the original effects. Alternative-specific constants are allowed to vary between minus and plus twice their original values, providing greater flexibility to reproduce observed modal shares.

Each parameter evaluation requires a complete ActivitySim simulation and corresponding elasticity test. To keep the calibration computationally feasible, the optimization is limited to 60 evaluations and may terminate earlier if successive evaluations no longer produce meaningful improvements in the objective function.

IV. Results

The behavioural performance of ActivitySim was evaluated to determine whether the model responds plausibly to changes in travel conditions and whether calibration can improve this response while maintaining representative aggregate travel patterns. The results are presented in this section.

To reduce computation time during the many repeated model evaluations required for sensitivity analysis and calibration, the model behaviour analysis was performed using a random sample of 10,000 households. Comparison with the full MRDH population showed only minor differences in aggregate outcomes. Modal-share differences remained below 0.3 percentage points, while VKT per capita differed by only 0.271 km. The sampled population was therefore considered sufficiently representative for the subsequent analyses and calibration.

A. Sensitivity analysis

The Morris sensitivity analysis was used to identify which mode-choice parameters have the greatest influence on simulated modal shares. Separate analyses were performed for alternative-specific constants (ASCs) and travel-time coefficients, activity-specific parameters, and socio-demographic parameters. The complete results are provided in Appendix A.

Table III shows the most influential parameters from the analysis containing the ASCs and travel-time coefficients. The car ASC has the highest influence on car modal share, followed by several travel-time and mode-specific parameters.

TABLE III: Most influential parameters from the ASC and travel-time sensitivity analysis.

Rank	Parameter	μ^*
1	ASC_{car}	0.0819
2	$\beta_{tt,bike}$	0.0243
3	ASC_{PT}	0.0190
4	$\beta_{tt,car}$	0.0173
5	$\beta_{tt,PT}$	0.0162

Across the three Morris analyses, mode-specific parameters were generally found to be more influential than activity-specific and socio-demographic parameters. The prominence of the ASCs indicates that the baseline attractiveness of transport modes plays an important role in determining simulated mode choice. For example, within the ASC and travel-time analysis, the car ASC is approximately four times more influential than the car travel-time coefficient.

This difference is substantial but not extreme. Travel-time coefficients remain among the most influential parameters in the model, suggesting that changes in travel conditions should still produce meaningful behavioural responses. Nevertheless, the strong influence of the ASCs highlights the importance of verifying whether the model responds realistically when travel conditions change.

Among the socio-demographic parameters, car ownership was found to be the most influential variable, which is consistent with expectations given that vehicle availability strongly constrains the set of feasible travel modes.

B. Travel-time elasticity analysis

The travel-time elasticity analysis was used to assess whether the model responds realistically to changes in travel conditions. Car travel times were increased by 10%, and the resulting direct and cross-elasticities were compared with values reported in the literature.

The baseline model produced a realistic direct response to increased car travel times. A 10% increase in car travel time resulted in a car-demand elasticity of -0.25, which falls within the range reported in the literature. However, the response of alternative modes was considerably weaker. Bicycle, walking, e-bike, and public transport demand increased only marginally, resulting in weaker modal substitution than indicated by the literature-based benchmark.

To further evaluate this behaviour, a recovery-rate analysis was performed. The recovery rate measures the share of reduced car trips that reappear as trips by alternative modes, rather than being suppressed altogether. In the baseline model, only 28.8% of lost car trips were recovered by other modes, while 71.2% disappeared completely. Together with the weak cross-elasticities, this suggests that the model primarily represented higher car travel times through trip suppression rather than modal shift.

A series of model experiments was subsequently conducted to identify the source of these weak cross-elasticities. Travel-time coefficients, activity-specific parameters, value-of-time assumptions, generalised-cost specifications, destination-choice sensitivity, and alternative-specific constants were evaluated. No single parameter or model component was found to be responsible. Instead, the weak cross-elasticities emerged from interactions between multiple parts of the model.

Based on these experiments, a limited set of expert-based adjustments was made before starting the formal calibration process. These adjustments reduced sensitivity to distant destinations and modified the alternative-specific constants to improve the relative attractiveness of competing modes. The adjustments were selected based on their ability to improve modal substitution while preserving the overall behaviour of the model. Consequently, the final model does not retain the

original estimated specification unchanged, as selected parameters in both the mode-choice and destination-choice components were adjusted where the elasticity analysis indicated unrealistic behavioural responses. The subsequent calibration was then applied to this adjusted model specification.

Table VIII compares the resulting elasticities with those of the baseline model and with literature values.

TABLE IV: Travel-time elasticities after a 10% increase in car travel time.

Mode	Baseline	Modified	Literature
Car	-0.2506	**-0.2208**	-0.17
Car Passenger	0.0325	**-0.3656**	-0.27
Bike	0.0253	**0.0834**	0.15
E-bike	0.0479	**0.0976**	0.10
Walk	0.0105	**0.0777**	0.05
Public transport	-0.0093	**0.0323**	0.20

The modified model shows substantially stronger modal substitution behaviour. Cross-elasticities increased for all sustainable transport modes, while the direct elasticity of car demand remained within the expected range. The bicycle elasticity increased from 0.03 to 0.08, walking increased from 0.01 to 0.08, and the e-bike elasticity closely matched the literature value. Public transport remained less responsive than expected, but changed from a slightly negative to a positive elasticity.

These improvements are also reflected in the recovery-rate analysis, shown in Table IX. The share of reduced car trips recovered by alternative modes increased from 28.8% to 60.6%, indicating that most of the reduction in car travel was now absorbed by other transport modes rather than being suppressed.

TABLE V: Modelled recovery of reduced car-mode trips following a 10% increase in car travel time.

Model	Recovered by other modes	Suppressed trips
Original	28.8%	71.2%
Modified	**60.6%**	**39.4%**

Overall, the results demonstrate that the modified specification produces a substantially more realistic behavioural response to changes in car travel conditions. The resulting parameter set was therefore adopted as the starting point for the Bayesian calibration procedure.

C. Bayesian calibration

Bayesian calibration was used to further improve the model by simultaneously targeting observed modal shares and literature-based travel-time elasticities. The optimization revealed a clear trade-off between these objectives. Parameter sets that closely reproduced the observed modal shares did not necessarily match the target elasticities, whereas parameter sets with better elasticity performance generally produced larger modal-share errors.

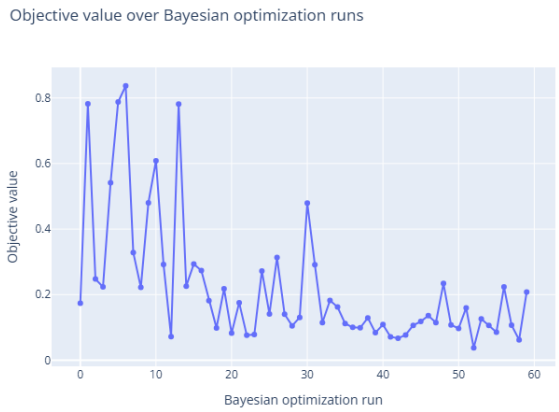


Fig. 1: Objective value obtained during the Bayesian optimization iterations.

Figure 1 shows the objective values obtained during the optimization. Of the 60 parameter combinations evaluated, Run 52 achieved the lowest overall objective value (Table VI). While Run 12 produced the lowest modal-share error and Run 42 achieved the lowest elasticity error, neither provided the best overall performance. Run 52 did not outperform all other runs on either objective individually, but offered the best balance between the two and was therefore selected as the final parameter set.

TABLE VI: Best-performing calibration runs identified during Bayesian optimization.

Run	Modal share error	Elasticity error	Objective value
52	0.0137	0.0240	0.0376
58	0.0218	0.0400	0.0618
42	0.0461	0.0205	0.0666
41	0.0350	0.0363	0.0713
12	0.0090	0.0626	0.0716

Figure 2 compares the modal shares produced by Run 52 with the observed targets. The selected parameter set reproduces most modal shares reasonably well, although differences remain, most notably for bicycle. The calibrated bicycle share of 21.7% is 10.3 percentage points below the target of 32.0%, compared with a difference of only 1.2 percentage points in the original model.

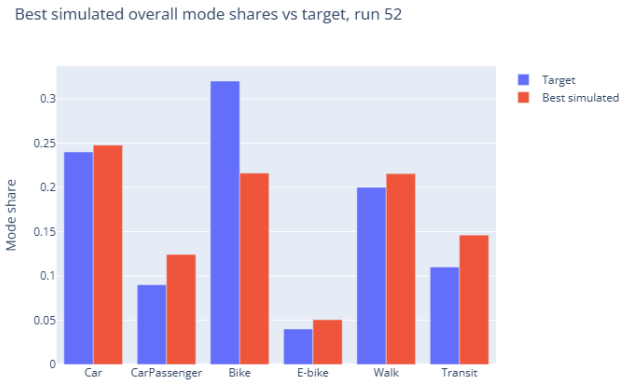


Fig. 2: Comparison of modal shares for the selected calibration result and the target values.

Figure 3 compares the corresponding elasticities with the literature-based targets. The selected parameter set reproduces most elasticity targets more closely than the original model, although differences remain, most notably for public transport. Its calibrated elasticity of 0.035 remains substantially below the literature-based target of 0.20, despite improving from the negative elasticity of -0.009 in the original model.



Fig. 3: Comparison of travel-time elasticities for the selected calibration result and the target values.

These remaining discrepancies reflect the trade-off involved in simultaneously calibrating modal shares and travel-time elasticities. Run 52 therefore represents a compromise between reproducing the observed modal distribution and improving the model's response to changing travel conditions.

D. Calibrated model performance

The final calibration improved the model's response to changing car accessibility while maintaining a representative modal split. Table VII compares the original and calibrated modal shares with the observed target distribution.

The calibrated model remains close to the observed modal shares, showing that the improvement in behavioural response was not achieved at the expense of the aggregate modal distribution.

TABLE VII: Comparison of modal shares before and after calibration.

Mode	Original	Calibrated	Target
Car	17.50	**24.10**	24.00
Car passenger	5.07	**12.40**	9.00
Bike	33.20	**21.70**	32.00
E-bike	5.77	**5.30**	4.00
Walk	26.20	**21.60**	20.00
Public transport	12.20	**14.90**	11.00

The improvement in behavioural response is further shown by the elasticities in Table VIII, which compares the original model, the intermediate modified model, and the final calibrated model.

TABLE VIII: Comparison of travel-time elasticities before and after calibration.

Mode	Original	Modified	Calibrated	Literature
Car	-0.2506	-0.2208	**-0.1812**	-0.17
Car passenger	0.0325	-0.3656	**-0.3481**	-0.27
Bike	0.0253	0.0834	**0.1108**	0.15
E-bike	0.0479	0.0976	**0.1310**	0.15
Walk	0.0105	0.0777	**0.0930**	0.05
Public transport	-0.0093	0.0323	**0.0349**	0.20

The calibrated car elasticity of -0.18 closely approaches the literature benchmark of -0.17. Bicycle and e-bike elasticities also move substantially closer to their target values, while walking becomes somewhat more responsive than the literature benchmark. Public transport remains comparatively insensitive to changes in car travel time, although its elasticity changes from negative in the original model to positive after calibration.

