A new fare system: fair system?

Examining the impact of fare differentiation on train travel behaviour in the Netherlands

Master Thesis

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A new fare system: fair system?

Examining the impact of fare differentiation on train travel behaviour in the Netherlands

by

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Preface

This thesis marks the culmination of a six-month research project on the impact of fare differentiation on the behaviour of train passengers in the Netherlands. It also signifies the end of a long academic journey. When I began my studies in 2017, I had no idea what was ahead of me. Looking back, it has been a remarkable and educational period. Although not every moment was easy, I have mostly enjoyed the experience. Writing this thesis has been a largely positive process, despite occasional setbacks and moments of doubt. When I look back now I can proudly say that I exceeded my own expectations.

I would like to extend my gratitude to several individuals who provided invaluable support and inspiration throughout this process. First and foremost, I thank the committee, without whose guidance this thesis would not have been possible. I am especially grateful to my primary supervisor, Maarten Kroesen, for his unwavering support and readiness to answer my questions. Our meetings were always productive, and I appreciated the balance of light-hearted conversation and in-depth discussions about the thesis.

My thanks also go to Bert van Wee, the chair of the committee. My initial discussions about this thesis were with Bert, and he inspired me to pursue this topic and connected me with NS. The meetings with Bert were always insightful, and his feedback was highly valuable. I also want to acknowledge my second supervisor, Nihit Goyal. Although we had less frequent contact, Nihit provided thorough and sharp feedback on multiple drafts of my thesis.

The collaboration with NS was excellent. I am especially grateful to Noor van den Hurk for giving me the space to conduct my research and for her continuous involvement and interest from the very beginning. I could always turn to Noor with internal questions, and we had regular updates twice a week. I deeply appreciated her engagement, interest, and trust. I would also like to thank the team I worked with during this six-month period. It was a pleasure to be part of the team, and I always felt welcome.

Finally, I wish to thank my family, friends, and especially my partner for their constant support. I spent many evenings in my study, which was not always ideal, but she remained unwaveringly supportive. My family frequently discussed my research with me, which was very helpful. Lastly, to my friends: thank you for your interest and sparring sessions, and thanks for the confidence you had in my ability to solve any train delays and disruptions during my internship at NS.

Lennard Steketee
Rotterdam, September 2024

Summary

Following the COVID-19 pandemic, travel behaviour in the Netherlands underwent significant changes, which were also seen by the Dutch Railways (NS). Notably, there was a higher concentration of travellers on Tuesdays and Thursdays, with fewer on other days. Travellers increasingly preferred specific time slots, resulting in a sharper morning peak where more passengers travel within a shorter time frame. NS bases its deployment of rolling stock on the highest peak of the day, which, in nearly all cases, is the morning peak. Consequently, much of the rolling stock is underutilised during off-peak hours, with approximately 70% of seats occupied on average throughout the day. The costs for rolling stock and personnel are distributed evenly among all travellers.

To reduce costs and optimise the use of rolling stock, NS proposed introducing peak-hour surcharges. This would mean higher fares during peak hours, with the highest charges during the most crowded periods, termed the hyperpeak, and gradually decreasing fares towards the edges of the peak. Passengers travelling outside peak hours would receive a discount. The intended effect is to distribute peak-time travellers more evenly across the peak period, thereby reducing the need for additional rolling stock on a given day. This thesis examines the potential impact of peak-hour surcharges on travellers. The research question is: *what are various traveller profiles among train travellers in the Netherlands and how are different travellers likely to alter their travel behaviour in response to fluctuations in ticket fares during peak hours?*

To quantitatively answer this question, a Multinomial Logit Model (MNL) and a Latent Class Choice Model (LCCM) were employed. The MNL model assumes homogeneity among all travellers, making no distinction between trip and traveller characteristics. In contrast, the LCCM assumes heterogeneity, categorising travellers based on socio-economic and socio-demographic characteristics. Qualitatively, the research investigates whether the status quo bias affects respondents' perceptions of the fairness of peak-hour surcharges. The status quo bias refers to the tendency of individuals to prefer their current situation over a new one. This bias was tested using dependent and independent t-tests.

The conceptual model (figure 1) outlines the trip and traveller characteristics identified in the literature and internal NS studies that influence respondents' decision-making processes. For example, an individual with a high income (top right block) is likely to be less sensitive to a price increase (top left block) and therefore less inclined to alter their behaviour (left oval), meaning this respondent would be less likely to choose (bottom right block) a different travel time if a trip becomes more expensive.

A choice experiment was designed to test such relationships. Initially, respondents were asked about the various characteristics shown in the top right corner of the conceptual model. They were then presented with a choice experiment where they indicated which hypothetical trip they would choose, with varying levels of crowdedness and fare. Respondents could also opt out of choosing any trip. The survey was completed by 1,419 individuals, and after data cleaning, responses from 1,388 participants were deemed usable for further analysis. The respondent group was not representative of the peak traveller population, as it had an older average age and a different age distribution. Fewer respondents in the sample travelled for educational purposes compared to the peak traveller population. The sample also had relatively more highly educated individuals and more non-working individuals compared to the population.

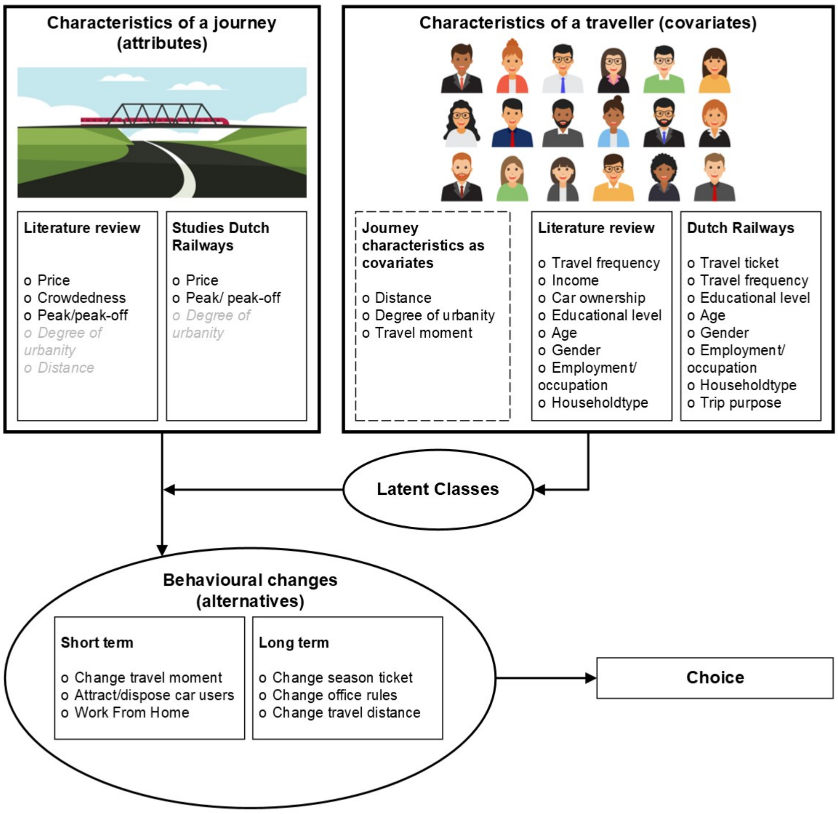

Figure 1: Conceptual model summary

The MNL model showed that travellers are primarily influenced by the absolute fare of a trip. An increase in fare decreases the perceived value of the trip. Respondents are also influenced by the relative change in fare: the higher the base fare (without adjustments), the less sensitive they are to a fare increase. Additionally, travellers are sensitive to crowdedness in the train; this relationship is exponential, meaning that the marginal decrease in the utility of a trip becomes greater as the level of crowdedness increases. The MNL model also revealed that respondents place high importance on departing at their usual time, which is the most significant factor in choosing a particular trip. The MNL model has a ρ^2 of 0.4512.

The LCCM identified four distinct categories of respondents. These categories are differentiated based on two main factors: who pays for the train trip and the respondent's usual departure time. All other characteristics presented in the conceptual model in figure 1 were also tested, but the relationships were not significant. In some cases, including certain characteristics made the model less powerful but more complex. Therefore, only two characteristics were used to categorise respondents. The LCCM has a ρ^2 of 0.5811. The LCCM distinguished four types of travellers:

- The first category is the **Rigid Traveller**. This group is unaffected by relative price increases and train crowdedness; their only concern is departing at their usual time. Their Willingness-to-Pay to depart at their usual time is €41.80.
- The second category is the **Semi-Flexible Peak Traveller**, the only group sensitive to train crowdedness. This category carefully weighs fare, crowdedness, and departure time. However, they still have a relatively high Willingness-to-Pay to depart at their usual time, which is €31.70 in the extreme case. Compared to the Rigid Traveller, fewer individuals in this group have a standard departure time before 07:00 or after 09:00.
- The third category is the **Off-Peak Traveller**. This group includes more individuals who pay for their own travel compared to the Rigid Traveller. Additionally, there are more people in this group with a standard departure time after 09:00. They are not influenced by crowdedness but are

sensitive to fare. Notably, these respondents value the opt-out option, indicating a preference for not choosing any trip. Their Willingness-to-Pay to depart at their usual time is €17.28.

- The fourth category is the **Price-Sensitive Traveller**. This group includes fewer individuals who travel before 06:30 and more who partially or fully pay for their own travel compared to the Rigid Traveller. They are unaffected by crowdedness but are highly sensitive to fare changes. Their Willingness-to-Pay to depart at their usual time is €3.51, making them the most sensitive to price adjustments among all categories.

The effect of fare differentiation varies by traveller category. Implementing a tariff system that includes peak charges means that the price of a trip during the hyperpeak will increase by €2.50, while a trip during the shoulder peak will cost an additional €1.50. On the edges of the peak hours, a trip will cost €0.50 more, and outside the peak hours, a trip will be €0.50 cheaper. For a trip costing €12.20 (e.g., Rotterdam Centraal to Utrecht Centraal), the effect of fare differentiation is that the number of check-ins at 07:45 will decrease by at least 8.4%. The NS aims for peak-hour fare surcharges to reduce the number of travellers during peak hours by at least 5%. In this sample, the introduction of fare differentiation has the desired effect.

The qualitative finding of this thesis is that status quo bias plays a role in the acceptance of the introduction of a new pricing system. The respondent group was divided into two groups: one group had a pricing system without peak charging as their status quo, while the other group's status quo included peak charging. Both groups indicated that they considered their respective status quo the fairest form of pricing. This demonstrates that status quo bias is applicable in this situation. All results found were statistically significant.

The main findings of this thesis are:

- Off-peak passengers who check in before the morning peak (i.e., before 06:30) respond significantly less to price changes compared to those who check in after the morning peak (i.e., after 09:00). While existing literature treats off-peak passengers uniformly, this thesis demonstrates that distinctions should be made based on the departure time during off-peak hours to assess price sensitivity.
- The payment profile (whether a passenger pays for their journey themselves) is a covariate that can determine the category in which a passenger is classified. Self-paying passengers are more likely to be classified into a price-sensitive category compared to those who do not pay for their journey themselves.
- People experience a smaller reduction in utility when moving from crowdedness level 1 to level 2 than when moving from level 2 to level 3. So people prefer travelling alone, tolerate sitting next to someone less, but find standing strongly unpleasant.
- In the sample of this thesis, the number of passengers checking in during the hyperpeak decreases by 8.4% when peak pricing is applied, provided the usual average trip price does not exceed €12.20.
- If more than 88% of the peak population consists of Rigid Travellers, fare differentiation fails to achieve the desired effect when the average trip price during the hyperpeak exceeds €12.20.
- Support for the implementation of a new fare system is potentially determined by the status quo bias.

Based on this thesis, further research could explore the impact of fare differentiation. This study lays the groundwork for such investigations. NS could assess the sizes of the identified groups within the peak-time population, as the composition of this population determines the effect of fare differentiation. However, this lies beyond the scope of this thesis. Academically, this thesis could form a basis for further research into whether respondents are inclined to choose an earlier or later journey when they do not select their most common travel time. No distinction has been made in this thesis regarding whether individuals opt for an earlier or later trip when deviating from their usual travel pattern, and the literature also lacks this information, specifically concerning train travellers in the Netherlands in relation to peak pricing. Additionally, it is unclear whether the response to peak-time surcharges during the morning peak will mirror that of the afternoon peak. Neither this thesis nor the literature provides sufficient evidence to extend the conclusions drawn here to the afternoon peak.