The change in behavioural response is also reflected in the recovery rate (Table IX). The proportion of reduced car-mode trips recovered by alternative modes increased from 28.8% in the original model to 66.8% after calibration. The share associated with trip suppression consequently decreased from 71.2% to 33.2%.

TABLE IX: Recovery of reduced car-mode trips following a 10% increase in car travel time.

Model	Recovered by other modes	Suppressed trips
Original	28.8%	71.2%
Modified	60.6%	39.4%
Calibrated	**66.8%**	**33.2%**

Overall, the results show that the original ActivitySim model already produced a plausible direct response of car demand to travel-time changes, but responded to worsening car accessibility mainly through trip suppression rather than substitution towards alternative modes. The model experiments

showed that this behaviour resulted from interactions between several model components rather than a single parameter. Targeted modifications improved the underlying response, after which Bayesian calibration provided a parameter set that balanced modal-share fit and behavioural plausibility. Although discrepancies remain, particularly for public transport and car-passenger travel, the calibrated model provides a more plausible combination of aggregate travel patterns.

V. Discussion

Together, these findings show that reproducing observed travel patterns does not necessarily ensure realistic behavioural responses. The sensitivity and elasticity analyses revealed that model behaviour depends on interactions between multiple components and may therefore remain unrealistic even when aggregate calibration targets are reproduced. The Bayesian calibration further highlighted a trade-off between modal-share fit and behavioural-response targets, as improvements in one objective could come at the expense of the other. The selected parameter set therefore reflects a balance between reproducing observed travel behaviour and producing plausible responses to changes in accessibility.

Several limitations should be considered when interpreting the results. First, the calibrated model does not perfectly reproduce all target modal shares and elasticity values. Although calibration substantially improved model performance, exact agreement was not achieved within the available optimization budget of 60 model evaluations. This reflects both the computational constraints associated with activity-based model calibration and the complexity of the behavioural interactions represented within ActivitySim.

Second, uncertainty exists in the calibration targets themselves. The elasticity benchmarks were derived from the Dutch National Model System (LMS) (Hofman, 2024), which is itself a transport model rather than an observed dataset and is not an ABM. Differences between the calibrated ActivitySim results and the target values may therefore partly reflect differences in model structure rather than behavioural inaccuracies in ActivitySim.

More broadly, the study demonstrates both the strengths and challenges of activity-based modelling. By representing travel decisions at the level of individual travellers and households, ActivitySim provides insights into behavioural adaptation that are difficult to obtain from aggregate models. Such capabilities are becoming increasingly important as transport planning expands beyond questions of mobility and capacity towards accessibility, equity and behavioural adaptation. At the same time, this richer behavioural representation comes with increased model complexity and calibration effort. The workflow developed in this study therefore contributes not only a calibrated parameter set, but also a structured approach for evaluating and improving behavioural performance before applying activity-based models to policy analysis.

VI. Conclusion & recommendations

A. Conclusion

This paper investigated the question: *To what extent do activity-based models reproduce realistic travel behaviour, and how can their behavioural performance be improved through calibration?*

The results show that ActivitySim was able to reproduce several aspects of realistic travel behaviour, including a plausible direct response of car demand to changes in travel time. However, the behavioural analysis revealed that the original model relied heavily on trip suppression and produced relatively weak modal substitution effects. Behavioural realism therefore could not be assessed from aggregate model fit alone.

The proposed workflow, combining sensitivity analysis, travel-time elasticity analysis and Bayesian optimization, improved both the representation of observed modal shares and the plausibility of behavioural responses. The calibrated model produced stronger modal substitution, reduced trip suppression and elasticity values that more closely matched literature benchmarks.

Overall, the findings demonstrate that activity-based models can reproduce realistic travel behaviour, but that calibration should extend beyond matching observed travel patterns. Explicitly evaluating behavioural responses provides additional confidence that the model will respond plausibly when applied to transport-policy scenarios and changing accessibility conditions.

B. Recommendations

First, future research could focus on more extensive empirical validation of behavioural responses. While it is quite straightforwards to compare simulated changes in car travel with observed traffic intensities, validation opportunities for other modes are more difficult to acquire. Additional data sources, such as public transport passenger data, bicycle and pedestrian counts, shared-mobility usage, travel surveys and mobile-device data, could provide a more comprehensive assessment of model performance.

Second, further research is recommended to establish suitable behavioural benchmark values specifically for ABMs. The elasticity benchmarks used in this study were derived from the LMS, which is not an ABM, and differences in model structure may therefore effecteffect their comparability with ActivitySim. Developing ABM-specific benchmarks would provide a stronger basis for evaluating behavioural responses, while the calibration method developed in this study could still be applied using these alternative benchmark values.

Third, future calibration efforts could incorporate additional behavioural indicators, such as destination choices, trip-length distributions or activity-participation patterns. Behavioural responses across different population groups could likewise be included as calibration targets, allowing differences between socio-demographic groups to be explicitly considered during calibration. Including a broader range of behavioural targets may further improve the representation of travel behaviour and reduce trade-offs between calibration objectives.

Fourth, future elasticity analyses could be extended beyond car travel time to include travel costs, parking costs, public transport travel time and fares. This would provide a broader understanding of behavioural sensitivity to different policy instruments and help identify which combinations of measures are most likely to produce the intended responses.

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APPENDIX

A: SENSITIVITY ANALYSIS GRAPHS

This appendix presents the complete results of the Morris sensitivity analysis. The figures report the mean absolute elementary effect (μ^*) for each parameter, indicating its relative influence on the selected model outputs.