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1 Introduction

In recent years, it has become evident that climate issues are becoming increasingly relevant to individuals and society. One potential way to curb the rising temperatures is by reducing the emission of carbon dioxide (CO2) (Seneviratne et al., 2016) and other Green House Gasses (GHG). The transportation sector is one of the industries that significantly contributes to GHG emissions. Transportation contributes to 14% of global GHG emissions, generated by both the road transport sector and passenger and freight activities (Hensher, 2008b). In the Netherlands, the transportation sector accounts for 12% of the total GHG emissions. Within this sector, road transport contributes to approximately one-fourth of the emissions (CBS, 2022). In the United States, the transportation sector is also crucial for reducing GHG emissions; in recent years, the transportation sector in America has surpassed the power sector as the largest source of GHG emissions. One of the strategies to reduce the emissions in the sector is by investing in public transportation, to increase its use substantially and make that people make a shift from cars to public transport (Bleviss, 2020). Policies regarding public transport are also mentioned in the article of Seneviratne et al. (2016) as possible strategies to reduce GHG emissions. The advantages of an increase in use of public transport is broader than only the reduction of GHG emissions. It can be concluded that the public transportation infrastructure holds the potential to generate significant environmental and health benefits, while also effectively mitigating a substantial amount of greenhouse gas emissions. In general, it possesses the capability to diminish air pollution, traffic-related injuries, noise, congestion, and physical inactivity (Kwan and Hashim, 2016). Hence, the primary objectives of European transport policy are to increase the utilization of public transportation and reduce usage of private cars (Minelgaitė et al., 2020).

1.1. Research context

During the COVID-19 pandemic, there was a notable transformation in the utilization of public transport. The perceived risks associated with using public transportation underwent a shift, as this sector was identified as a location where the transmission of the coronavirus was relatively high (Singh et al., 2023). In the aftermath of the pandemic, the travel patterns of train users witnessed a transformation. Although there was an increase in the use of public transport in the Netherlands, it did not reach the same level as observed before 2019. Preceding the crisis, the daily average number of travellers was approximately 1.3 million, whereas in 2023, the daily average stood at around 1.1 million people. Travel behaviour has permanently changed; during the week less people use the train. However, Tuesdays and Thursdays witness significant congestion, particularly during peak hours. According to Dutch Railways (NS), the number of travellers on weekends remains consistent with the pre-crisis levels.

The current train capacity is insufficient to accommodate the demand from travellers during peak periods on Tuesdays and Thursdays. NS could address this issue by deploying additional trains, but these trains would remain underutilized during off-peak hours. The peak operating hours for the additional train compartments would amount to less than 8 hours per week, making it a relatively substantial investment for limited usage (N. van den Hurk [1], personal communication, 2024). The Dutch Railways is creating a large capacity to handle the peak at one moment of the day and only at two moments in the week. The extra costs that will appear when deploying these extra equipment and extra employees is paid by the traveller (T. Smit [2], 2023). Today these costs are shared among all the travellers; each traveller, regardsless the moment of the day, pays an equal amount of money for a ticket, solely based on the travel distance.

The Dutch Railways aims to avoid deploying additional trains, as these would remain largely empty for most of the day. Ideally, peak-time travellers would distribute more evenly across the peak hours. Consequently, the current peak observed during the busiest period (hyperpeak) would become less pronounced and more spread out, encouraging more passengers to travel outside the hyperpeak, during the shoulder peak. The implementation of a new fare system, including fare differentiation, is currently mentioned by NS as one of the instruments to reduce the amount of travellers during the peak hours (NOS, 2023). NS proposes that implementing fare differentiation could financially benefit 80% of trips, particularly those taking place during off-peak hours. However, for 20% of trips, the total journey cost would rise (Bremmer, 2023). Ticket fares would be calculated based on distance, moment of travelling (off-peak /peak) and the quality of the trip.

The proposal for implementing fare differentiation encountered considerable resistance in the House of Representatives. The primary concern is that there will be, a non-negligible number of individuals who cannot choose an alternative way of travelling other than the train at a specific moment in time (during peak hours), so they are sort of penalized for their travel behaviour (Verbeek, 2023). The prevailing argument posits that imposing an additional fee on approximately 20% of trips would be unfair for travellers who cannot choose an alternative means for these trips.

A way to handle resistance towards a policy is the counterfactual check: discuss with the proponents of controversial policies the counterfactual (van Wee et al., 2023). A recent discussion paper highlights the phenomenon of growing support for controversial policies post-implementation, stating that ”the support for controversial policies in the area of transport often increases after real-world implementation” (van Wee et al., 2023,p.79). This suggests that individuals who were initially opposed to the implementation of a (transport) policy tend to exhibit less negativity towards the policy after it is put into effect. Given this insight, the paper outlines some implications that could prove useful during discussions about policies. In an editorial, one of the authors of the aforementioned article further elaborated on this topic and provided several illustrative examples where he applied the counterfactual check (van Wee, 2023). Fare differentiation is considered a controversial policy which encounters a lot of resistance.

1.2. Knowledge gap and research questions

As indicated by the research context, Dutch Railways is seeking a solution to the current capacity issue. The proposed remedy may involve the implementation of a new fare system. Through this new policy, NS aims to ensure a more evenly distributed demand for public transport throughout the day, thereby smoothing the hyperpeak periods. The academic literature extensively addresses public transport, transport policies, and travel behaviour. According to Paulley et al. (2006), the demand for public transportation influenced by several factors, with the most significant being fare differentiation, service quality, income, and car ownership. The public transportation provider can address two of these factors, namely fare differentiation and service quality. The income of the traveller and car ownership are aspects that do not fall within the scope of the train operator, meaning that the train operator has no further influence on these factors directly.

Implementing fare differentiation, as outlined by Paulley et al (2006), involves varying the price of a particular journey at different times. The impact of introducing fare differentiation is closely tied to the price elasticity of demand. Price elasticity measures the ratio of the percentage change in demand to the percentage change in price. The existing price elasticity used in calculations by NS is partly derived from scenarios where prices are raised during periods of inflation. The price increase roughly paralleled the inflation rate at that time, resulting in hardly any real price escalation. It is quite uncertain

[1] Sr Pricing Manager / Product Owner at NS
[2] Managing Director, CCO, Board of Directors at NS

how behavioural changes will unfold following a price adjustment without the influence of inflation. The hypothesis is that the price elasticity of demand differs when price increases are in tandem with inflation compared to price changes independent of inflation. NS is aware of the elasticity when prices are increased parallel to the inflation rate, but the price elasticity of the demand remains unknown in the case where the price increase is not parallel to the inflation rate. In the case of price differentiation, such as charging higher rates during peak hours in terms of monetary value, that elasticity will come into play.

Multiple studies have examined the impact of price fluctuations on traveller behaviour, as evidenced by various sources (Kholodov et al., 2021; Hortelano et al., 2016; Liu and Charles, 2013). Researchers have reported different effects of alternative fare structures or price adjustments under different circumstances. Kholodov et al. (2021) identified an overall elasticity of -0.46. These researchers differentiated between travellers using buses, metros, or trains, noting that the elasticity varies by mode of transport; train passengers exhibit higher elasticity than bus passengers. Wardman (2022) conducted a meta-analysis of price elasticities of travel demand in Great Britain, identifying numerous elasticity figures. In essence, research on traveller behaviour has yielded diverse elasticity values. The literature cites numerous studies conducted in various countries, yet none have specifically focused on the Netherlands in the context of train travel behaviour. Hence, it remains unclear whether the findings from other studies are applicable to the Netherlands.

Investigating fare differentiation inevitably involves making assumptions. Typically, research projects operate under the assumption that travellers constitute a homogeneous group. Nevertheless, an argument can be made for the heterogeneous nature of travellers. Different groups may exhibit diverse responses to fare differentiation. Acknowledging the heterogeneity among travellers emerges as a crucial consideration when endeavoring to identify price elasticities (Small and Yan, 2001). The literature does not seem to cover what the heterogeneity of Dutch travellers is and how their travel behaviour will change when charging a fee during different moments of the peak and non-peak hours.

Another frequently made assumption is that changes in travel behaviour will be uniform throughout the day. The belief is that price differentiation will yield consistent behavioural adjustments, regardless of the time of day. However, this assumption may not hold true, as the value of time appears to vary by different times of the day (Tseng and Verhoef, 2008). The outcomes indicate that shadow prices related to time exhibit significant variations throughout the morning peak, highlighting a strong time-dependency in the values of travel time savings.

There is a lack of a case study in the literature that directly applies to the current situation in the Netherlands. Consequently, it is not possible to ascertain the effect that applying fare differentiation will have on the demand for train travel in the Netherlands. This thesis addresses this gap by examining the implementation of fare differentiation and its impact on travel behaviour among various passenger demographics in the Netherlands. Specifically, the research investigates how travel patterns may shift in response to varying ticket prices throughout the day.

Status quo bias

Although the primary aim of this thesis is to provide quantitative support for a pricing strategy for train journeys in the Netherlands, it also intends to make a qualitative contribution to the strategy. The qualitative contribution focuses on an examination of the role of the status quo bias. As explained in section 1.1, the implementation of fare differentiation has not been approved by the House of Representatives. A potential factor contributing to this resistance in the Second Chamber, as well as in the media and society, is the role played by the status quo bias. This bias frequently prevents governments from adopting policies that economists consider to enhance efficiency. There tends to be a bias towards maintaining the current state when the winners and losers of a reform cannot be accurately predicted in advance. Some reforms, which may eventually gain sufficient political support after adoption, may have initially failed to secure approval (Fernandez and Rodrik, 1991).

No literature has been found investigating the status quo bias in the context of implementing a new fare system in public transport. Eliasson (2021) explored attitudes towards efficient pricing to combat congestion in major cities. The main finding of the study is that public support for congestion charges tends to decline as implementation approaches, but significantly increases post-implementation, partly due to greater-than-expected benefits and lower adjustment costs. The role of the status quo bias is that people initially focus on potential losses they may incur with the introduction of new policies. However, after implementation, public opinion tends to become more positive as individuals adapt and experience the benefits. In the research by Paha et al. (2011), the extent to which travellers are influenced by existing competition on commercial passenger railways was examined. The study found that travellers exhibit a preference for the service provider on whose trains they were interviewed. This demonstrates that the status quo bias plays a role for these respondents.

The literature appears to offer no clear answer as to whether status quo bias also influences public and political opinion on the implementation of fare differentiation. This thesis aims to contribute to the literature by addressing this knowledge gap.

Research questions

The outcomes of this thesis hold the potential to enrich the existing literature by shedding light on the significance of different attributes, indicators and covariates. Subsequently, other researchers can incorporate these findings into their own studies. Additionally, the implications of this research may extend to countries sharing substantial similarities with the Netherlands in terms of travel behaviour.It is important to note that traveller behaviour differs across countries, although certain similarities exist (Christensen et al., 2014).

To address the research problem and the objectives of this study, the following main research question is answered:

What are various traveller profiles among train travellers in the Netherlands and are different travellers likely to alter their travel behaviour in response to fluctuations in ticket fares during peak hours?

The main question is divided into the following sub-questions:

1. *What travel-related attributes influence travel behaviour of train travellers in the Netherlands*
   The identification of attributes is conducted through a literature review and an internal study of NS data. Determining which attributes are influential is achieved by estimating a multinomial logit model in the first instance. To capture heterogeneity within the passenger population, a Latent Class Choice Model is also estimated. The analysis of different profiles and attribute preferences of train travellers is carried out using R-Studio, specifically the 'Apollo' package.
2. *To what extend do these travel-related attributes influence the preferences of train travellers?*
   This questions is answered by estimating the Multinomial Logit Model and the Latent Class Choice Model. The weight of the attributes are be compared by calculating the relative importance of the attributes.
3. *Which socio-demographic and socio-eonomic characteristics influence the preferences of train travellers in the Netherlands?*
   The identification of these characteristics is conducted through a literature review and an internal NS data study. Determining which characteristics are influential are achieved by estimating the Latent Class Choice Model.
4. *What is the role of the status quo bias on the perceived fairness of the implementation of fluctiations in ticket fares during peak hours?*
   The perceived fairness of the respondents is measured and the counterfactual check is executed. The results are calculated by SPSS.

1.3. Report outline

In chapter 1 of the report, the research context of the study is explained. Firstly, the research problem is described. Subsequently, this chapter outlines where a literature gap is identified. To address this knowledge gap, research questions have been formulated. For each of the sub-questions is described how they are answered.

Chapter 2 forms part of the conceptualisation. This chapter discusses various research paradigms, which serve as the foundation for this thesis. The explanation of statistical methods aims to provide insight into the possibilities for studying travel behaviour. The chapter presents how different paradigms are combined and why this statistical method is highly suitable for the thesis research.

Chapter 3 is also part of the conceptualisation. It extensively describes the existing literature on travel behaviour, from which valuable insights can be obtained. The first part of chapter 3 describes various topics, such as mapping behavioural changes and examining which characteristics of a journey which personal characteristics influence decision-making. The second part of the chapter describes the examination of three internal studies conducted by the Dutch Railways. The conclusion of this chapter marks the end of the conceptualisation, and is presented graphical.

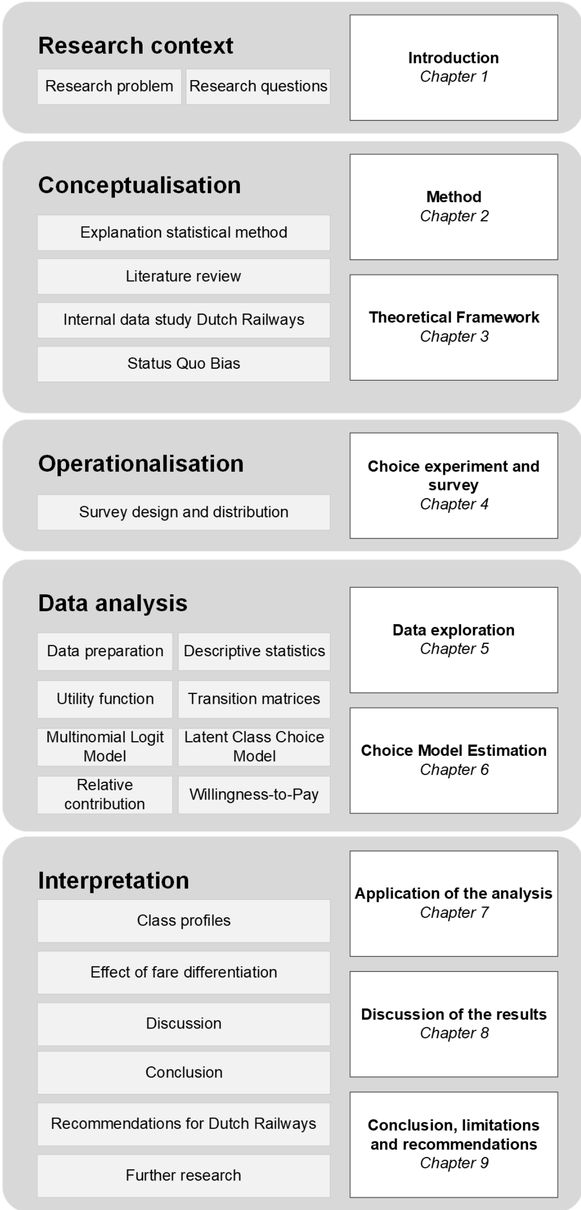


Figure 1.1: Research design

Chapter 4 forms a crucial part of the operationalisation process, containing all the necessary information before data collection commences. The first section details the construction of the choice tasks within the choice experiment. The second section explains the structure of the survey and its distribution method.

Chapter 5 of this thesis outlines the preparation of the collected data for analysis. It also describes the filtering process applied to the data, along with the rationale behind the chosen filtering criteria. The filtered data is then compared to the composition of the peak-hour population to roughly estimate whether the sample aligns with the actual population.

Chapter 6 begins by detailing the development of the utility function. It also explains the use of transition matrices. Further on, the chapter describes the creation and application of a Multinomial Logit Model. Subsequently, it outlines the development and application of a Latent Class Choice Model. Various parameters and their values are compared to clarify the relative contribution of each parameter. For the different latent classes, the Willingness-to-Pay to depart at their usual time is determined.

In chapter 7, the practical implications of the results are explored. The chapter clarifies the concrete outcomes and the potential impact of tariff differentiation on the sample. The profiles of the different classes are also described.

In chapter 8 the results of the thesis are discussed, compared and contrasted with existing literature.

Chapter 9 addresses the research sub-questions and the main research question. Following the discussion, a section on limitations identifies the constraints of the thesis and their potential influence on the results. The chapter concludes with specific recommendations for further research.

2 Method

The primary research question and the sub-questions seek a statistical approach. Numerous studies have explored a similar topic, employing statistical methods (Sharma et al., 2019; Choi et al., 2021). The referenced studies employ different statistical methods to examine travel behaviour. Sharma et al. (2019) focuses on a purely econometric approach, whereas Choi et al. (2021) adopts a mobility-style approach. The difference between approaches is explained in this chapter. In total, there are seven paradigms that could serve as the foundation for modeling travel behaviour (M. Kroesen, personal communication, February 13, 2024[1]).

To answer the main question and subquestions, it is essential to understand choices made by different types of travellers. To uncover people's characteristics and choices, a survey is conducted, including a stated choice experiment. A traditional Multinomial Logit (MNL) choice model, assuming that one-size-fits-all, is a simplistic approach to modeling behaviour. Combining two travel behaviour paradigms (econometric and mobility style) offers a solution to bypass this one-size-fits-all assumption. This combination, known as a Latent Class Choice Model, effectively captures the diversity among various respondents (Greene and Hensher, 2003). By extracting the right information from the survey, it is possible to provide answers to the research questions.

2.1. Econometric paradigm

This paradigm is employed to address the first two subquestions. These initial subquestions concern the attributes influencing respondents' choices and to what extent. The econometric method investigates which attributes influence people's choices to what degree.

The econometric paradigm is a variant of Discrete Choice Modeling. The rationale for employing this modeling approach is to predict any variable of interest for the researcher. This paradigm specifically delves into the preferences of travellers to garner insights into their decision-making considerations. When these preferences are clearly understood, it becomes feasible to devise a system that optimizes its outcomes based on user preferences. The underlying theory for this approach may involve a Random Utility Model (RUM), or alternatively, a researcher could opt for a Random Regret Model (Hensher et al., 2013).

The estimations conducted in this master thesis are based on the RUM theory, so the econometric approach, and especially the RUM theory, needs a more in-depth explanation. The Multinomial Logit (MNL) model arises from the RUM theory. This model assumes homogeneous preferences among all consumers, meaning it assumes a single class of consumers.

In figure 2.1 a conceptual model of this paradigm is presented. The illustration posits that there are three attributes for each of the options x, y, and z. The utility for each attribute is calculated, and based

[1]Associate Professor at TU Delft

on this utility, a choice is expected. The following paragraphs further elaborate on this conceptual model. Additionally, its application to this thesis is discussed.

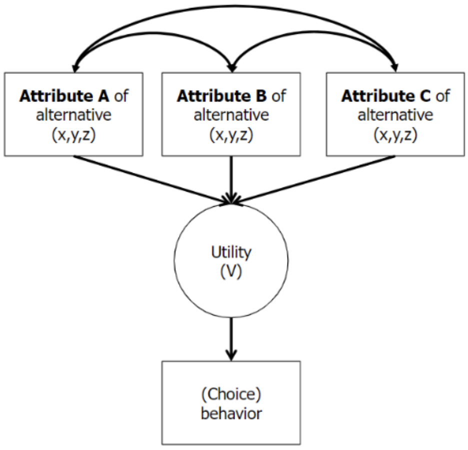


Figure 2.1: Conceptual model econometric paradigm

Equations

Utility is the measure of personal well-being or satisfaction experienced when choosing between two or more options. In the process of human decision-making, individuals naturally lean towards choices that optimize their overall satisfaction. The decisions made by individuals are rooted in a limited set of alternatives. Respondents will select alternatives from a specific range of choices with the goal of maximizing their own satisfaction (II, 2016). The utility equation looks like follows:

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

The expression U_{in} represents the utility that an individual n experiences when choosing alternative i. V_{in} represents the utility measured by the researcher, given that the identified values are significant. This is referred to as systematic utility. The last part of the equation, ϵ_{in}, serves as the error term, capturing all unobserved factors, or in other words, everything else that influences choices of the individual (Concha, 2018). V_{in}, which is the systematic utility, is formed based on attribute levels and their corresponding weight β. The function of the systematic utility looks like follows:

$$V_{in} = \sum_{m} \beta_{mn} * x_{im} \tag{2.2}$$

The systematic utility is the summation of the attribute level of attribute m of alternative i (x_{im}) multiplied by the corresponding taste parameter β_{mn} for choices made within a choice set by individual n (C. Chorus, personal communication, November 10, 2020[2]). The final utility equation looks like the following:

$$U_{in} = \sum_{m} \beta_{mn} * x_{im} + \epsilon_{in} \tag{2.3}$$

The utilities that are computed for an individual per option in a choice set, can be used to estimate and predict the choices that an individual will make. This can be done, using the Mixed Logit Model (MNL). The model estimates the possibility that an individual will choose a certain option. The equation looks the following:

[2]Faculty Dean and Professor of Choice behaviour modelling at TU Delft

$$P_{in} = \frac{e^{V_{in}}}{\sum_j e^{V_{jn}}} = \frac{e^{\sum_m \beta_{mn} * x_{im}}}{\sum_j e^{\sum_m \beta_{mn} * x_{jm}}} \tag{2.4}$$

With this equation the probability that an individual n chooses option i from a given choice set is calculated. The probability is determined by taking the exponent of the utility associated with option i for individual n and dividing it by the sum of the exponents of utilities for all options within the choice set. This sum includes the utility of option i as well, and j represents the total number of options available in the choice set (Concha, 2018). The inventor of the MNL model, Daniel McFadden, won a Nobel price for his work.

Strengths and weaknesses

In the MNL model, the unobserved part, so the error term ϵ, is not included, and it is crucial to acknowledge this simplification. The assumption is that ϵ is independent and identically type I Extreme Value distributed across alternatives, choice situations, and individuals, with a variance of $\pi^2/6$. A small β is equivalent to a large variance in ϵ. The greater the value of β/ϵ, the more information the beta value conveys, and the less noise there is (C. Chorus, personal communication, November 10, 2020).

The data utilized in this programming approach is either revealed or acquired through the execution of a stated choice experiment. The last option, so stated preferences, exhibit low correlations between attributes. Another advantage is that a researcher can identify the non-chosen alternative. However, a drawback of this method is the presence of hypothetical bias, indicating that what individuals claim they would do hypothetically may not necessarily align with their real-world actions.

The advantage of revealed preferences is that it has high ecological validity, meaning that you are certain that the respondent has chosen a specific option. Therefore, there is no concern about hypothetical bias. However, drawbacks include the potential for high correlations between attributes. Additionally, details such as which options the respondent chose are unknown, making the non-chosen alternative undisclosed.

The econometric paradigm's overarching strength lies in its robust capability to predict demand for (new) services and infrastructures. Based on this paradigm, it can be confidently asserted, provided the identified values are significant, that certain attributes influence people's decision-making behaviour. However, a drawback of this method is the assumption that respondents are not bounded by rationality, implying that individuals systematically evaluate all options before making a specific choice. Nevertheless, it can be suggested that this may not always hold true, as respondents may simply be constrained by their existing knowledge. This phenomenon is referred to as 'bounded rationality.' Another shortcoming of this method is that socio-demographic and psychological attitudes/preferences are often neglected. As a result, the psychological processes remain a black box (M. Kroesen, personal communication, February 13, 2024).

The process of the econometric approach

The application of the econometric paradigm contributes to answering the primary and subsidiary questions. The development of the econometric paradigm will proceed in several stages. In the preparatory phase, a literature review is conducted, and internal NS data is examined to form a conceptual model. The literature review investigates previous studies on the topic and identify which attributes particularly influence people's choice behaviour. It became apparent from several studies that for example the timing of travel is a crucial aspect; not only during peak and off-peak hours but also within peak periods (Kholodov, Liu, and Charles). This phenomenon is further investigated in this thesis. Additionally, the influence of price changes on traveller behaviour is examined. Common sense suggests that traveller behaviour will change if the price of a ride is altered. However, the extent of this change is not entirely clear. A more comprehensive literature review and data analysis (internally provided by NS) determines whether other attributes need to be considered.