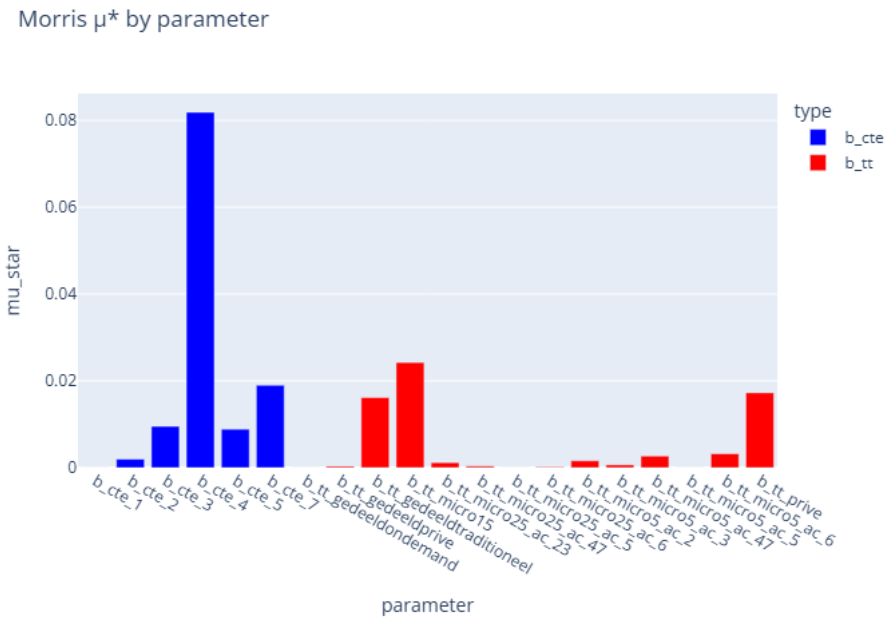


Fig. 4: Mode-specific parameters

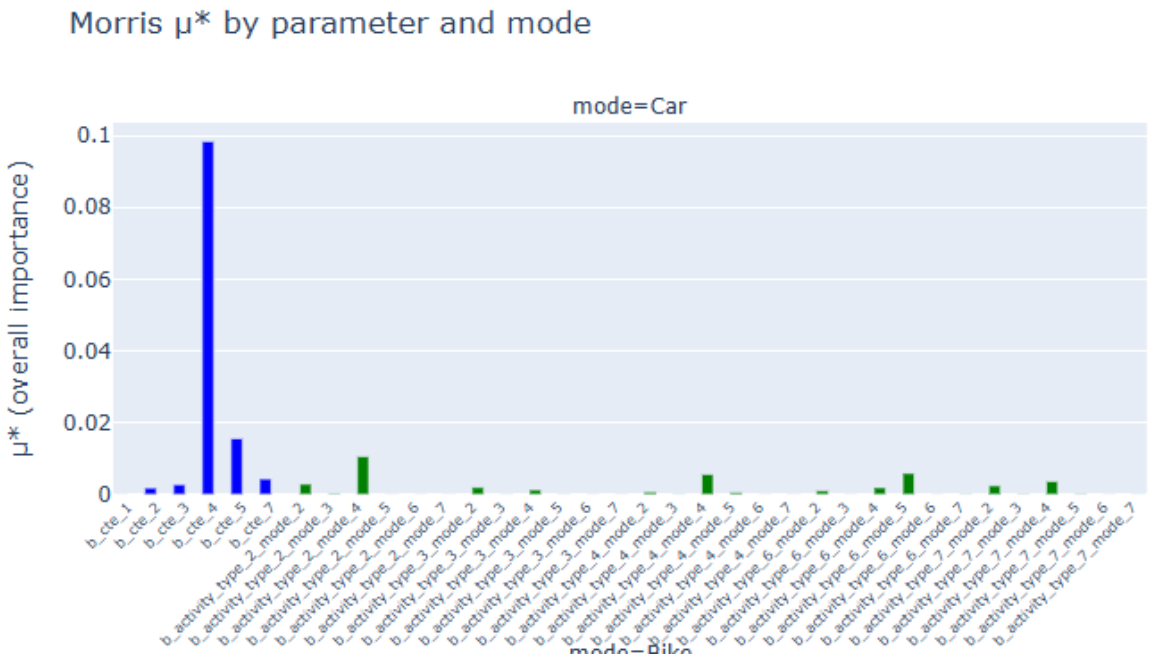


Fig. 5: Activity-specific parameters

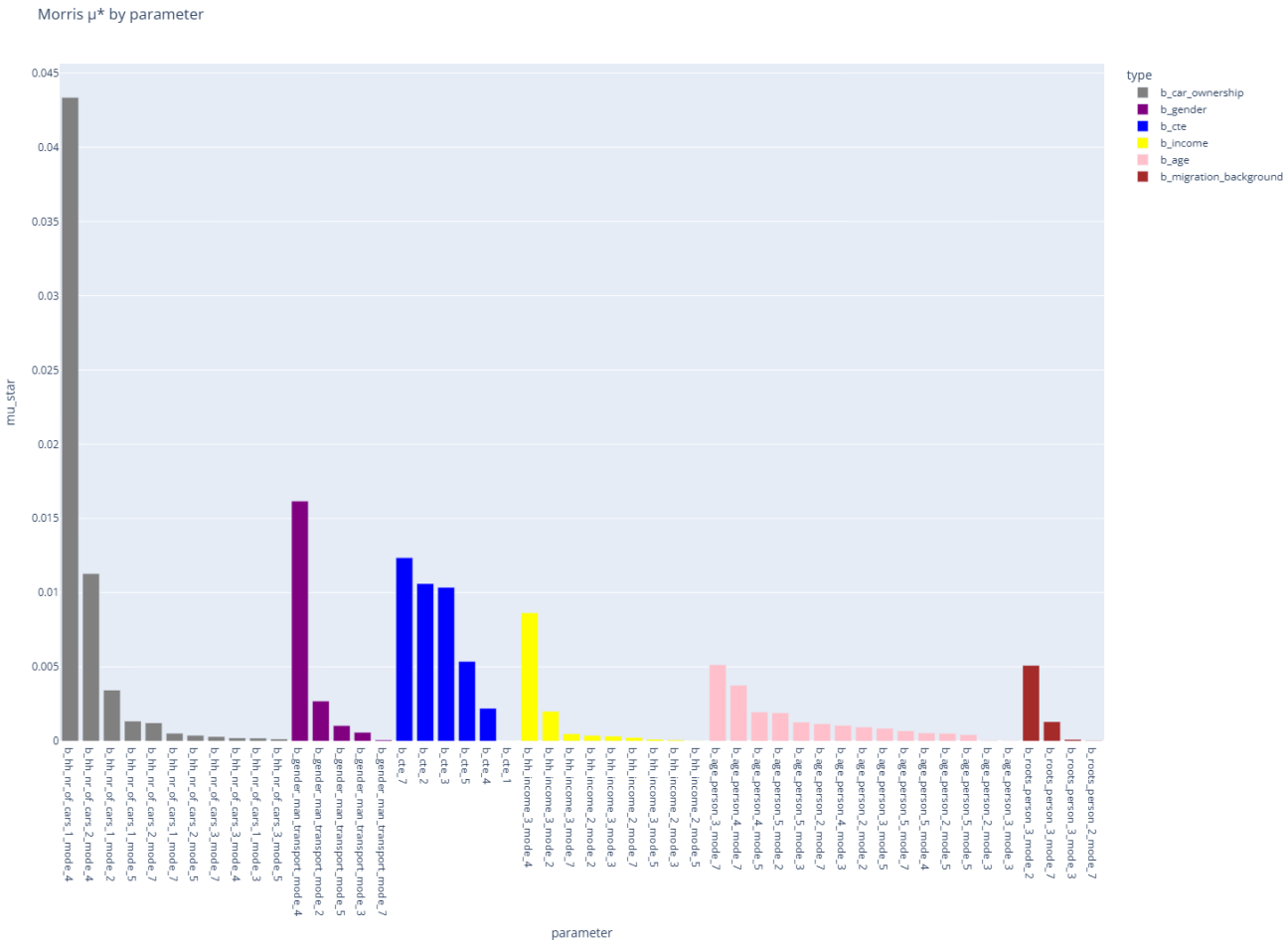


Fig. 6: Socio-demographic parameters

B

Results sensitivity analysis

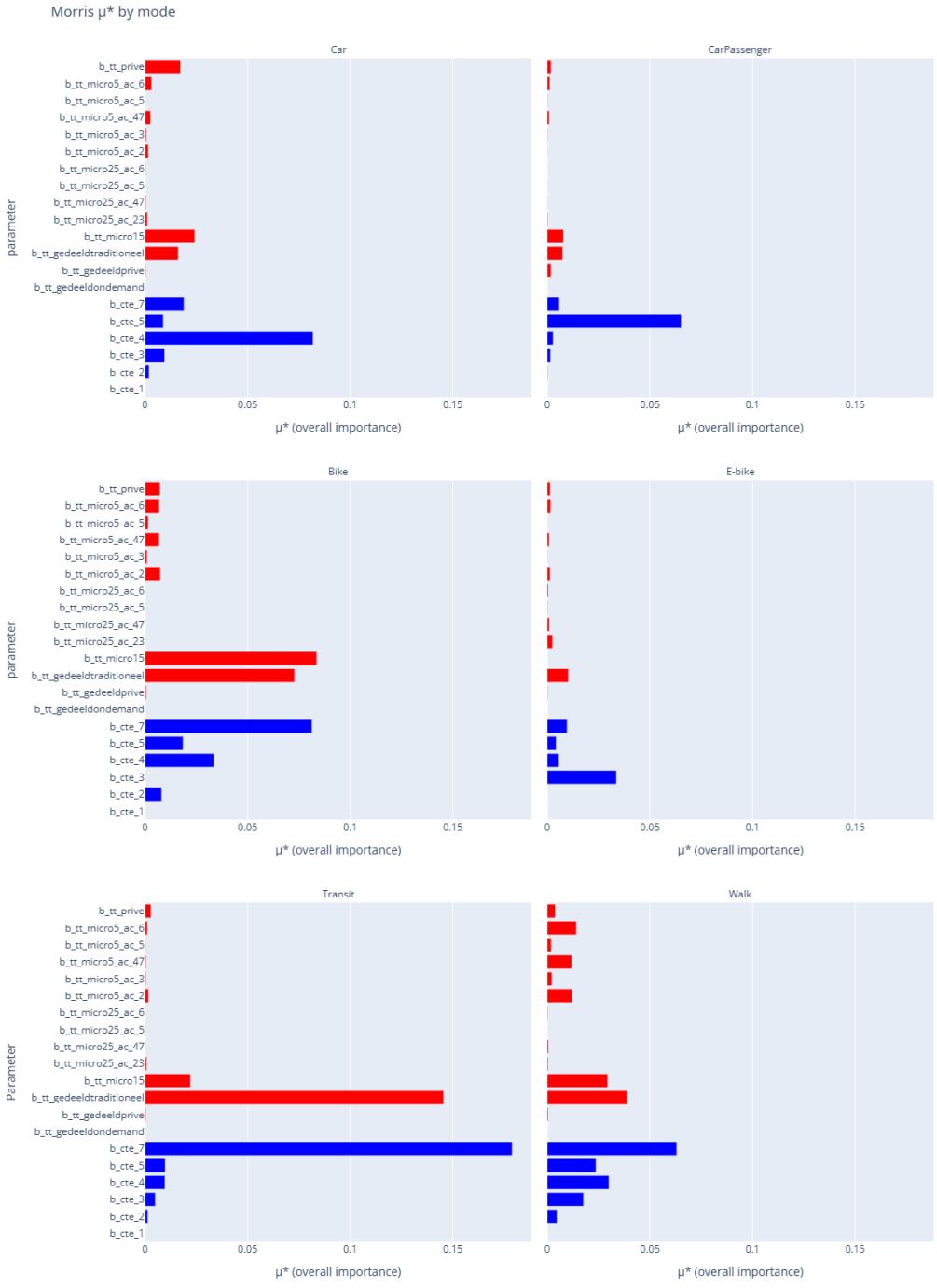


Figure B.1: Morris μ^* values for ASC and travel time parameters effecting modal share.

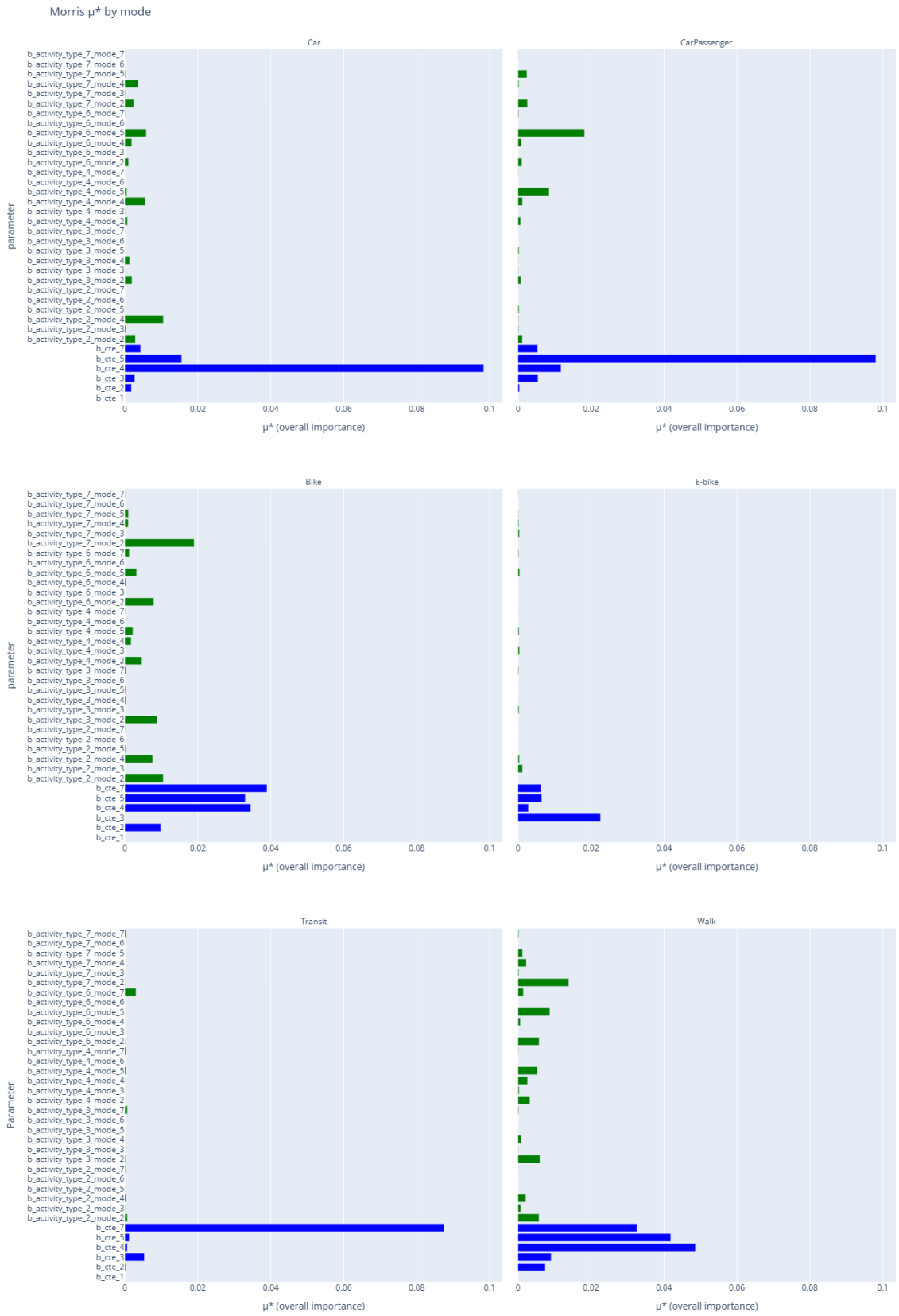


Figure B.2: Morris μ^* values for ASC and activity parameters effecting modal share.