Once the conceptual model is finalised, decisions can be made regarding which attributes are actually included in the choice experiment. It is also necessary to select attribute levels before an experimental design can be created. The development of attribute levels is ongoing throughout the thesis. Identifying the attributes crucial for the researcher to address the research question is necessary, as is determining their levels. Typically, attributes may have 2 to 4 levels each, as suggested by Molin[3] (personal communication, 2022), although this range is not necessarily restrictive. Using more than two levels per attribute allows for testing linearity. Molin stresses the importance of having a broad range of attribute levels to enhance validity; interpolation is considered more reliable than extrapolation. Attributes should not overlap and should be measurable, considering factors such as cost (Coast et al., 2012). Attribute levels may span various scales, including nominal, ordinal, interval, or ratio (Bernasco and Block, 2013). Crucially, these attributes should hold significance for the respondents to prevent them from imposing their own assumptions on the situation. Additionally, it should be feasible to influence these attributes through policy. Without this possibility, adjusting the attributes is not practical, making it impossible to influence the respondents' behaviour (E. Molin, personal communication, 2023).

After determining the attributes and attribute levels, alternatives are composed. When composing alternatives, it is possible to combine all attribute levels with each other. For example, if price and travel time are the only two attributes with two levels (cheap vs. expensive and short vs. long), the designer can compose 4 alternatives: cheap and short, cheap and long, expensive and short, expensive and long. Thus, the correlation between price and travel time is zero. However, when multiple attributes with multiple levels are examined, the number of alternatives quickly escalates. To prevent a researcher from having to actually combine all alternatives, a fractional factorial design can be devised.

Ultimately, several alternatives are presented together to form a choice set. This constitutes the final experimental design. An experimental design ensures that the intercorrelation between various attributes is zero (Kanninen, 2007). In choice models, it is common to include an opt-out option (Kajanova et al., 2022). It is conceivable that in a certain scenario, the respondent may prefer taking a taxi or using their own car over travelling by train. This hypothesis is supported by other research indicating that car ownership significantly influences travel behaviour (Paulley et al., 2006). Alternatively, the respondent may opt to switch train subscriptions. This is why an opt-out option is provided.

Once the survey has been completed by the respondents, the results can be processed. This is done in several ways. Firstly, an MNL model is utilised, as outlined in the above paragraph. The MNL model does not differentiate between the characteristics of travellers. It is a generic model that treats all respondents alike. For all respondents, the weight of an attribute is equally significant. However, not all respondents are the same, which is why a Latent Class Choice Model is also estimated. This is part of the 'mobility style' paradigm. The elaboration of this is further explained in the following paragraph.

2.2. Mobility Style paradigm

This paradigm is employed to address the first two sub-questions at group level. The mobility style paradigm categorises respondents into different groups based on the preferences indirectly conveyed during choice tasks. Thus, at group level, the attributes influencing travel behaviour and the extent of their impact on behaviour have been calculated.

The concept behind the mobility style paradigm posits that the population comprises various latent groups characterized by similar mobility styles. It suggests that targeting the 'average' traveller is of limited utility, and that policy interventions should instead be tailored to accommodate the diverse motivations and constraints of these subgroups. The mobility style approach is a post-hoc classification technique; segments are interpreted inductively, which means that the clusters emerge from the data. Data that is used can be personal characteristics, psychological variables and psychological behaviour (M. Kroesen, personal communication, February 14, 2024).

A Latent Class Analysis (LCA) is a model-based probabilistic clustering method aimed at identifying groups of research units that exhibit similarity based on observed characteristics. The objective is to maximize homogeneity within clusters while promoting heterogeneity between clusters. The purpose of utilizing latent class modeling is to obtain a comprehensive understanding of behaviour through holistic profiles. A key distinction from traditional clustering approaches is that LCA relies on similarity in response patterns rather than the distance between respondents (as is the case with K-means clustering). Additionally, LCA can accommodate variables of various scales (nominal, ordinal, continuous,

[3] Associate professor at TU Delft

count) within a single model. The optimal number of classes can be determined using statistical tests (M. Kroesen, personal communication, March 5, 2024).

Indicators and covariates

There are two types of information that should be gathered to estimate latent classes. The first type of information is what is known as indicators, which can be measured. When conducting an LCA, classes are created based on these measured variables. The scale of the measurements can be ordinal, nominal, continuous, count, or binomial count. The underlying latent variable is formed around the performed measurements. The classes are not predefined beforehand; they can only be determined afterwards. For instance, in a study, if it turns out that a group of people frequently travels by train and never deviates from a specific travel pattern (meaning they are not influenced by, for example, a change in price), then the underlying latent variable could be termed as 'rigid traveller'. It is not known beforehand that this latent class is present in the sample, but the results of the LCA indicate that there is a latent class in the sample that is so-called rigid and therefore cannot be influenced in any way to adjust travel behaviour.

The classes that are searched for this thesis are formed around the weights (β) of the attributes. For each class that is created, the software R ensures that the attribute variables have different values. So, in one latent class, the traveller may not be influenced by, for example, price. While in another class the respondents are certainly sensitive to price. The latent classes to be created in this study are based on the attribute values that respondents have assigned per attribute.

The second category of information is the information about the respondent that is separate from the choice model the respondent has completed. This category consists of covariates. Covariates are personal characteristics in various areas, including socio-demographic and psychological characteristics of the respondent. If these covariates are significant, they influence the model. Based on these covariates, a probability can be assigned to a covariate (if significant) that a person belongs to a certain cluster. For example, consider someone's gender. If someone is male, there is a x% chance that he falls into a particular cluster. Thus, these socio-demographic and psychological characteristics are valuable for research into latent classes.

Equations

The equations used for an LCA allow for the calculation of the probability that a certain respondent is a member of a certain class. The equation is as follows:

$$\pi_{ijkl}^{ABCD} = \sum_{t=1}^{T} \pi_t^X \pi_{it}^{A|X} \pi_{jt}^{B|X} \pi_{kt}^{C|X} \pi_{lt}^{D|X} \tag{2.5}$$

Here, π_{ijkl}^{ABCD} represents the probability of observing a particular response pattern. For instance, it calculates the probability that a respondent chooses option *i* of question *A*, option *j* of question *B*, and so forth. This probability depends on the class membership of the respondent. The probability that a certain respondent is a member of a certain class is denoted by π_t^X. For example, it indicates that the probability that a respondent is a member of class *X* is *t* percent.

It is also possible to interpret the posterior membership probability. The question answered here is: what is the probability that an individual with a particular response pattern belongs to a specific latent class? This question is derived from Bayes' rule. "Bayes' rule is a rigorous method for interpreting evidence in the context of previous experience or knowledge," as stated by Stone (2013, p.1). Bayes' rule is expressed as follows:

$$\hat{\pi}_{tijkl}^{X|ABCD} = \frac{\hat{\pi}_t^X \hat{\pi}_{ijklt}^{ABCD|X}}{\hat{\pi}_{ijkl}^{ABCD}} \tag{2.6}$$

The denominator in this function represents the probability that a respondent gives a particular answer. It indicates the likelihood that a respondent chooses option *i* for question *A*, and so forth. The numerator represents the probability that a respondent gives a specific response pattern, given that the respondent is a member of class *X*. The result of the fraction represents the probability that a respondent is a member of class *X* when the respondent has a particular pattern of answers to the survey questions.

Using a logit function allows for the inclusion of covariates in the probability functions. For example, age can be used to predict the likelihood that a respondent adopts a particular pattern of answers. With an LCA, continuous variables can be used, as well as dummy variables or a 3-category nominal variable. The logit function is expressed as follows:

$$\hat{\pi}_t^{X|z_1 z_2} = \frac{exp(\gamma_{t0}^X + \gamma_{t1}^X Z_1 + \gamma_{t2}^X Z_2)}{\sum_{t'=1}^{T} exp(\gamma_{t'0}^X + \gamma_{t'1}^X Z_1 + \gamma_{t'2}^X Z_2)} \tag{2.7}$$

Suppose z_1 represents the age of the respondent, and the respondent is 30 years old. Let z_2 represent the income of the respondent, categorized into category 6. Then, the numerator of the function would be the exponent of the intercept indicating membership in class *X*, plus the intercept for the covariate age multiplied by 30, plus the intercept for the covariate income multiplied by 6. The denominator would calculate the same as the numerator, but for all classes, summing up the values. The probability that someone aged 30 with an income in category 6 chooses class *X* is then the outcome of this fraction.

2.3. Combination of the approaches

The combination of both approaches offers an elegant method to capture heterogeneity within respondents. This combination is known as a Latent Class Choice Model. Unlike the traditional MNL model (econometric approach), which adheres to a one-size-fits-all mindset, the Latent Class Choice Model rejects this notion. The prevailing assumption in the traditional model suggests that preferences, elasticities, and substitution patterns are the same for all respondents. However, individuals may employ different decision rules beyond utility maximization. The LCCM serves to relax the behavioural assumptions underlying the linear-additive RUM-MNL model (R. Faber, personal communication, April 2024[4]).

The information derived by a researcher from such choice models partly depends on the use of panel data. Utilising panel data means that a specific respondent has filled in a choice model where the respondent needed to make multiple choices. If panel data is not used, all obtained responses are from different respondents. When employing panel data, however, all obtained responses do not necessarily stem from the same number of respondents. Consequently, the number of respondents does not correspond to the number of responses. This raises the question of whether 1000 choice mode observations from 10 individuals (i.e. 10 x 100 observations) provide the same amount of information on the sample mean as 1000 x 1 choice observation. The answer to this is no; failing to account for panel data structure leads to underestimation of the standard errors (i.e. overestimation of the accuracy by which the parameters are being retrieved). Another reason why a researcher should explicitly consider the panel structure is that class membership allocation needs to occur at the individual level, not at the observation level. After all, the choice reflects an individual's preferences, which typically do not vary across observations.

[4] Researcher at KiM and PhD Candidate at Delft University of Technology.

Equations

The equation for the probability that a certain individual will choose a certain option is as follows:

$$P_n(i|\beta) = \sum_{s=1}^{S} \pi_{ns} P_n(i|\beta_s) \tag{2.8}$$

The equation for the probability that decision-maker *n* chooses alternative *i*, conditional on the set of model parameters β, involves a summation over all classes S ($\sum_{s=1}^{s}$), where the product is calculated of the class membership probability (π_{ns}) and the probability of decision maker *n* choosing alternative *i*, given that the decision-maker *n* belongs to class *s* ($P_n(i|\beta_s)$. This part of the formula represents the class membership model. In a Laten Class Choice Model the probability of observing choice *i* is the weighted sum of choice probabilityies of *i* across the S classes, with the class membership probabilities (π_{ns}) being used as weights. However, because panel data is used, this equation is slightly modified to avoid overestimating the accuracy of the retrieved parameters. The equation for panel structure data looks as follows:

$$L_n(i_t, ...i_T|\beta) = \sum_{s=1}^{S} \pi_{ns} \left(\prod_{t=1}^{T} P_n(i|\beta_s) \right) \tag{2.9}$$

It calculates the likelihood of observing the sequence of choices i_i,...i_T for decision-maker *n*, conditional on the model parameters β. That is done based on the probability that respondent *n* is a member of class *s*, multiplied by the product of the sequence of *T* choice probabilities, given that decision-maker *n* belongs to class *s*.

Conceptual model

The conceptual model of the combined paradigms can be found in Figure 2.2. This figure also clarifies which part belongs to which paradigm. The conceptual model illustrates that for each class, the utility for different alternatives varies because the weight per attribute (β) can differ for each class. This conceptual model forms the foundation of this thesis.

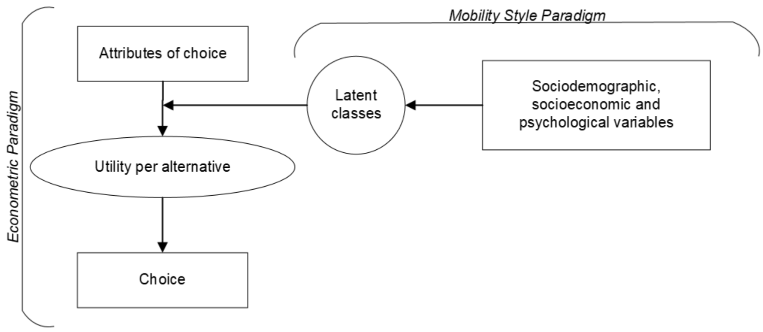


Figure 2.2: Conceptual model Latent Class Choice Model

The process of the combined approach

The process of the mobility style approach (in combination with the econometric approach) begins with a literature review and a data study. While the literature and data study in the economic approach are aimed at identifying attributes that may influence people's choices, the literature and data study in the mobility style approach aim to identify socio-economic and socio-demographic aspects that could influence respondents' choices. As previously mentioned, the literature review and the data study (conducted internally at NS) form the basis for the conceptual model.

Once the conceptual model is established, the next step is to determine which identified personal characteristics are included in the survey. Additionally, it is determined at which level personal characteristics can be measured (such as income as a count variable or income as a categorical variable). After the survey is distributed to respondents, the next step is data processing.

Data processing consists of several components. The first involves conducting a descriptive analysis, where descriptive statistics summarise the characteristics of the dataset. These statistics also enable a comparison between the sample and the broader traveller population. The second component estimates the Multinomial Logit Model and Latent Class Choice Model, using respondents' personal characteristics to predict class membership. The final stage applies the results of the analysis.

2.4. Measuring the status quo bias

To investigate the role of status quo bias in fare differentiation (so answering the fourth research question), the respondent group was divided into two subgroups. The first subgroup considers their current status quo as no fare differentiation. This group evaluates their current situation and also assesses their stance if fare differentiation were implemented. The second subgroup considers their current status quo as fare differentiation being present. This group also evaluates their current situation and assesses their stance in a scenario without fare differentiation. The results are analyzed using paired t-tests and independent t-tests. For these calculations SPSS is used.

2.4.1. Dependent t-test

The dependent t-test in statistical analysis, assesses mean differences within the same group across two conditions of a continuous, dependent variable. For instance, it could be applied to investigate if there is a change in students' test scores before and after a tutoring program. "Dependent Samples t-test is used to compare two groups of scores and their means in which the participants in one group are somehow meaningfully related to the participants in the other group" (Gerald, 2018, p.52). This t-test is employed to determine whether the evaluations for both scenarios by the same group significantly differ from each other. If this value is significant, it indicates that the observed difference between the two scenarios is not due to chance, and thus, the respondents genuinely perceive a difference between statement 1 and statement 2. The equation is as follows:

$$t = \frac{1}{\sqrt{\frac{\sum_{i=1}^{n}\left(\frac{x_{i1}-x_{i2}}{\bar{X}_1-\bar{X}_2}-1\right)^2}{n(n-1)}}} \tag{2.10}$$

Where:

n	$=$ sample size of the study
x_{i1}, x_{i1}	$=$ first and second result of participant *i* in the study, where *i = 1,2,3, ... , n*
$\bar{X}_1, \bar{X}_2$	$=$ sample scores from the first and second results of the study

2.4.2. Independent t-test

The independent t-test, assesses whether the means of a continuous, dependent variable differ between two distinct and unrelated groups. For instance, one might employ an independent t-test to determine if there is a discrepancy in average income between employees with different job titles within a company. Alternatively, one could utilize an independent t-test to investigate if there are variations in customer satisfaction scores between two different service providers. The following citation is a brief, but clear description of the t-test:

> Independent samples t-test is used to compare two groups whose means are not dependent on one another (University of Arizona Military Reach, 2009). Two samples are independent

> if the sample values selected from one population are not related or somehow paired or matched with the sample values selected from the other population. An independent sample t-test tells the researcher whether there is a statistically significant difference in the mean scores for the two groups or not. In statistical terms it means that the researcher is testing the probability that the two sets of data came from the same population. In other words, an independent sample is the sample in which the participants in each group are independent from each other (Gerald, 2018, p.51).

This t-test is employed to evaluate the significance of the differences in assessments between the two distinct groups for each statement. The t-test indicates whether subgroup 1 assigns a significantly different value judgement to a statement compared to subgroup 2. If this difference is significant, the researcher can conclude that the divergent value judgements of the two groups are not due to chance. The equation for this t-test is as follows:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\dfrac{\sum_{i=1}^{n} x_{i1}^2 - \dfrac{(\sum_{i=1}^{n} x_{i1})^2}{n_1} + \sum_{i=1}^{n} x_{i2}^2 - \dfrac{(\sum_{i=1}^{n} x_{i2})^2}{n_2}}{n_1 n_2 \left(1 - \dfrac{2}{n_1 + n_2}\right)}}} \tag{2.11}$$

Where:

n_1, n_2	= sample size of the first and second group
$\bar{X}_1, \bar{X}_2$	= sample mean of the first and second group
$\sum_{i=1}^{n} x_{i1}, \sum_{i=1}^{n} x_{i2}$	= sum of scores of the first and second group

3 Theoretical framework

This chapter outlines the theoretical foundation for the research. The first section introduces a conceptual model, focusing on potential short- and long-term behavioural changes among respondents. The second section examines journey characteristics that may affect preferences for an alternative, while the third section considers traveller characteristics that could shape preferences. The fourth section addresses status quo bias, offering relevant theoretical insights. Section five reviews internal research by Dutch Railways, and the final section presents the conceptual model developed from the preceding paragraphs.

3.1. Behavioural changes

By implementing a new fare system that applies fare differentiation, NS hopes to reduce the number of people traveling during peak hours and encourage them to spread out their journeys across peak periods. Therefore, the idea is to flatten the curve. To achieve this, the price of a train ticket would increase during the (hyper) peak hours. Fewer people travelling during the hyperpeak hours would enhance the quality of the journey, as it is likely that more seating capacity would become available. The factors undergoing change are thus the ticket price and the quality of the journey.

A distinction exists between short-term and long-term behavioural changes. Research on travel behaviour following a price change identified both short-term and long-term changes (Zeiske et al., 2021). Similarly, another study observed short-term and long-term behavioural changes following adjustments in travel quality (Eltved et al., 2021). These studies note variations in travel frequency, but it is also plausible that other behavioural changes occur. This section delves further into short-term and long-term behavioural changes. The exact definition of short- and long-term is not universally agreed upon, and different authors employ varying definitions. Table 3.1 illustrates the definitions used across multiple studies regarding behavioural changes in the use of public transport. The table also explains the factors influencing these behavioural changes. Consequently, it can be inferred that defining distinct short- and long-term time frames is challenging. After reviewing additional research and consulting experts in the field of NS, the following definition has been embraced for this study: changes observed within a one-year period following policy implementation are classified as short-term, while behavioural changes occurring after one year are considered long-term.

3.1.1. Short-term behavioural changes

In the new fare system, train tickets will become more expensive during peak hours and cheaper during off-peak hours. This may potentially result in short-term behavioural changes for train travellers. Not only the price, but also the quality of the trip, is likely to influence travellers' behaviour (Paulley et al., 2006). The potential behavioural changes of travellers are outlined in this section. There is also a subsection that delves deeper into the behavioural changes of individuals who are not currently train travellers, but may become so in the future. Train travellers can purchase tickets either through a

Table 3.1: Short-term and long-term definitions

Author	Factor	Short-term / long-term threshold
Imran and Matthews, 2015	Financial incentive	3 weeks
Zeiske et al., 2021	Quality incentive	3 months
Eltved et al., 2021	Public transport shut-down	10 years
Nguyen-Phuoc et al., 2018a	Quality incentive	1 year
MATAS, 2004	Quality incentive	1 year

season ticket or by buying individual tickets. Individual tickets can be purchased online or at the station, for instance. Another option is for people to check in using a debit card.

Change travel moment

A behavioural change that could occur is that travellers opt to travel at a different time. If travellers currently commute during peak hours, they may choose to travel at another time of day. This became clear during a case study in Shanghai (Ding et al., 2023). Initially, a distinction is made between the travellers, thus heterogeneity is assumed. The participants are classified based on the number of journeys they typically make per week and their usual travel time. The first cluster consists of individuals who do not travel during peak hours. The second group of individuals typically travels 4 days per week during peak hours and also indicates an inability to travel at other times. The final group travels 2.5 times per week during peak hours. The participants are encouraged to determine their willingness to pay by a peak charge and an off-peak discount. Especially the third group of participants indicates a willingness to consider travelling at a different time if a peak charge is introduced. However, in some cases, participants express a willingness to change their travel time if there is a price change of 70%. The ultimate recommendation made by the researchers is to make off-peak times cheaper. For the morning peak, the ticket price should be reduced by 40%. Between the morning and evening peaks, the ticket price should decrease by 10%, and after the evening peak, the ticket price should be reduced by 70%. In this scenario, it appears that, on average across the different clusters, 6.9% of morning peak travellers and 6.7% of afternoon peak travellers are willing to change their travel time to off-peak hours.

These findings were partly confirmed in a study on behavioural changes in Singapore when travelling on public transport becomes free or cheaper during pre-peak hours compared to peak hours (Adnan et al., 2020). It was found that during the afternoon peak, the number of travellers decreased. However, what is noteworthy is that it became busier during the morning peak. The explanation for this is that people switch from using their cars to using public transport. Thus, fewer people travel by car, and these individuals have switched to using public transport, ultimately making the morning rush hour busier.

Attract and dispose car users

From the preceding section, it becomes apparent that not only current train passengers are relevant in such research, but also non-train passengers. Research conducted in Singapore (Adnan et al., 2020) indicates that non-train passengers, coming from cars, are attracted to the train when the ticket price decreases during pre-peak hours. Although the morning peak problem in Singapore was not solved by lowering the price of a train ticket for the morning peak, it clearly indicates a shift from cars to trains. The first aspect related to cars, therefore, is that people shift from cars to trains when travel becomes cheaper. In the Netherlands, the morning peak starts at 6.30 a.m. and ends at 9.00 a.m. on the railways. With the introduction of the new fare system, the price of a train ticket will increase during the peak hours, and after before 6.30 a.m. and after 9.00 a.m. the ticket price will be cheaper than in the current fare system. Therefore, the cheaper price before 6.30 a.m. should attract car drivers to the train.

However, upon reviewing the literature, it can be observed that the price of a train ticket often is not the primary reason for a commuter to switch modes. Public Transport is frequently perceived as a poor alternative for car use (Steg, 2003). The research indicates that car users had a negative attitude towards public transport. This is partly because the car symbolises freedom and independence. Although the mentioned research dates back to 2001, its findings remain relevant. Subsequent studies reflect this independence through flexibility (Ahmed et al., 2021). Car users indicate that flexibility and convenience are the most valued advantages. Another insight drawn from these studies is that private car users opt for cars because public transport is crowded. To make public transport more appealing for both users and non-users, reliability is crucial. Potential public transport users experience high levels of reliability and flexibility in their current travel modes. Additionally, it depends on various psychological factors, as the group of travellers is not homogeneous. A reduced fare may potentially play a role (Göransson and Andersson, 2023).

Travellers can be attracted not only from cars to public transport but also vice versa. With the introduction of the new fare system, the price of a ticket will be higher during the morning peak and lower during off-peak hours. An increase in ticket fares correlates positively with car usage; a rise in ticket prices leads to more car users and fewer public transport users (Hörcher et al., 2020). This is not contradicted by other literature but is also not significantly supported. It appears that the demand for cars in response to changes in public transport attributes has a much smaller effect than the influence of changes in car attributes on public transport demand (Fearnley et al., 2017). A change in the price of public transport fares by 1% leads to a change in car demand of 0.055% in the mentioned case study.

In other studies, it is often concluded that the quality and reliability of public transport journeys play a significant role in travellers' decision-making. In a study conducted in Australia, it was found that mode choice is determined by individual-specific, context-specific, and journey-specific factors (Nguyen-Phuoc et al., 2018b). Long-term trends indicate that only context-specific factors influence the mode shift (from public transport to car). Other research has also shown that travellers are inclined to resort to the car as a mode of transportation if public transport becomes unavailable or if its quality significantly deteriorates (Nguyen-Phuoc, 2015). The overall quality and reliability of a journey may have a greater impact than changes in the price of a train ticket.

Work From Home

Since the outbreak of the COVID-19 pandemic, remote working has become an integral part of contemporary society (Huang et al., 2023). On average, depending on one's working class, individuals work from home for 2 days per week (Hensher et al., 2023). The attitude towards work from home varies based on commuting characteristics and socio-demographic factors. Commuters facing high expenses during their journeys tend to have a relatively more positive attitude towards remote working. The higher the commuting expenses, the more positive respondents were towards work from home (Zhao et al., 2024). A recent study concludes that 'working from home' (work from home) and travelling by train function as substitutes for each other (Kroesen et al., 2023). Thus, a potential behavioural change is that people opt not to use public transport but to stay at home instead.

3.1.2. Long-term behavioural changes

On the long term, behavioural changes may appear differently compared to the short term. Long-term behavioural changes are much more about breaking entrenched habits.