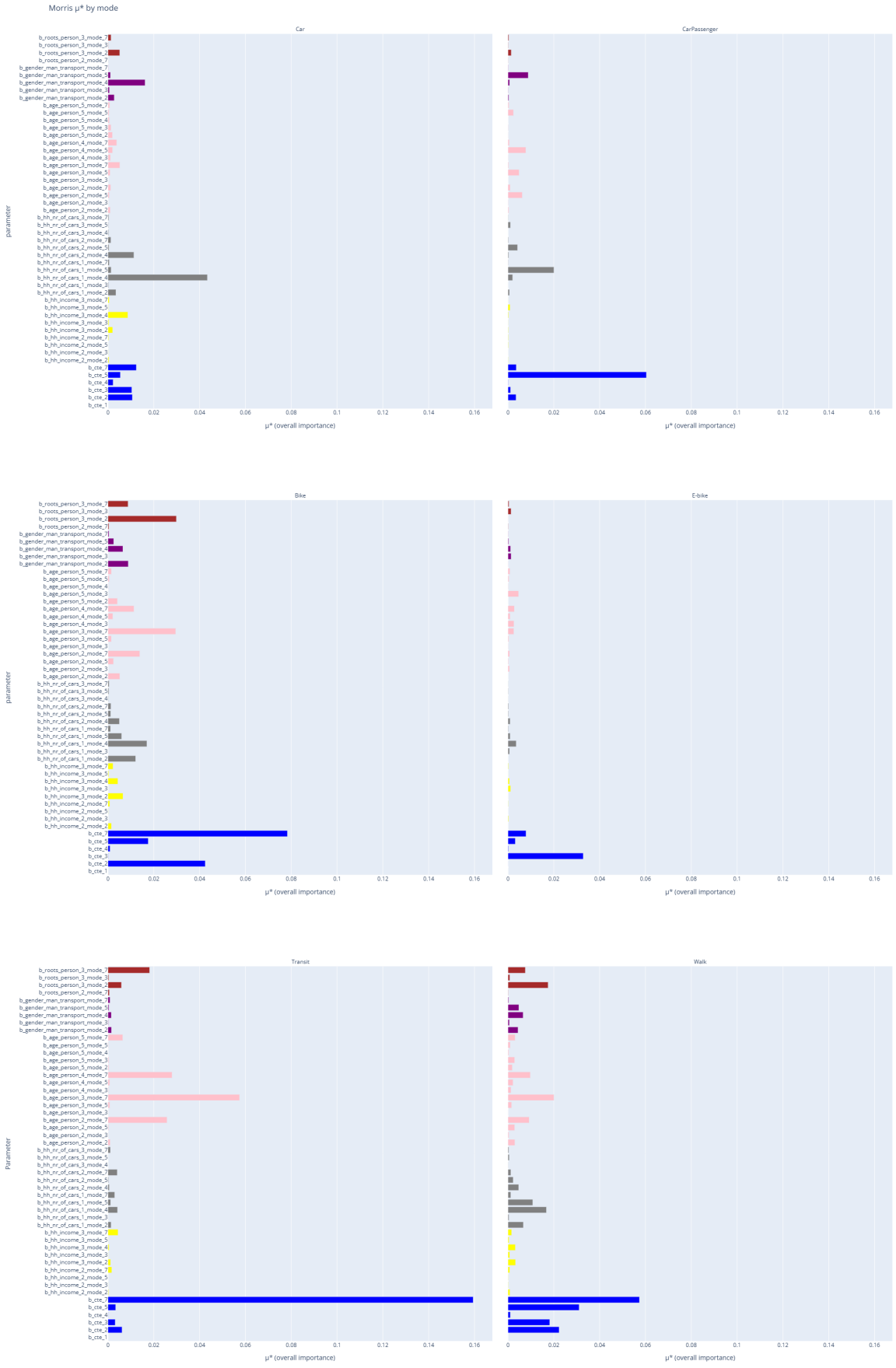


Figure B.3: Morris $\mu*$ values for ASC and socio-demographic parameters effecting modal share.

C

Parameter changes for elasticity

Table C.1: Parameter changes applied to improve model responsiveness

Model component	Parameter	Original	Modified
Tour mode choice			
	b_tt_gedeeldtraditioneel	0.5999	0.3999
	b_cte_2	0.0448	0.4481
	b_cte_7	-3.0377	-1.0377
	b_gender_man_mode_4	0.1740	0.0870
Workplace location			
	coef_dist_15_up	-0.0874	-0.0437
	coef_mode_logsum	0.5845	0.2923
Non-mandatory tour destination			
	coef_escort_dist_5_plus	-0.1221	-0.0611
	coef_shopping_dist_5_plus	-0.1860	-0.0930
	coef_eatout_dist_5_plus	-0.0546	-0.0273
	coef_othmaint_dist_5_plus	-0.1599	-0.0800
	coef_social_dist_5_plus	-0.0685	-0.0343
	coef_otherdiscr_dist_5_plus	-0.0955	-0.0478
	coef_mode_logsum	1.0513	0.5257
Trip destination			
	coef_mode_choice_logsum	1.2525	0.6263
Work tour scheduling			
	coef_mode_choice_logsum	1.0590	0.5295
School tour scheduling			
	coef_mode_choice_logsum	4.1834	2.0917

D

Results calibration algorithm

D.1. Comparison original and calibrated parameters

Table D.1: Comparison of original parameters and calibrated parameters from Run 52

Parameter	Original	Run 52	Absolute change	Change
Alternative-specific constants				
b_cte_2	0.0481	-0.3404	-0.3885	-807.6%
b_cte_3	-0.2113	-0.0177	0.1936	-91.6%
b_cte_4	1.3681	1.1940	-0.1741	-12.7%
b_cte_5	-0.5210	-0.5120	0.0090	-1.7%
b_cte_7	-1.0377	-1.5156	-0.4779	+46.1%
Travel time coefficients				
b_tt_gedeeldondemand	-0.0011	-0.0020	-0.0009	+82.7%
b_tt_gedeeldprive	-0.0513	-0.0517	-0.0004	+0.8%
b_tt_gedeeldtraditioneel	-0.0600	-0.0720	-0.0120	+20.0%
b_tt_micro15	-0.0451	-0.0376	0.0075	-16.6%
b_tt_micro25_ac_23	-0.0572	-0.0992	-0.0420	+73.5%
b_tt_micro25_ac_47	-0.0547	-0.0732	-0.0185	+33.8%
b_tt_micro25_ac_5	-0.0479	-0.0959	-0.0480	+100.2%
b_tt_micro25_ac_6	-0.0494	-0.0546	-0.0052	+10.4%
b_tt_micro5_ac_2	-0.0296	-0.0472	-0.0176	+59.5%
b_tt_micro5_ac_3	-0.0047	-0.0023	0.0024	-50.4%
b_tt_micro5_ac_47	-0.0299	-0.0519	-0.0220	+73.5%
b_tt_micro5_ac_5	-0.0293	-0.0472	-0.0179	+61.1%
b_tt_micro5_ac_6	-0.0243	-0.0305	-0.0062	+25.7%
b_tt_prive	-0.0500	-0.0465	0.0035	-6.9%
Purpose-mode interaction coefficients				
b_activity_type_2_mode_2	0.4253	0.3413	-0.0840	-19.7%
b_activity_type_2_mode_3	0.9797	0.5534	-0.4263	-43.5%
b_activity_type_2_mode_4	0.7203	0.6791	-0.0412	-5.7%
b_activity_type_2_mode_5	-0.2055	-0.1796	0.0259	-12.6%
b_activity_type_2_mode_6	-2.5408	-2.3208	0.2200	-8.7%
b_activity_type_2_mode_7	0.0892	0.1785	0.0893	+100.1%
b_activity_type_3_mode_2	-1.4072	-2.8144	-1.4072	+100.0%
b_activity_type_3_mode_3	-1.1255	-1.4843	-0.3588	+31.9%
b_activity_type_3_mode_4	0.1419	0.0710	-0.0709	-50.0%
b_activity_type_3_mode_5	-0.3936	-0.1968	0.1968	-50.0%
b_activity_type_3_mode_6	-4.3738	-8.7475	-4.3737	+100.0%
b_activity_type_3_mode_7	-1.0380	-0.9517	0.0863	-8.3%
b_activity_type_4_mode_2	-0.4989	-0.2884	0.2105	-42.2%
b_activity_type_4_mode_3	0.1839	0.2304	0.0465	+25.3%
b_activity_type_4_mode_4	1.1727	2.3454	1.1727	+100.0%
b_activity_type_4_mode_5	1.0508	0.5254	-0.5254	-50.0%
b_activity_type_4_mode_6	-1.6270	-2.2763	-0.6493	+39.9%
b_activity_type_4_mode_7	-2.1828	-2.0274	0.1554	-7.1%
b_activity_type_6_mode_2	-0.3460	-0.2552	0.0908	-26.2%
b_activity_type_6_mode_3	-0.0213	-0.0228	-0.0015	+7.0%
b_activity_type_6_mode_4	0.1594	0.2112	0.0518	+32.5%
b_activity_type_6_mode_5	0.9539	1.1056	0.1517	+15.9%
b_activity_type_6_mode_6	-1.9239	-1.2146	0.7093	-36.9%
b_activity_type_6_mode_7	-2.2309	-1.7413	0.4896	-21.9%
b_activity_type_7_mode_2	-0.5618	-0.8220	-0.2602	+46.3%
b_activity_type_7_mode_3	-0.2276	-0.1842	0.0434	-19.1%
b_activity_type_7_mode_4	-0.2254	-0.4508	-0.2254	+100.0%
b_activity_type_7_mode_5	0.9779	1.0666	0.0887	+9.1%
b_activity_type_7_mode_6	-0.6718	-0.3359	0.3359	-50.0%
b_activity_type_7_mode_7	-1.8591	-1.4782	0.3809	-20.5%

D.2. Objective function over optimization runs

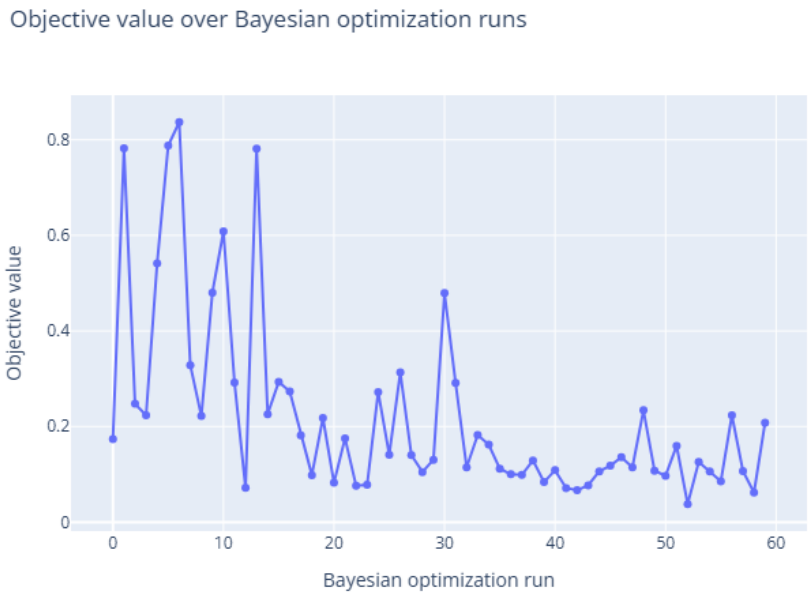


Figure D.1: Objective value over Bayesian optimization runs

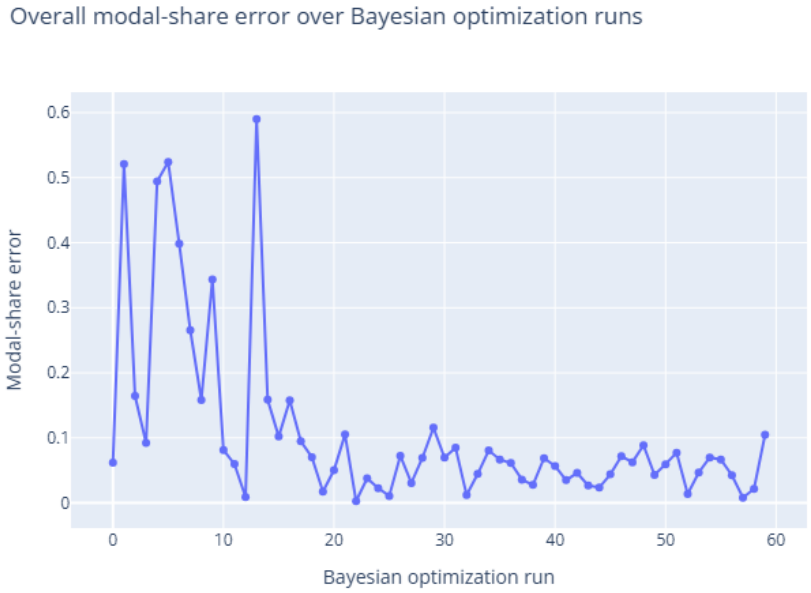


Figure D.2: Modal share error over Bayesian optimization runs

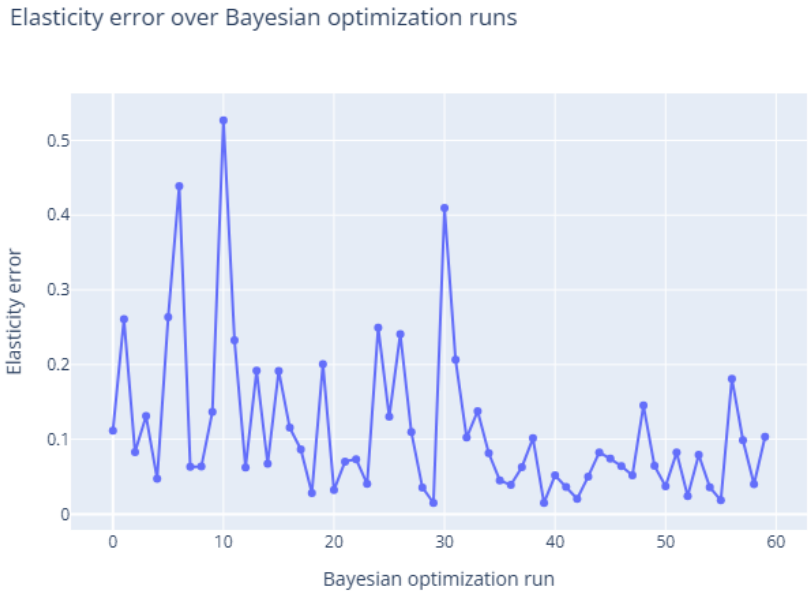


Figure D.3: Elasticity error over Bayesian optimization runs

E

Personas

Vincent, 19

Multi-modal young traveller

Vincent is a young and flexible traveller who combines multiple transport options depending on the situation. Living mainly in urban environments and often still studying, he adapts easily between public transport, cycling, and car travel. His mobility is characterized by versatility rather than dependence on a single mode.

Table E.1: Probability distributions defining persona Vincent.

Variable	Category	Probability
Age	16–25	0.80
	26–45	0.17
	46–65	0.03
	65+	0.00
Gender	Male	0.56
	Female	0.44
Car ownership	No car	0.31
	Has car	0.69
Student	No	0.25
	Yes	0.75
Worker	No	0.60
	Yes	0.40
Urbanization	Urban	0.49
	Moderately urban	0.38
	Non-urban	0.13
Education	Low	0.60
	Middle	0.30
	High	0.10
Income class	1	0.23
	2	0.08
	3	0.39
	4	0.30
Cars per household	0 cars	0.03
	1 car	0.33
	2 cars	0.37
	3+ cars	0.27
Household composition	Adults, no children	0.47
	Child under 12	0.32
	Child 12–17	0.19
	Single	0.02
Migration background	No	0.87
	Yes	0.13
Mode use (days/year)	Walk	146
	Bike	123
	E-bike	60
	Transit	222
	Car	112

Tessa, 23

Urban young traveller

Tessa represents young urban students whose lifestyle is closely aligned with active and sustainable mobility. She relies heavily on the transport options available in cities and has relatively little need for private vehicle access. Her travel patterns inlcudemotly bike and public transit.

Table E.2: Probability distributions defining persona Tessa.

Variable	Category	Probability
Age	16–25	0.82
	26–45	0.16
	46–65	0.02
	65+	0.00
Gender	Male	0.44
	Female	0.56
Car ownership	No car	0.60
	Has car	0.40
Student	No	0.30
	Yes	0.70
Worker	No	0.65
	Yes	0.35
Urbanization	Urban	0.64
	Moderately urban	0.29
	Non-urban	0.07
Education	Low	0.66
	Middle	0.27
	High	0.07
Income class	1	0.15
	2	0.13
	3	0.47
	4	0.25
Cars per household	0 cars	0.07
	1 car	0.51
	2 cars	0.30
	3+ cars	0.12
Household composition	Adults, no children	0.54
	Child 12–17	0.35
	Child under 12	0.09
	Single	0.02
Migration background	No	0.87
	Yes	0.13
Mode use (days/year)	Walk	158
	Bike	167
	E-bike	25
	Transit	180
	Car	56

Youssef, 32

Car enthusiast

Youssef enjoys the flexibility and independence that driving provides. The car is his preferred mode for most trips and plays a central role in his daily mobility. Rather than adapting travel choices to different circumstances, he tends to favour the convenience, comfort, and control offered by private vehicle use.

Table E.3: Probability distributions defining persona Youssef.

Variable	Category	Probability
Age	16–25	0.27
	26–45	0.53
	46–65	0.19
	65+	0.01
Gender	Male	0.39
	Female	0.61
Car ownership	No car	0.00
	Has car	1.00
Student	No	0.95
	Yes	0.05
Worker	No	0.15
	Yes	0.85
Urbanization	Urban	0.45
	Moderately urban	0.45
	Non-urban	0.10
Education	Low	0.25
	Middle	0.45
	High	0.30
Income class	1	0.25
	2	0.09
	3	0.39
	4	0.27
Cars per household	0 cars	0.00
	1 car	0.25
	2 cars	0.43
	3+ cars	0.32
Household composition	Adults, no children	0.08
	Child 12–17	0.50
	Child under 12	0.34
	Single	0.08
Migration background	No	0.91
	Yes	0.09
Mode use (days/year)	Walk	104
	Bike	47
	E-bike	32
	Transit	8
	Car	245

Cynthia, 44

Car-dependend traveller

Cynthia's daily activities are closely organised around car availability. Whether for commuting, household responsibilities, or leisure activities, the car provides the flexibility needed to maintain a busy lifestyle. As a result, alternative transport modes play a secondary role, with travel choices largely shaped by the convenience and accessibility of private vehicle use.

Table E.4: Probability distributions defining persona Cynthia.

Variable	Category	Probability
Age	16–25	0.06
	26–45	0.39
	46–65	0.48
	65+	0.07
Gender	Male	0.59
	Female	0.41
Car ownership	No car	0.04
	Has car	0.96
Student	No	0.99
	Yes	0.01
Worker	No	0.25
	Yes	0.75
Urbanization	Urban	0.44
	Moderately urban	0.45
	Non-urban	0.11
Education	Low	0.24
	Middle	0.45
	High	0.31
Income class	1	0.16
	2	0.16
	3	0.46
	4	0.22
Cars per household	0 cars	0.01
	1 car	0.50
	2 cars	0.37
	3+ cars	0.12
Household composition	Adults, no children	0.11
	Child 12–17	0.48
	Child under 12	0.33
	Single	0.08
Migration background	No	0.92
	Yes	0.08
Mode use (days/year)	Walk	143
	Bike	49
	E-bike	59
	Transit	8
	Car	167

Henk, 42

Pragmatic traveller

Henk balances a busy job with family responsibilities, often juggling work, childcare, and leisure activities throughout the week. As a result, he approaches mobility in a practical way, choosing the mode that best fits the trip at hand. While the car is used frequently, he is equally willing to walk or cycle when these provide a convenient alternative.

Table E.5: Probability distributions defining persona Henk.

Variable	Category	Probability
Age	16–25	0.10
	26–45	0.47
	46–65	0.39
	65+	0.04
Gender	Male	0.47
	Female	0.53
Car ownership	No car	0.04
	Has car	0.96
Student	No	0.99
	Yes	0.01
Worker	No	0.10
	Yes	0.90
Urbanization	Urban	0.51
	Moderately urban	0.41
	Non-urban	0.08
Education	Low	0.16
	Middle	0.42
	High	0.42
Income class	1	0.20
	2	0.12
	3	0.43
	4	0.25
Cars per household	0 cars	0.01
	1 car	0.48
	2 cars	0.38
	3+ cars	0.13
Household composition	Adults, no children	0.07
	Child 12–17	0.39
	Child under 12	0.46
	Single	0.08
Migration background	No	0.93
	Yes	0.07
Mode use (days/year)	Walk	166
	Bike	80
	E-bike	60
	Transit	13
	Car	184

Sam, 35

(Environmentally) conscious traveller

Sam leads an active lifestyle with many activities spread throughout the week, resulting in frequent travel. While he values flexibility and convenience, he is also mindful of the environmental impact of his choices and regularly incorporates walking and cycling into his daily routines. Rather than relying exclusively on the car, he chooses the mode that best balances practicality with sustainability.

Table E.6: Probability distributions defining persona Sam.

Variable	Category	Probability
Age	16–25	0.06
	26–45	0.41
	46–65	0.46
	65+	0.07
Gender	Male	0.44
	Female	0.56
Car ownership	No car	0.04
	Has car	0.96
Student	No	0.99
	Yes	0.01
Worker	No	0.10
	Yes	0.90
Urbanization	Urban	0.48
	Moderately urban	0.43
	Non-urban	0.09
Education	Low	0.11
	Middle	0.39
	High	0.50
Income class	1	0.28
	2	0.08
	3	0.36
	4	0.28
Cars per household	0 cars	0.01
	1 car	0.48
	2 cars	0.38
	3+ cars	0.13
Household composition	Adults, no children	0.09
	Child 12–17	0.41
	Child under 12	0.44
	Single	0.06
Migration background	No	0.94
	Yes	0.06
Mode use (days/year)	Walk	198
	Bike	104
	E-bike	69
	Transit	20
	Car	165

Mei, 55

Environmentally conscious (car-free) urbanite

Mei embraces an urban lifestyle where most destinations are easily reached without a car. Comfortable navigating the city on foot, by bicycle, or by public transport, she sees sustainable travel as a natural part of everyday life rather than a sacrifice. Her mobility choices reflect both the opportunities offered by city living and a conscious preference for less car-dependent travel.

Table E.7: Probability distributions defining persona Mei.

Variable	Category	Probability
Age	16–25	0.06
	26–45	0.40
	46–65	0.47
	65+	0.07
Gender	Male	0.50
	Female	0.50
Car ownership	No car	0.65
	Has car	0.35
Student	No	0.98
	Yes	0.02
Worker	No	0.15
	Yes	0.85
Urbanization	Urban	0.85
	Moderately urban	0.14
	Non-urban	0.01
Education	Low	0.14
	Middle	0.41
	High	0.45
Income class	1	0.06
	2	0.30
	3	0.51
	4	0.13
Cars per household	0 cars	0.84
	1 car	0.16
	2 cars	0.00
	3+ cars	0.00
Household composition	Adults, no children	0.28
	Child 12–17	0.03
	Child under 12	0.07
	Single	0.62
Migration background	No	0.86
	Yes	0.14
Mode use (days/year)	Walk	200
	Bike	142
	E-bike	34
	Transit	134
	Car	34

Martha, 58

Vulnerable traveller

Martha lives a relatively local and low-mobility lifestyle, with most activities taking place close to home. Maintaining access to essential destinations is often more important than travelling frequently or over long distances. As a vulnerable traveller, she tends to prioritise simplicity and ease of travel, relying on familiar routines and nearby opportunities in her daily life.