Change in season ticket

When travelling by train, there is a choice of 18 different types of season tickets. Within these season tickets, a distinction is made in two ways. The first distinction concerns the method of payment. One can pay in advance, which is on a 'travelling on balance' basis. The second option is to pay afterwards for a journey. In that case, one takes an NS Flex subscription and at the end of the month, the traveller receives an invoice. Finally, it is possible to take a business subscription if it is legally applicable. This last category is used by employers and self-employed individuals. The second distinction that can be made concerns the proposition that a subscriber chooses. Within the three subscriptions, various propositions can be chosen. Not every season ticket allows for a certain type of proposition to be chosen. An overview of the possibilities can be found in table A.1 in appendix A. Table A.2 provides an overview of what the different propositions entail. Options include choosing a discount subscription or a free subscription. With a discount subscription, the cardholder receives partial discount on a journey, whereas with a free subscription, the cardholder receives full discount on a journey. The proposition mentioned second is more expensive.

It is not straightforward to predict which subscription a cardholder might opt for when a price change is implemented. Table A.2 in appendix A outlines the possible changes a cardholder could make. From this data, it appears unlikely that a subscription holder will switch subscriptions if a peak surcharge of €2.50 is introduced. Compared to the current situation, no additional financial benefit would be gained by switching subscriptions in the new scenario. If the subscription holder does not currently switch subscriptions, it is also unlikely that they will do so when the new fare structure is introduced.

The propositions 'Intercity Direct discount' and 'Intercity Direct Free' are not taken into consideration, as these options are chosen on a monthly basis and apply to a very specific route. Another proposition is 'keuzedagen', which is available to people aged 60 years or older who already have a 'dal-voordeel' season ticket. Holders of the 'keuzedagen' subscription can select seven days per year on which they can travel for free during off-peak hours. This proposition is also not taken into account because, firstly, seven days per year makes it a very sporadic season ticket, and secondly, it is only valid during off-peak hours. Therefore, users of this season ticket will definitely not travel during peak hours, making them irrelevant to this thesis.

Changes in the office

To prevent employees from travelling during the most expensive time of the day (during the peak hours), the employer can implement various adjustments within the office. The first adjustment could be allowing employees to start earlier or later, enabling them to avoid the peak hours. Employees may still travel during rush hour, but it would occur during relatively less congested times. Alternatively, employees could travel completely outside of peak hours, such as before 6.30 a.m. or after 9.00 a.m. This constitutes a significant change in travel behaviour, seemingly influenced more by factors other than the price of the transportation ticket. Empirical studies conducted in countries like the Netherlands and Belgium have demonstrated that removing regulatory constraints on working hours (e.g., 8.30 a.m. to 5.30 p.m.) has not led to workers staggering their morning start times (Breedveld, 1998; Glorieux et al., 2008). This is because there is a certain social pressure to arrive at work on time. Two norms contribute to people wanting to go to work around the same time, even if they have the freedom to arrive later: the norm of the disciplined worker and the norm of the dedicated executive (Munch, 2020). However, transgressing social norms is a costly process, so this behavioural change takes time. Increasing fares during peak hours does not have a direct effect on the number of travellers during those times, but it may have an indirect effect in the long term (Bicchieri and Funcke, 2018).

A second adjustment could involve people going to the office on different days, meaning that telecommuting days and office days are (partially) swapped. The current trend is that people work from home on Mondays and Fridays, and from Tuesday to Thursday, they work in the office (Barrero et al., 2023). This trend is similarly reflected in NS data, except that Wednesday is significantly less crowded than Tuesday and Thursday. The decision people make to work from home or in the office regarding commuting is mainly influenced by commute time (Barbour et al., 2024). In another study on road congestion, working from home is also mentioned as a viable policy to reduce road congestion. If this line of thought is extended to public transport, working from home could result in less crowding. Encouraging working from home through higher prices during peak hours might help alleviate the hyper-peak rush (**work from home**).

Change travel distance

If travelling under the new fare structure becomes too expensive, a commuter may choose to shorten their travel time. They may opt to live closer to work or seek a new job closer to their place of residence. Housing decisions are primarily driven by job commitment and not the other way around (van Leuvensteijn and Koning, 2004). In another, more recent study, research has been conducted on the influence of commuting burden on aspects such as job commitment (Li et al., 2021). Commuting burden can be understood as the relationship between the costs incurred by workers to access their jobs and the income they generate. It can be observed that individuals with a higher commuting burden are less committed to their jobs. Therefore, a higher price for commuting may discourage employees in their job commitment, potentially leading to a choice for a different job in the long term. The direct effect of peak-hour charges may not be evident, but indirectly, it could lead to changes in place of residence or workplace.

3.1.3. Conclusion

This paragraph distinguishes between short and long-term behavioural changes. Long-term behavioural changes are indirectly influenced by the implementation of peak-hour charges. Therefore, it is chosen not to further delineate these behavioural changes. Short-term behavioural changes are of greater relevance. Firstly, it is important to consider that travellers adjust their travel times. As indicated earlier in this paragraph, it is quite possible that people are willing to adjust their travel times due to price changes. This is strongly supported by the research of Andrike Mastebroek. Based on this research and others, it can be concluded that a distinction should be made between different time slots during peak hours. An internal NS study suggests that approximately 50% of peak-hour travellers indicate they could shift their travel time by half an hour. Additionally, there should be an opt-out option. Literature indicates that respondents may choose not to use the train anymore if the price of a ride increases.

Regarding covariates, this paragraph emphasizes the importance of whether someone owns a car and if the respondent uses the car as the main mode of transportation to their destination. This is queried from the traveller.

3.2. Characteristics of a journey

In several previous studies, research has been conducted on the price elasticity of demand for public transport. A price increase generally leads to a decrease in demand. However, the extent of this decrease depends on the elasticity of demand. This thesis is also closely related to the price elasticity of demand. However, price elasticity is not the sole factor influencing demand changes. Characteristics of the journey also significantly influence people's travel behaviour. These characteristics are referred to as attributes. By assigning different weights to attributes, a respondent can make trade-offs between them. Therefore, this section explores which journey characteristics are important. Paulley et al. (2006) discovered that a public transport operator can affect the attractiveness of a journey by adjusting either the price or the quality. To explore how this can be put into practice, several case studies have been examined.

3.2.1. Peak and off-peak

Primarily, consideration can be given to the timing of travel. Research indicates that there is a difference in response when measured during peak and off-peak periods. A study conducted in Stockholm County (Kholodov et al., 2021) confirms this. The aim of this study was to gain insights into specific fare elasticities for distinct socioeconomic groups and public transport modes. This study found that off-peak elasticities are higher than peak elasticities, indicating that respondents are less sensitive to a price change during peak times. The same holds for a research which was done in Santiago (de Grange et al., 2013). Respondents were presented with a choice set comprising four different options for each day. Therefore, respondents could choose the departure time (between 6 and 7 or between 7 and 8) and the mode of transportation (bus or metro) for each day. The study does not specify a particular numerical value for elasticity. Instead, it presents various elasticities for different modes of travel. The overview distinctly shows that the off-peak elasticity for the metro is closer to -1 than the elasticity during peak hours, indicating that travellers are less sensitive to price changes during peak hours. Paulley et al. (2006) found similar results in the UK, where the elasticity during off-peak hours in absolute terms is nearly twice as high as the elasticities during peak hours. This indicates that people are more sensitive to a price change during off-peak hours than during peak hours. According to the study, the explanation is that during peak hours, people primarily travel for work and education purposes, so their trips tend to be relatively fixed in time and space. Off-peak trips, on the other hand, are predominantly leisure trips, shopping, and personal journeys that are much more flexible in terms of destination and time. In a study by Hensher (2008a), this finding is also supported. Hensher also finds that the price has less of an impact on people's travel behaviour during peak hours compared to off-peak hours. Hörcher and Tirachini (2021) similarly found that peak demand is less sensitive to tariffs than off-peak demand.

3.2.2. Trip distance

Fare elasticities are expected to rise with increasing travel distance (Balcombe et al., 2004). Kholodov et al. (2021) discovered a variance in elasticity as journey distance alters. The study highlights that sensitivity to fare changes increases with the journey distance. The elasticity for short distances (0-1 kilometre) averages approximately -0.28, for medium distances (1-10 kilometres) it averages around -0.38, and for long distances (10-20 kilometres), it is roughly -1. For distances exceeding 20 kilometres, the elasticity surpasses -1, with a value of approximately -1.2.

The hypothesis posits that travellers may consider using a private vehicle as distance increases. This was also observed in a study in Spain, which examined the elasticity of demand when train ticket prices rise (Hortelano et al., 2016).Specific attention was given to respondents' alternative transportation choices. The alternatives included the car or plane. The latter option is of little significance in the Netherlands, as domestic flights occur exceptionally rarely. However, Hortelano et al. (2016) do confirm that distance influences a traveller's behavioural shift. Similarly, Paulley et al. (2006) investigated the impact of distance on price elasticity of demand in London. In contrast to Kholodov et al. (2021) it was found that fare elasticity decreases with distance. The explanation lies in the fact that the fare per kilometre decreases as the number of kilometres increases. This form of fare structuring is also employed by NS: the more kilometres one travels (fare units), the cheaper the cost per kilometre will be. Another study also addresses this issue, examining, among other things, the influence of distance on price elasticity (Wardman, 2022). This research argues that indeed there is a distinction in elasticities when the distance between the origin and destination varies. However, this difference can be simplified by distinguishing between urban travels, meaning trips within a city, and inter-urban travels, referring to journeys between two cities.

3.2.3. Urban and rural areas

As demonstrated by the research of Wardman (2022), whether the journey occurs within a city or between cities makes a difference. Wardman distinguishes between the urbanity levels of the origin and destination. Hörcher and Tirachini (2021) discovered that elasticities in rural areas surpass those in metropolitan regions. It is evident that urban areas display distinct price elasticity compared to non-urban areas. This distinction is highlighted in the earlier mentioned case study in Spain (Hortelano et al., 2016). Another study supports this notion, indicating that metropolitan areas generally exhibit lower price elasticity than rural regions (Dargay et al., 1999). In a case study that is done in the UK it was found that respondents residing in non-urban areas are more responsive to fare changes than those in urban areas (Wardman, 2014b). The rationale behind this lies in the fact that individuals outside urban areas typically have the option to use a car as an alternative, while urban dwellers are less inclined to choose this alternative. This assertion is also supported by De Grange et al. (2013), who argue that large cities tend to have lower elasticity than suburbs or rural areas due to the higher proportion of travellers reliant on public transport.

3.2.4. Crowding (dis)comfort

Another aspect of a journey is the comfort experienced by passengers due to crowding. Some individuals are sensitive to crowding, while others are less affected, as revealed in a study conducted in Santiago, Chile (Tirachini et al., 2017). The study distinguished between standing and seating arrangements. Generally, sitting was found to be more comfortable than standing. However, within the respondent group, the influence of sociodemographic and socioeconomic variables affected how individuals perceived crowding. The group least sensitive to crowding were identified as young people, men, with high incomes. Conversely, older individuals, those with lower incomes, and women were generally more sensitive to crowding in public transport. In the research by Wardman and Whelan (2011), the valuation of a journey in terms of seating/standing and crowding is measured. Individuals seated appear to dislike increased crowding (i.e., more people per square meter) more than those who are already standing. Passengers who are already standing are less bothered by increased crowding in the train. However, whether seated or standing, a more crowded trip consistently diminishes the enjoyment of the journey. In Singapore, research has also explored how individuals weigh crowding and travel time against each other (Tirachini et al., 2016). This study found that a significant portion of respondents are willing to choose a longer journey if the crowding in the vehicle they take is low. The busier a vehicle becomes, the less enjoyable the journey is perceived to be.

3.3. Characteristics of a traveller

Characteristics of a traveller significantly influence the choices they make. Not every traveller is alike, and the importance of a particular attribute can vary between individuals. This topic is extensively discussed in the literature, distinguishing between socio-economic and socio-demographic factors, which are elaborated upon in the following sections.

3.3.1. Socioeconomic factors

The socioeconomic status of one is defined as a measure of one combined economic and social status. According to the Cambridge Dictionary the socioeconomic status is related to the differences between groups of people caused mainly by their financial situation. In the literature are some socioeconomic factors found which are contributing to the choices one makes.