Table E.8: Probability distributions defining persona Martha.

Variable	Category	Probability
Age	16–25	0.00
	26–45	0.11
	46–65	0.53
	65+	0.36
Gender	Male	0.71
	Female	0.29
Car ownership	No car	0.89
	Has car	0.11
Student	No	1.00
	Yes	0.00
Worker	No	0.70
	Yes	0.30
Urbanization	Urban	0.71
	Moderately urban	0.26
	Non-urban	0.03
Education	Low	0.62
	Middle	0.32
	High	0.06
Income class	1	0.02
	2	0.44
	3	0.47
	4	0.07
Cars per household	0 cars	0.88
	1 car	0.12
	2 cars	0.00
	3+ cars	0.00
Household composition	Adults, no children	0.33
	Child 12–17	0.01
	Child under 12	0.12
	Single	0.54
Migration background	No	0.94
	Yes	0.06
Mode use (days/year)	Walk	127
	Bike	17
	E-bike	65
	Transit	26
	Car	28

Ben, 68

Active elder traveller

Ben represents older adults who remain socially and physically active after retirement. Although daily obligations are fewer than during working life, maintaining independence and participating in local activities remain important. Mobility supports an engaged lifestyle that is focused on health, recreation, and community participation.

Table E.9: Probability distributions defining persona Ben.

Variable	Category	Probability
Age	16–25	0.00
	26–45	0.00
	46–65	0.02
	65+	0.98
Gender	Male	0.59
	Female	0.41
Car ownership	No car	0.06
	Has car	0.94
Student	No	1.00
	Yes	0.00
Worker	No	0.95
	Yes	0.05
Urbanization	Urban	0.50
	Moderately urban	0.42
	Non-urban	0.08
Education	Low	0.40
	Middle	0.41
	High	0.19
Income class	1	0.15
	2	0.16
	3	0.57
	4	0.12
Cars per household	0 cars	0.01
	1 car	0.90
	2 cars	0.08
	3+ cars	0.01
Household composition	Adults, no children	0.79
	Child 12–17	0.01
	Child under 12	0.00
	Single	0.20
Migration background	No	0.95
	Yes	0.05
Mode use (days/year)	Walk	202
	Bike	66
	E-bike	99
	Transit	15
	Car	123

Adrie, 79

Older traveller with reduced mobility

Adrie's daily activities are increasingly shaped by the limits of her mobility. Travel remains important for maintaining independence and social connections, but journeys tend to be carefully chosen and focused on essential destinations. Familiar routes, nearby facilities, and accessible transport options play a key role in her daily life, reflecting a lifestyle in which mobility has become more restricted and valuable than it once was.

Table E.10: Probability distributions defining persona Adrie.

Variable	Category	Probability
Age	16–25	0.00
	26–45	0.00
	46–65	0.05
	65+	0.95
Gender	Male	0.54
	Female	0.46
Car ownership	No car	0.10
	Has car	0.90
Student	No	1.00
	Yes	0.00
Worker	No	0.98
	Yes	0.02
Urbanization	Urban	0.52
	Moderately urban	0.41
	Non-urban	0.07
Education	Low	0.40
	Middle	0.40
	High	0.20
Income class	1	0.12
	2	0.19
	3	0.59
	4	0.10
Cars per household	0 cars	0.01
	1 car	0.83
	2 cars	0.13
	3+ cars	0.03
Household composition	Adults, no children	0.73
	Child 12–17	0.02
	Child under 12	0.00
	Single	0.25
Migration background	No	0.94
	Yes	0.06
Mode use (days/year)	Walk	155
	Bike	31
	E-bike	74
	Transit	10
	Car	123

Modal shift across socio-demographic factors

F.1. Modal shift across socio-demographic factors

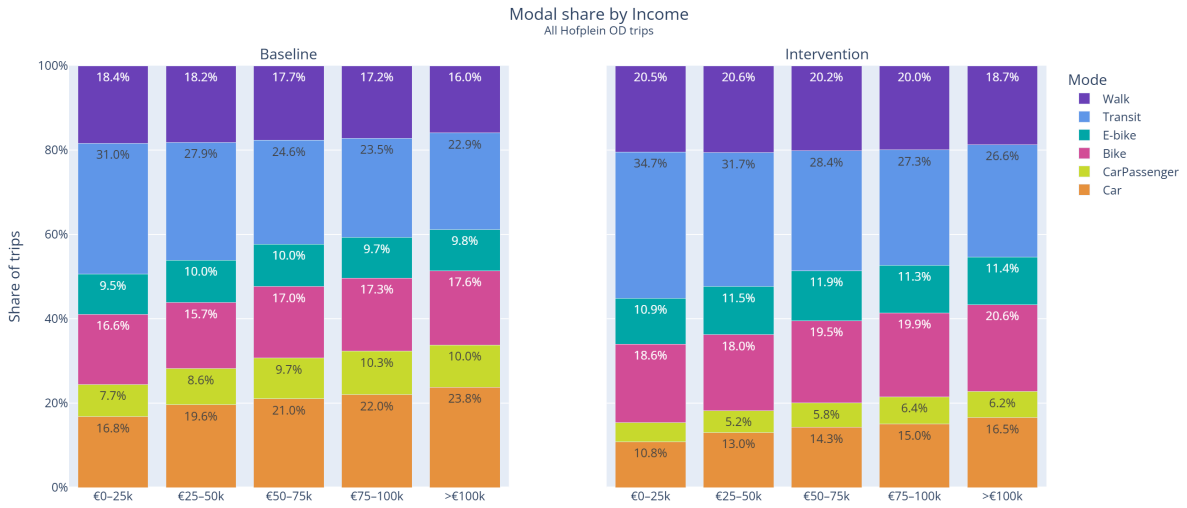


Figure F.1: Modal share by income category.

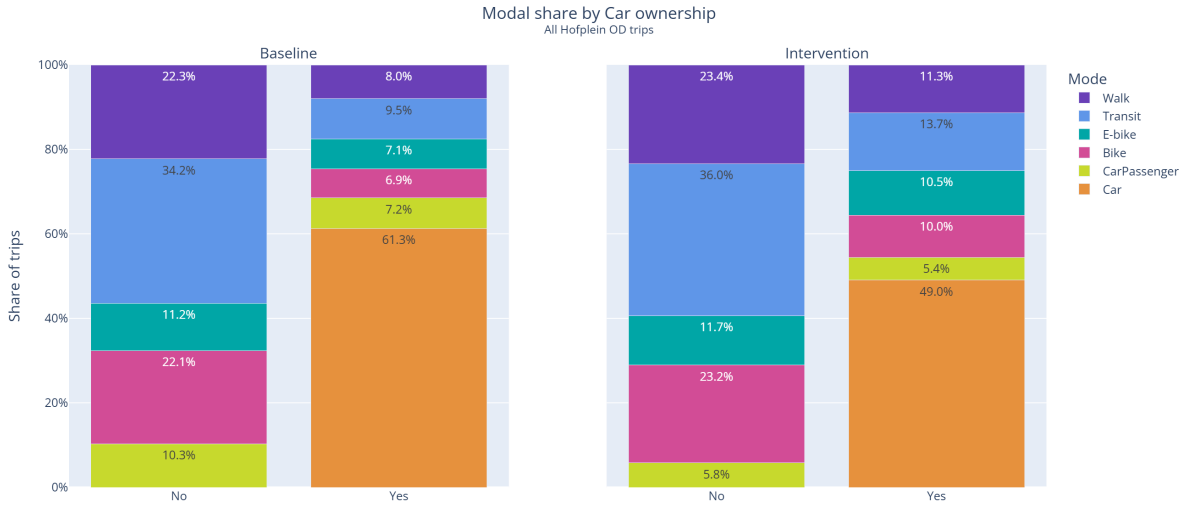


Figure F.2: Modal share by car ownership.

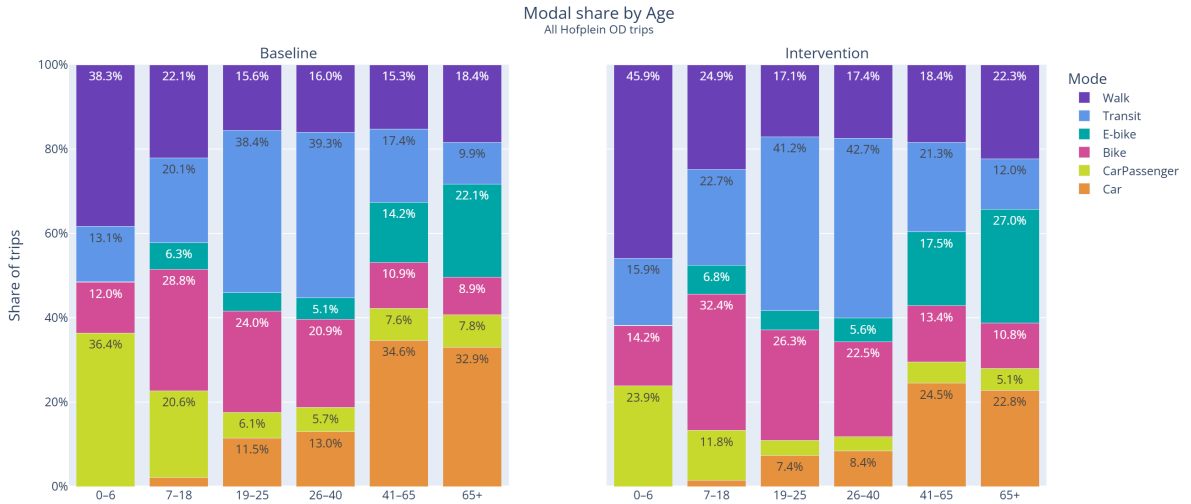


Figure F.3: Modal share by age category.

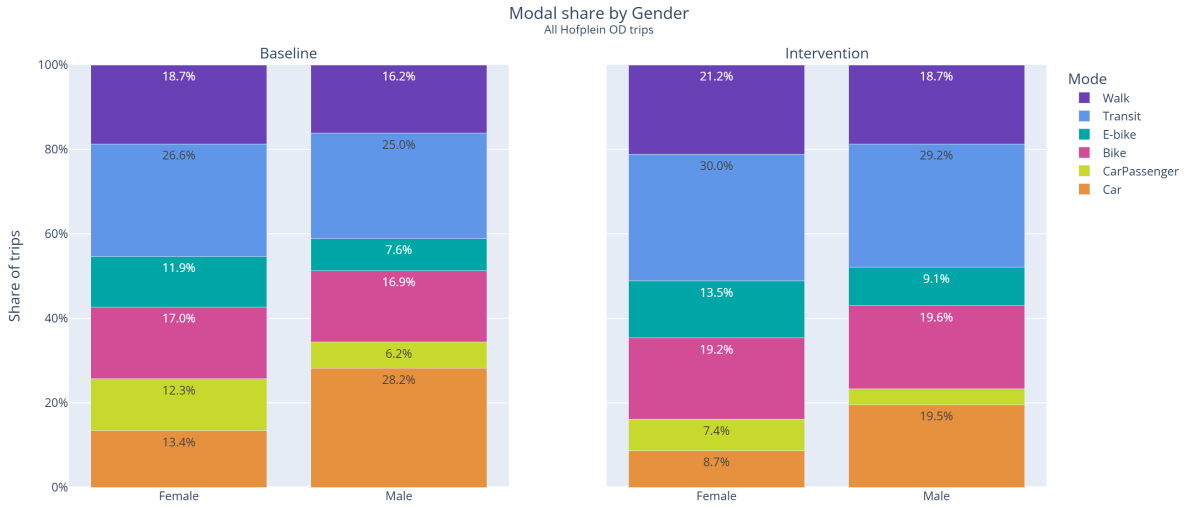


Figure F.4: Modal share by gender.

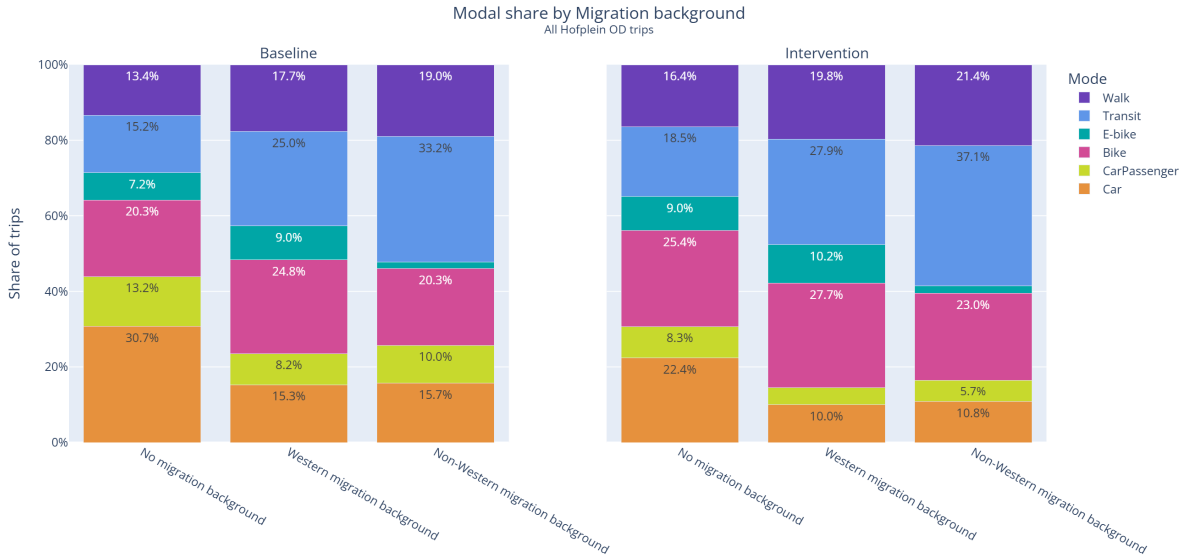


Figure F.5: Modal share by migration background.

F.2. Modal shift across socio-demographic factors for car users

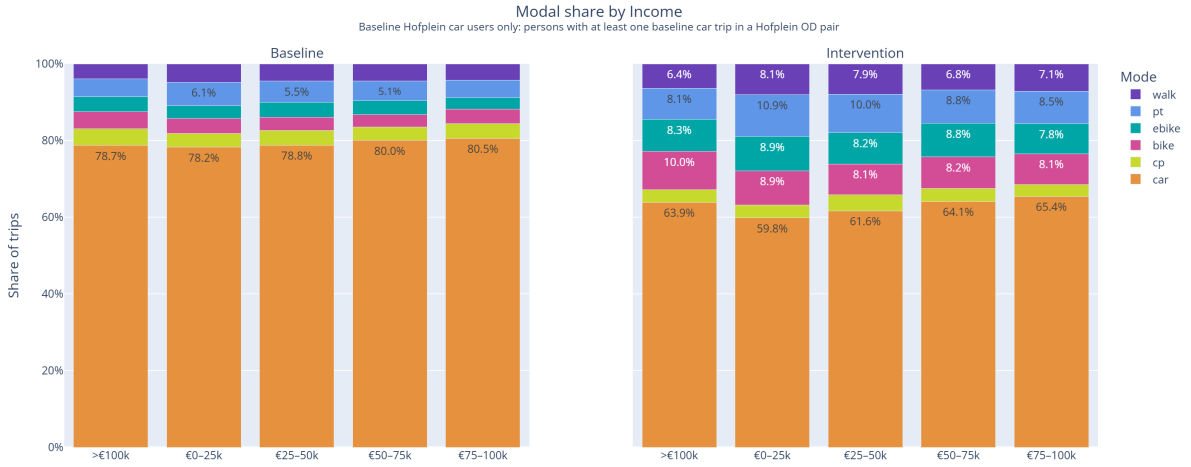


Figure F.6: Modal share by income category for baseline car users.

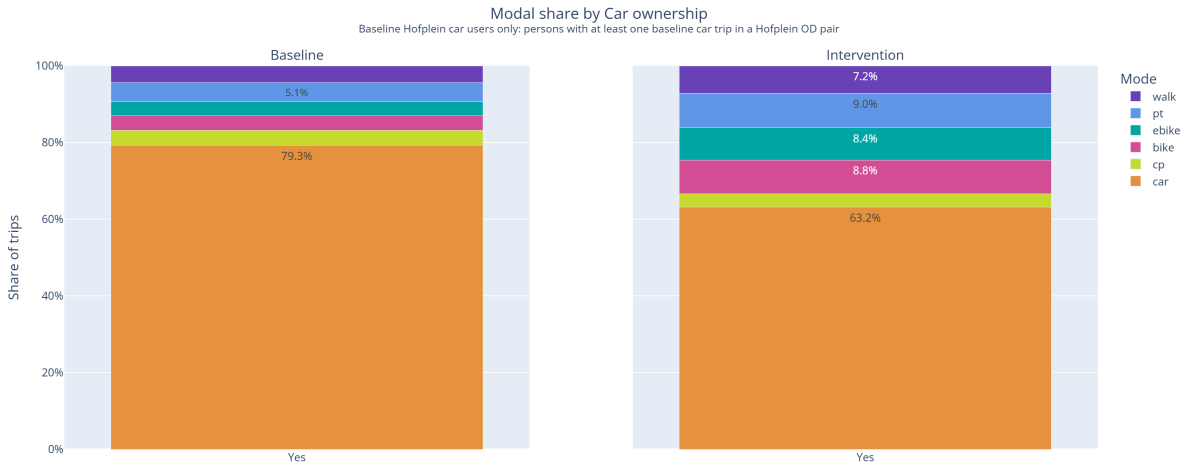


Figure F.7: Modal share by car ownership for baseline car users.

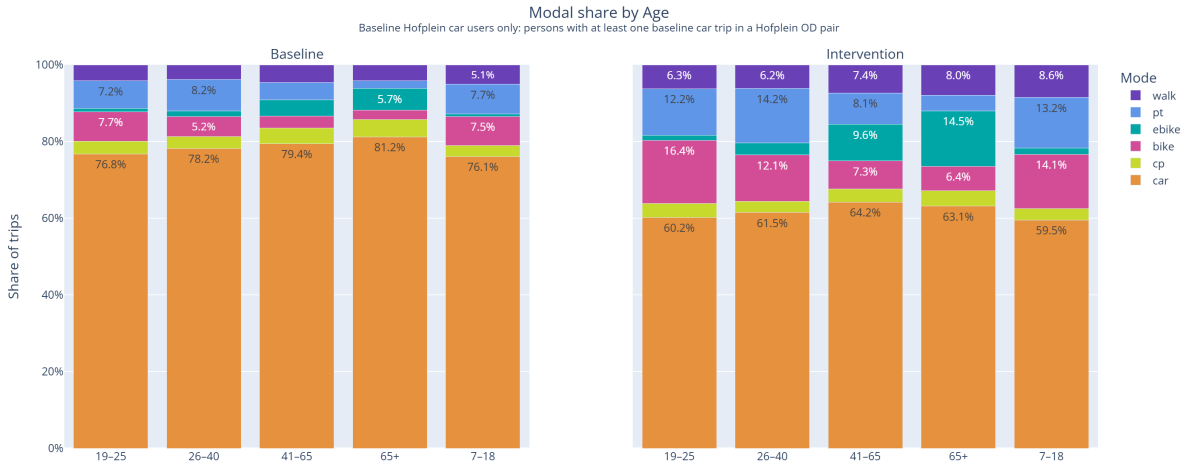


Figure F.8: Modal share by age category for baseline car users.

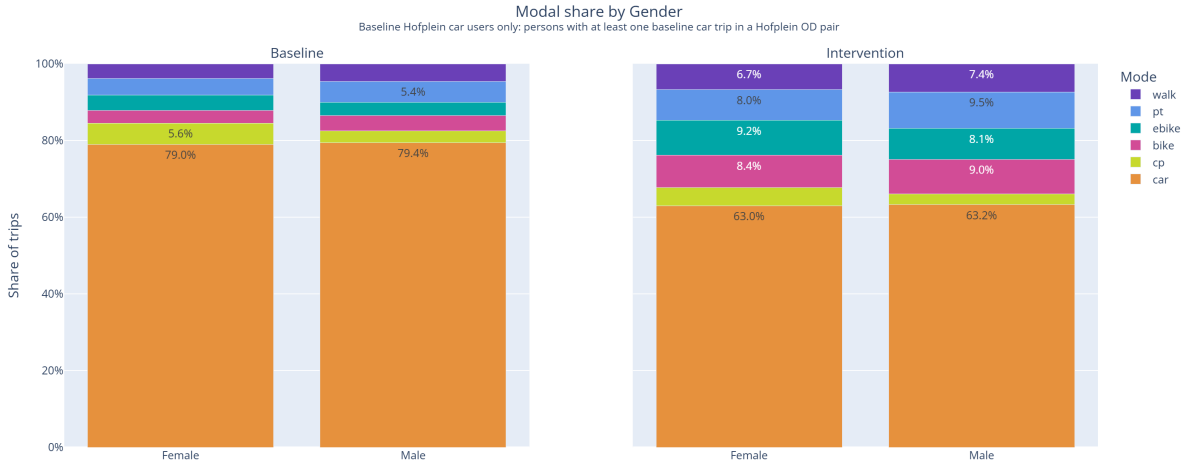


Figure F.9: Modal share by gender for baseline car users.