Income

In the aforementioned study on travel behaviour in Stockholm County, it was found that individuals with lower incomes have lower elasticity compared to those with higher incomes (Kholodov et al., 2021). Individuals with moderate incomes are most sensitive to price changes. This contradicts the hypothesis that high-income individuals are less sensitive to price changes. However, the explanation is as follows: individuals with low incomes often have no alternative (i.e., no car), so a price change will not alter their behaviour. High-income individuals are not sensitive to price changes because they have a lot of money, so price is not a concern for them. Individuals with moderate incomes are sensitive to price and may have an alternative mode of transport, making this group most sensitive to price changes. The relationship between public transport demand and income can vary significantly from country to country. In London (Paulley et al., 2006), it is observed that public transport demand increases with income, while in Colombia, it is the opposite (Toro-González et al., 2020). Public transport is considered an inferior good in Colombia: the higher the income, the less public transport is used. This also applies to a case study in Chengdu, China, where higher income negatively correlates with the use of public transport. Finally, the research by Van et al. (2014) also indicates that public transport is an inferior good, meaning demand for the good decreases as income rises. The literature does not provide insight into the price elasticity of demand for public transport, so it is unclear what the price elasticity is for individuals with high and low incomes. In the above studies, except for the Stockholm study (Kholodov et al., 2021), the change in income is seen as the cause and the demand for public transport as the effect. However, only the study by Kholodov et al. (2021) has taken the change in the price of public transport as the cause.

Car ownership

Car ownership is a socioeconomic factor closely linked with income. Individuals with higher incomes typically own at least one car, while those with lower incomes may not always have access to a car (Dargay, 2001). This relationship between income and car ownership influences transportation choices of people. Paulley et al. (2006) highlights car ownership as one of the key factors impacting individuals' decisions between using a car or public transport. Many other studies also emphasize this connection (Dargay, 2001). Research indicates that individuals with lower incomes may be unable to afford a car and therefore rely on public transport to travel from point A to point B. In the study of Holmgren (2007), the relationship between car ownership and public transport demand shows an elasticity lower than -1, indicating a high level of elasticity. This suggests that private cars and public transport are interchangeable options. Yang et al. (2015) found that individuals who own cars predominantly choose to travel by car, a significant trend in their results. Overall, car ownership emerges as a significant factor influencing individuals' transportation choices. Those with cars are likely to already use them and may be sensitive to price changes. Conversely, respondents without cars may be less affected by price changes, as they have no alternative transportation option besides public transport.

Education

The level of education significantly influences commuters' mode choice between car and public transport, according to Yin et al. (2020). Conversely, a lower income is associated with a higher demand for walking and biking (Zhao et al., 2018). In a study by Zhao and Yuan (2023), the relationship between education and travel behaviour in China is extensively explored. The first finding suggests that individuals with higher education levels prefer public transport more than those with lower education levels. This could be attributed to limited access to public transport modes for those with lower educational attainment. Moreover, in a mega city like Beijing, with a complex public transport system, some less educated residents may struggle to navigate the subway due to difficulties in locating stations, obtaining route information, and purchasing tickets independently. This finding is supported by the research of Veterník and Gogola (2017), which indicates that demand for transport and the proportion of public transport use increases with higher levels of education.

The second finding in the study in China is that individuals with higher education levels are more likely to drive a car (Zhao and Yuan, 2023). There appears to be a positive correlation between education level and car usage rate. Overall, individuals with higher levels of education tend to travel more frequently and use public transport or cars more often. Additionally, it is observed that a higher education level negatively correlates with the number of walking trips a person makes, which is also noted by Zhao et al. (2018). A study conducted in Kaunas, Lithuania, found that individuals with higher levels of education are more likely to use cars, while those with lower educational levels are more often found using public transport (Dėdelė et al., 2020). Finally, a Dutch study concludes that individuals with higher educational attainment have the highest density in trains (Limtanakool et al., 2006).

A common theme across all these studies is that educational level is often associated with overall socio-economic status. Individuals with higher levels of education often have higher incomes and are usually employed (Dėdelė et al., 2020; Zhao and Yuan, 2023; Veterník and Gogola, 2017).

3.3.2. Sociodemographic factors

Sociodemographic factors refer to a combination of a social and demopgrahihc factors that define invidivuals in a particular group or population. Characteristics include for example age, sex, migration background, marital status, household composition etc. Some of these factors contribute to varying degrees to the choices that a respondent will make.

Age, gender and employment

A study conducted in the Netherlands also concludes that age contributes to the choices individuals make regarding travel (Limtanakool et al., 2006). For example, age may influence the preference for driving a car and using it as a mode of commuting to work (Focas and Christidis, 2017). Focas and Christidis observed that young people tend to abandon public transport and start commuting by car, while older individuals are more likely to increase their use of public transport. The study suggests that younger people engage in more social activities, leading to a higher need for a car. Another study in the Netherlands found that age is a significant indicator of travel behaviour choices (Campisi et al., 2022). It indicates that individuals of different ages have varying sensitivities to price changes, with older individuals being less sensitive to price changes (McCollom and Pratt, 2004). Similarly, in the Tokyo metropolitan area, it was found that age significantly influences travel behaviour choices (Abe, 2021).

A study conducted in the Greater Dublin Area investigated the determinants of mode of transport to work (Commins and Nolan, 2011). It was found that gender, household type, and marital status play a significant role in determining modal choice. Women are significantly less likely to walk or cycle to work; they are more inclined to use public transport instead. Several other studies have also included gender as one of the covariates in their stated choice models (Abe, 2021; Paulley et al., 2006; Yang et al., 2015; Anable, 2005). Therefore, gender is also considered in this research. Anable (2005) mentions employment as a relevant sociodemographic variable in travel behaviour research. Cordera et al. (2015) also consider an individual's employment status in their study.

3.4. Theory about the status quo bias

Other factors that could influence travellers' behaviour are linked to psychological factors. In research on travel behaviour, attitudes are also frequently investigated. These studies often delve into how attitudes impact mode choice, drawing partly from the theory of planned behaviour (Ajzen, 1991). Conversely, some studies suggest an inverse relationship, proposing that individuals may adjust their attitudes to align with their actions (Kroesen et al., 2017). Therefore, the influence of psychological factors and attitudes represents a personal trait requiring thorough examination.

One of the psychological factors warranting further elucidation is the so-called *status quo bias*. This phenomenon has been studied as far back as the previous century. Samuelson and Zeckhauser (1988) elaborate on this, highlighting that most real-life decisions include a status quo alternative, wherein maintaining the current or previous decision is considered an option. This tendency often impedes governments from adopting policies that economists deem efficiency-enhancing. There exists a bias towards the status quo when the beneficiaries and losers of reform cannot be accurately identified beforehand. Certain reforms, which may garner sufficient political support post-adoption, may have failed to secure approval initially (Fernandez and Rodrik, 1991). The status quo bias significantly influences how individuals make choices between options (Godefroid et al., 2023). For instance, Dean et al. (2017) discovered that, when presented with choices between bundles of goods x and y, the introduction of a status quo that favours x over y can prompt individuals to switch their preferences from y to x.

Empirical evidence supporting this theory has been provided, among others, by Lang et al. (2021). They investigated the influence of this bias in the context of carbon mitigation. Individuals were approached with a survey, wherein they were directly asked about their willingness to pay for their state to participate in a regional carbon mitigation policy. The survey consisted of two randomized frames, differing in whether or not their state was already part of the policy. The researchers discovered that respondents who believed Rhode Island would be joining the policy for the first time had a willingness to pay to join of $170. Conversely, those who believed Rhode Island was already part of the policy were willing to pay $420 to stay in the program.

A similar demonstration of a status quo bias was uncovered by Linnerud et al. (2019). Through a two-stage framing experiment involving students, evidence of this bias was revealed. Interestingly, both groups of students exhibited a preference for the existing state of affairs. An implication arising from their findings is that policymakers could potentially aid individuals in becoming more accustomed to novel situations, such as new ownership models, through demonstrations, pilot projects, and the dissemination of information.

As mentioned in the introduction, the introduction of peak-hour charges is also a controversial policy that has met with significant resistance among travellers. Nearly unanimously, the Dutch House of Representatives voted in favour of a motion requesting the government not to introduce peak-hour surcharges in the main rail network concession (2023). The primary reason for this is that individuals without alternatives often have limited financial means and would consequently face increased costs for their travel. Additionally, it weakens the competitive position compared to driving. However, there may also be an element of status quo bias at play. If the situation were reversed, with peak-hour charges already in place, new policy might also encounter resistance from travellers and in the House of Representatives.

As highlighted in the earlier study by Lang et al. (2021), individuals' willingness to pay varies depending on their reference points. The hypothesis derived from this is that people are more willing to pay during peak hours if they have always been subjected to this situation. If individuals have consistently faced additional costs during peak hours, their willingness to pay is likely to be higher than if they had never had to pay extra during peak times. Conversely, the opposite holds true: if individuals have always been able to travel more affordably during off-peak hours and this changes, they will likely resist the new situation much more than if they could travel cheaper during off-peak hours but faced higher costs during peak times.

3.5. Internal research of the Dutch Railways

Research on passengers and passenger behaviour is conducted on a very regular basis, within NS. Multiple studies are elaborated upon in this section. These include a study called *'Journeys and Passenger Research'*, a study on the price elasticity of the various propositions offered within NS and a study about flattening the hyperpeak.

3.5.1. Journeys and passenger research

Every five years, NS conducts an internal study on the composition of passengers and their corresponding travel behaviour. The most recent iteration of this research was conducted in 2023. The data from the study are very recent. At the passenger level, sociodemographic and socioeconomic characteristics are examined, while at the journey level, attention is given to factors such as the timing of most journeys and whether the journey occurred in an urban or rural area. This section provides further detail on the latest passenger survey.

Sociodemographic and socioeconomic variables

The choice of travel ticket is one of the things that is investigated. Travellers can choose to travel based on a season ticket, but it is also possible to buy a separate ticket. Appendix A provides a detailed report of the possible season tickets a passenger can choose. A travel characteristic which in mentioned in the research is the degree of urbanity. The higher the degree of urbanity, measured on a 5-point Likert scale, the higher the percentage of train travellers. The region of the origin also plays a role (Nielsendistrict). It can be seen that in the Randstad area there is much more train travel than outside the Randstad area. The travel frequency of the travellers is also enquired by the survey of NS. It appears that a higher frequency of travel positively correlates with the preferences of one for the train. However, high-frequency train travellers do not consciously choose the train very often; they do so out of habit. Less frequent train users relatively more often make a conscious choice whether or not to travel by train or by car. Also, there is a certain trend in educational level. The level of the highest education attained positively correlates with the number of people on the train. This does not necessarily mean that education is a cause of travelling by train, but there is a clear positive correlation in the data. The age of the respondent is normally distributed with a mode falling into the category of 16 to 24 years. Students, people working for the government, and self-employed individuals are overrepresented in the population of travellers. Roughly, three groups can be distinguished: travellers for work, travellers for study, and other travellers. In the population of travellers, it is noted that the number of women on the train decreases more sharply than the number of men on the train. Another detail about travellers is the travel expense reimbursement. Roughly half of train travellers have their travel costs reimbursed. For a small portion of people, it is unknown who pays, and over 30% of travellers pay for the journey entirely by themselves. The remaining travellers are partially reimbursed for the journey.

Clusters in the passenger research

In the population of travellers, the passengers are divided into 5 clusters. The first cluster consists of individuals with a season ticket. The majority of those with a subscription are employed in wage labour (38%). Interestingly, the primary travel motive for these passengers is 'social'. This may be because 26% of the individuals in this cluster are retired. The second cluster comprises customers who have travelled with a single fare ticket. Nearly half of these individuals are employed in wage labour, and their travel motive is 'recreational'. However, 63% of the people in this cluster have indicated that they use a single fare ticket less than 6 times a year. Therefore, the conclusion is that wage workers have sporadically purchased a single ticket. The third cluster consists of customers who travel with a student travel card. The average train travel frequency for 64% of the travellers is more than once a week. Nearly 90% of the people in this cluster identify as students. In the business cluster, which is the fourth cluster, 62% of the travellers are found on the train more than once a week, and 67% of the individuals in the cluster state that they are employed in wage labour. Consequently, the primary travel motive is commuting. The last cluster comprises individuals from the resell cluster. Almost two-thirds of the people in this cluster report travelling by train more than once a week. 59% of the individuals in this cluster work for the government.