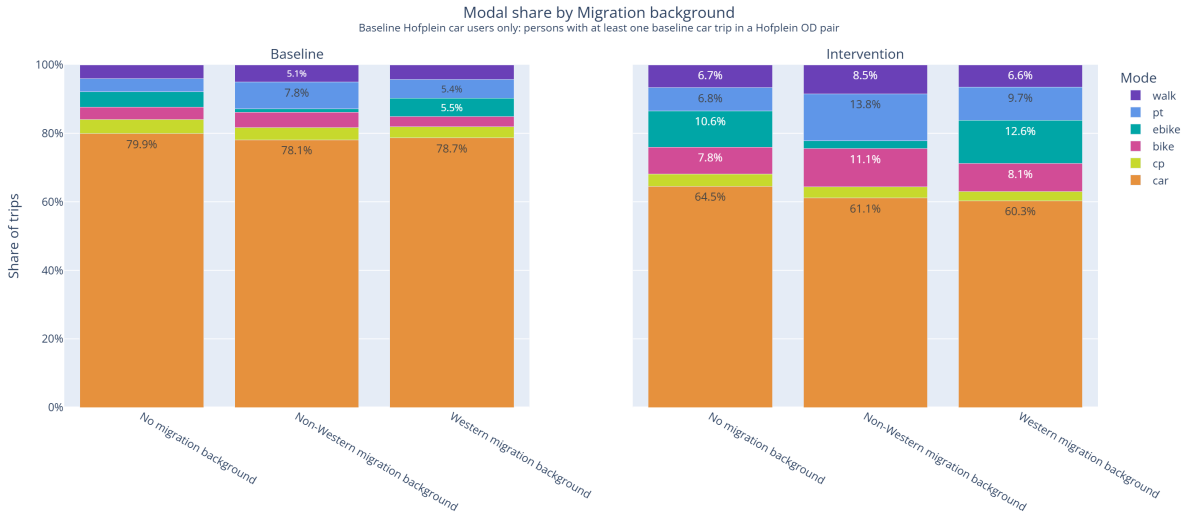


Figure F.10: Modal share by migration background for baseline car users.

G

Sankey per persona

Figure G.1 presents detailed Sankey diagrams for the five personas with the largest number of lost car trips. The figures show differences in redistribution patterns between personas.



Figure G.1: Behavioural response of the five personas with the largest reduction in car trips.

Figure G.2 presents Sankey diagrams for all personas. The figure provides a complete overview of the behavioural response distribution for each persona.

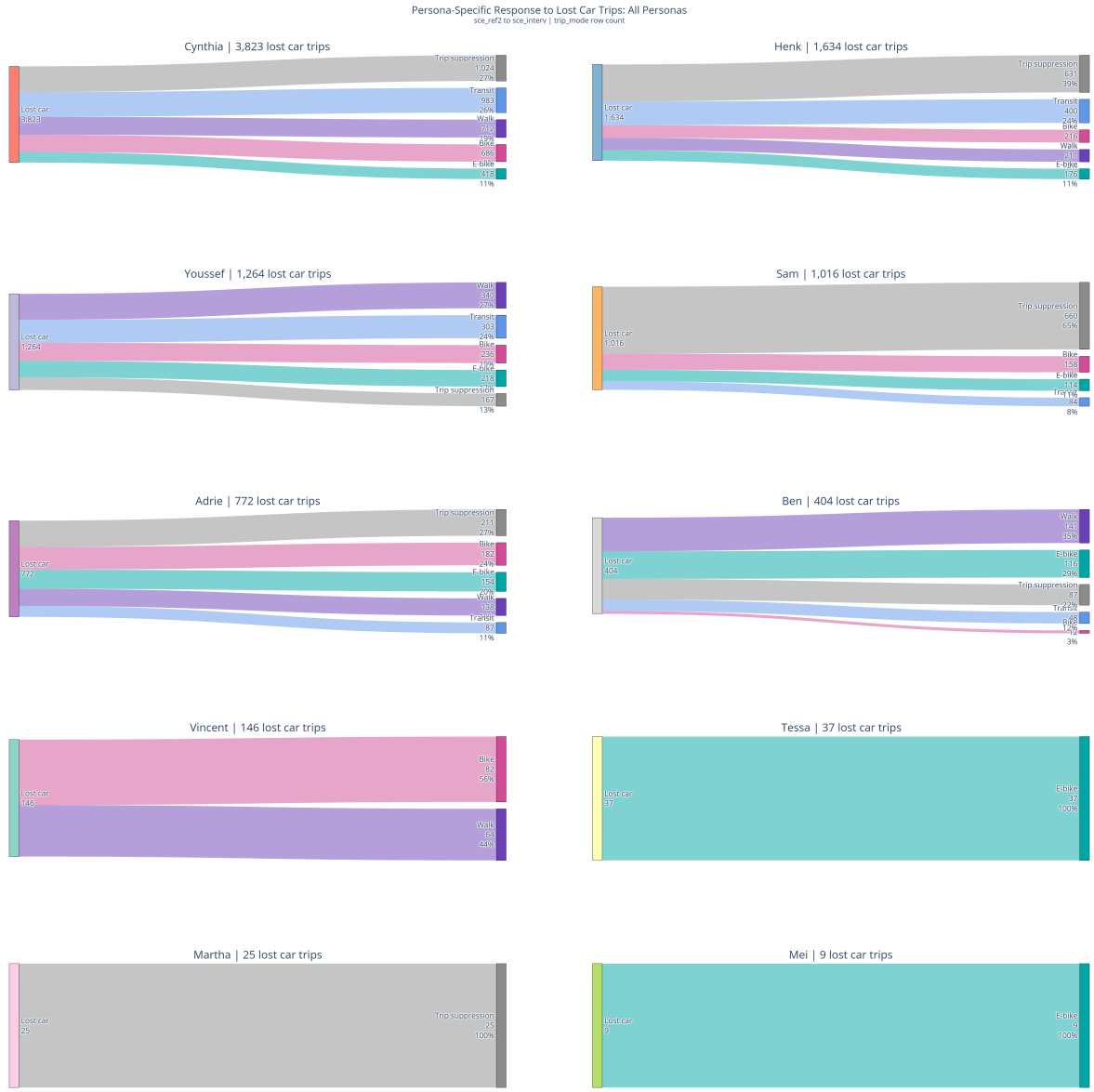


Figure G.2: Behavioural responses for all personas.

H

VRI intersection drawings

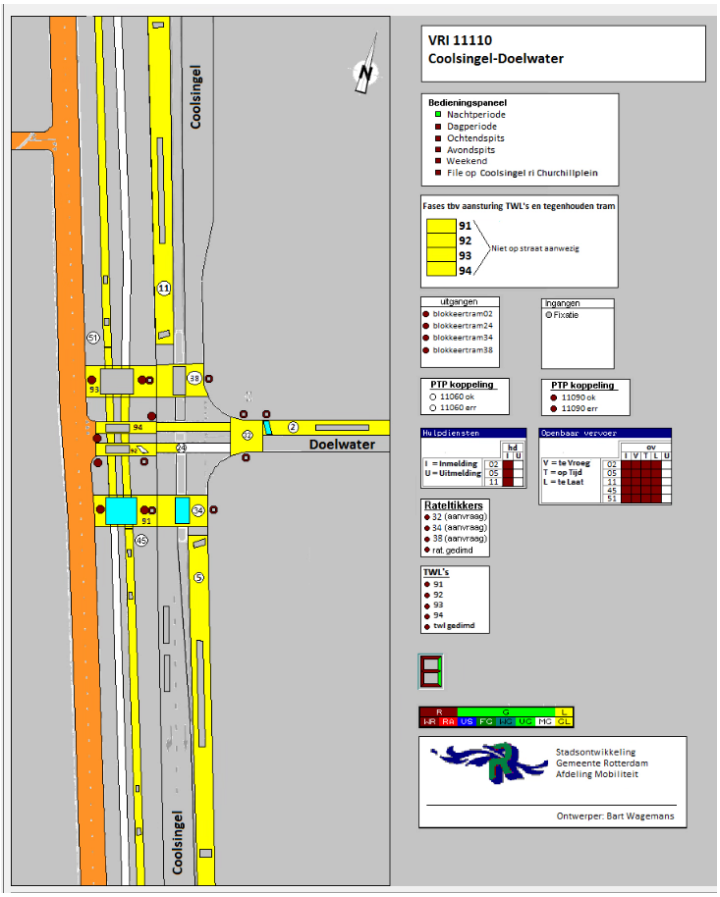


Figure H.1: VRI data point at Coolsingel

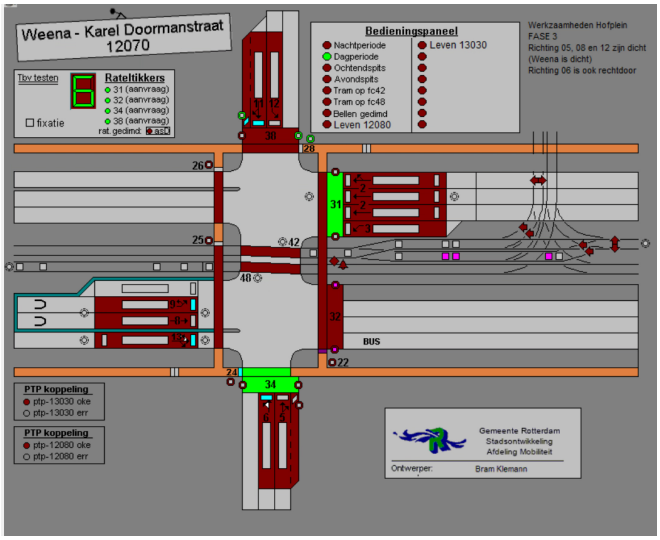


Figure H.2: VRI data point at Weena

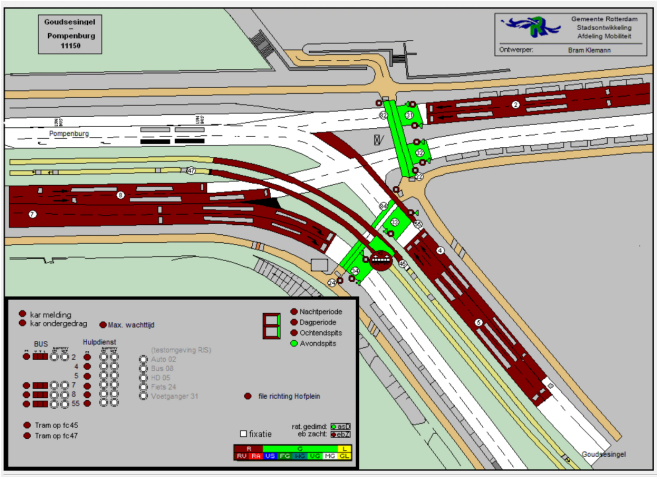


Figure H.3: VRI data point at Pompenburg

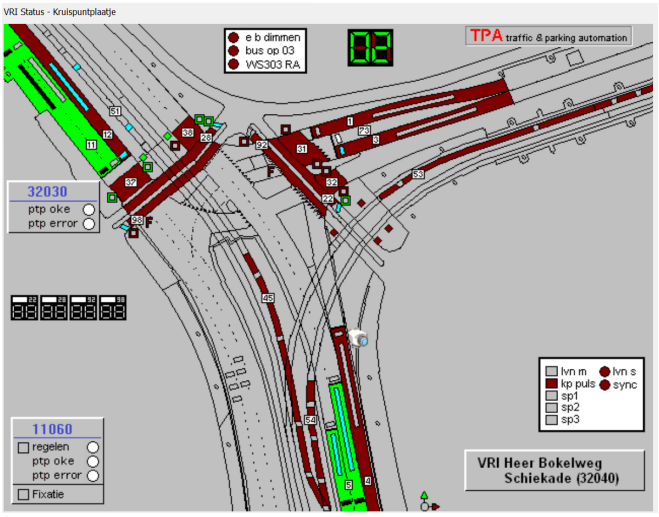


Figure H.4: VRI data point at Schiekade