3.5.2. Sensitivity per season ticket

In a recent internal study conducted by NS, the sensitivity to price changes was examined. Distinctions were made among travellers based on their type of ticket. The measured elasticity varies for the different propositions available (see appendix A). The elasticity for single tickets is a maximum of 0.67 points below zero. Those with an NS Flex Basic ticket are the most sensitive to price changes. Within the season tickets, the behavioural change of those with the 'Dal Vrij 2e klas' proposition is elastic. This means that a change in price leads to a significant change in demand, resulting in proportions that are skewed such that proportionally more people leave than the price increases. However, the group with an off-peak subscription is unlikely to travel during the morning rush hour, as an off-peak subscription is disadvantageous during peak hours. The subscriptions 'Traject Vrij 2e klas' and 'Altijd Vrij 2e klas' are relatively sensitive to price changes. The elasticity lies between 0 and -1, meaning the demand change is still inelastic, but this group indicates being more sensitive to a price change than other season tickets. Those travelling with these propositions may still travel during peak hours, as their subscription is not necessarily focused on off-peak hours.

3.5.3. Flattening the hyperpeak

The last study, which was conducted in 2017, investigates whether it is possible to flatten the hyperpeak (A. Mastebroek, personal communication[1]). The issue that is caused by this hyperpeak is already described in chapter 1. In Mastebroek's study, a solution was developed to shift hyperpeak travellers to the shoulder peak. The question posed is whether a financial incentive can induce this travel behaviour. One of the different NS subscriptions (see appendix A) is the so called *Altijd Voordeel* season ticket. A traveller who uses this season ticket is given a discount of 40% when travelling during off-peak hours and 20% during peak hours (between 06:30 a.m. and 09:00 a.m.). Data showed a peak in number of check-ins just before and just after the peak hours, where the discount transitions from 40% to 20% and vice versa. The hypothesis derived from this is that people tend to arrive slightly earlier or later at the station to maximize their discount. Passengers are thus willing to adjust their travel time slightly to benefit from discounts.

To confirm this hypothesis an experiment was conducted whereby the peak hours for the *Altijd Voordeel* were altered for a specific duration. The peak hours were adjusted to run from 07:30 a.m. to 08:30 a.m., resulting in a one-hour peak. During this hour the discount for the subscribers is 20% while the discount is 40% for off-peak hours. As a result a proportion of travellers with a *Altijd Voordeel* subscription altered their travel behaviour and opted to travel later than usual. The conclusion drawn from this is that a financial incentive can indeed influence travellers to adjust treir travel times.

3.6. Conceptual model

All findings from the literature and from NS's internal data studies are visually represented in a conceptual model in figure 3.1. In the preceding paragraphs, a distinction was made between personal characteristics and journey characteristics. In the conceptual model, some aspects of journey characteristics are not included as attributes, but as covariates. For instance, the degree of urbanity is typical a characterstic of a journey but it is also person-specific. Not every traveller commutes from and to the same departure and arrival stations. Ticket price is also linked to the departure and arrival stations of the traveller, as well as whether they travel first or second class.

This conceptual model is elaborated in the previous chapter (chapter 2). The characteristics of a journey, which influence the perceived utility of the trip, are depicted in the upper left block. A respondent's experienced utility during a journey is affected by the attributes found in this upper left block. Subquestions 1 and 2 address these attributes. The block to the right illustrates the personal characteristics of a traveller. These personal characteristics explain why Traveller A might perceive a price increase differently than Traveller B. For instance, a hypothetical example could be that a person with a high income is less sensitive to price changes than someone with a low income. Travellers are categorised based on their personal characteristics, forming different classes according to their sensitivity to the

[1] Sr Pricing Marketeer at NS

journey attributes. The oval in the lower left indicates the behavioural changes identified from the literature and internal research conducted by NS. Not all these behavioural changes are examined. This thesis focuses solely on the behavioural change 'change travel moment,' as the main question, sub-questions, and the thesis's objective are directed towards flattening the hyperpeak.

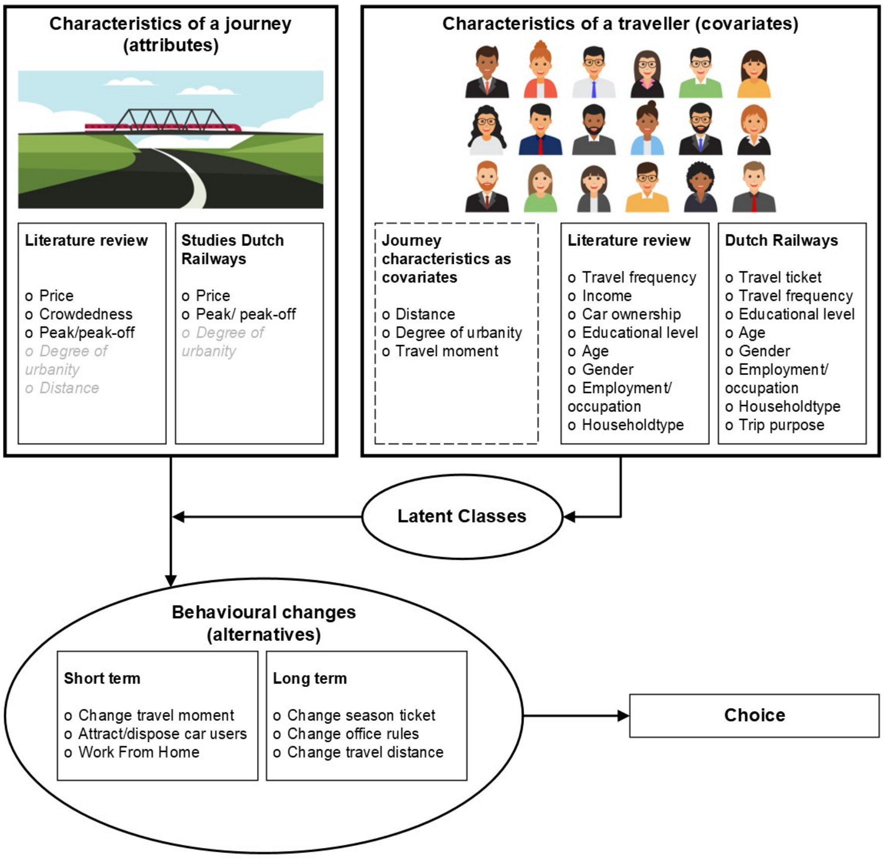


Figure 3.1: Conceptual Model

3.6.1. Implications for the thesis

From the preceding sections, it is evident that NS has conducted extensive research. For instance, the composition of travellers is well understood through journey and passenger surveys. NS also possesses knowledge of the price elasticity of travellers based on the type of ticket used. However, what remains unclear after the elasticity study is the precise behaviour of passengers in response to a price change. Price elasticity indicates the percentage decrease in the number of passengers relative to a percentage change in price. This elasticity is uniform over time, exhibiting no temporal variation. As indicated by the literature, sensitivity to price may vary at different times of the day (section 3.2.1). Mastebroek's study demonstrates that people are willing to consider travelling at different times if prices vary accordingly. Despite NS's comprehensive research efforts, there remains a limited understanding of peak-time travel behaviour under fare differentiation. For this thesis, it is crucial to gain insights into this behaviour. Therefore, the choice experiment includes price, crowding, and travel time as attributes. The literature suggests that various behavioural changes may occur following a price adjustment. This thesis focuses solely on the behavioural change of 'changing travel time'. Additionally, it is possible that a traveller might opt not to travel by train at all (if no suitable alternative travel time exists), so it is important for respondents to be able to indicate this preference. Subsequently, for NS (and thus for this thesis), it is irrelevant whether this traveller chooses to drive or work from home on that day. Regarding covariates, all identified covariates have been included in the model, with each covariate's influence on the class assignment of a respondent estimated. Figure 3.1 lists all covariates identified in the literature and internal NS research.

4

Choice Experiment and Survey

In this chapter, the structure of the survey is outlined. The survey primarily consists of two parts: the first part gathers the personal characteristics of the respondent, and in the second part of the survey, a stated choice experiment is conducted. Based on the results, a Latent Class Choice Model is estimated. In appendix B, an elaboration of the survey can be found; some questions about socio-demographics and socio-economics are included in the appendix.

4.1. Designing the choice sets

The design of the choice sets comprises several components. Firstly, the attribute levels are selected for the different attributes. Subsequently, combinations are made of the various attribute levels to obtain a complete picture of a particular alternative. The next step in designing the choice sets is determining how these alternatives are compared alongside each other. An explanation is provided regarding which alternatives are compared alongside each other and how these alternatives were developed.

The main challenge of stated choice experiments is threefold (E. Molin, personal communication). Firstly, it is essential to create sufficient variation in the choice situations so that the intended utility functions can be estimated. Secondly, it is crucial to create this variation in a way that ensures estimated parameters are reliable and have small standard errors. This can be achieved by selecting an appropriate experimental design and by creating choice tasks that do not overwhelm respondents. Finally, it is vital to create the variation in such a way that ensures estimated parameters are valid, meaning constructing choice situations that closely resemble real-world choice scenarios as much as possible.

4.1.1. Attribute levels

It is crucial that the attributes included are the most significant ones for respondents. This can be somewhat ambiguous, as the main goal of the researcher is to determine which attributes are important to respondents. Therefore, the researcher must select attributes based on literature, other studies and interviews. These attributes should also be relevant for policy design, allowing for the inclusion of attributes that can be influenced by policy. In this thesis, the following attributes are chosen: price of the journey, time of travel, and train crowding (see figure 3.1).

The number of attribute levels is typically limited to two to four levels, but this is not always the case. To test the linearity assumption, attribute levels should be more than two. Testing for linearity requires at least three attribute levels. For attributes with an interval and ratio scale, the range of the attributes should be chosen as wide as possible. There are three reasons for this. Firstly, a broad range of levels ensures that all levels of existing alternatives fit in, as well as the levels of future alternatives after implementing policy measures. Secondly, a broad range of levels increases the validity of the research, as interpolation is more reliable than extrapolation. Thirdly, a broad range of levels increases the reliability, as it increases the standard errors of the parameters. It is important to note that all combinations of attribute values should make sense. Additionally, the researcher should maintain equidistance in attribute levels whenever possible to ensure orthogonality between attributes.

Price change of a journey

As outlined in chapter 1, this thesis aims to explore whether a new fare system could address the issue of hyper-peak travel on Tuesdays and Thursdays. Under this proposed system, ticket prices would increase during peak hours and decrease during off-peak hours. Therefore, in a stated choice experiment, the price of a journey is varied to determine the significance of this attribute. To ensure that the fare displayed in the stated choice experiment closely reflects the actual fare of the respondent's trip, the first part of the survey includes questions regarding this matter. The respondents are asked about their most frequent departure and arrival stations, considering trips taken during morning peak hours. Additionally, the travel class of the respondent is queried in the initial survey section. Based on the departure and arrival stations, the length of a trip can be determined. The trip length, expressed in tariff units, forms the basis for the fare of a train journey. First-class travellers pay 170% of the fare paid by second-class travellers. Therefore, once the distance and class are known, the fare for a specific respondent's trip can be determined. In the stated choice experiment, the fare is varied around the original trip price. Since this thesis focuses solely on peak hours, any discounts applicable during off-peak hours are not considered. Consequently, the fare for a journey only increases compared to the original fare. The attribute levels for the fare of a journey vary by an increase ranging from €1 to €6. The upper threshold of €6 is chosen because it facilitates interpolation rather than extrapolation; it is easier to assess changes in behaviour when the price change falls within the attribute level boundaries rather than outside them. The different levels are €1, €2, €3, €4, €5, and €6 respectively, ensuring equidistance in attribute levels and guaranteeing orthogonality between attributes.

Crowdedness of the train

Based on the literature review, it was also decided to include the crowdedness of the train as an attribute. The discomfort associated with standing during a trip instead of sitting could be a reason for a respondent to choose another trip (Tirachini et al., 2017; Tirachini et al., 2016). In the current NS system, crowdedness during a trip can be indicated at three different levels. When the train is quiet, a single green figure is displayed in the app, indicating that there are enough seats available. Two orange figures indicate that the train is moderately crowded and that there are still seats available. Finally, three red figures indicate that the train is crowded and that there may be no seats available. Therefore, the crowdedness of the train is expressed in three different ways. This is also the case in the choice experiment. The system with crowdedness figures is also used in the choice experiment. For the traveller, this is a recognisable symbol, ensuring that the choice made by the traveller reflects the choice they would make in reality. Figure 4.1 shows what the crowdedness symbols look like.

Figure 4.1: Crowdedness indicators

Variation in time

The timing of a respondent's journey can also serve as an indication of the value of a particular trip. This is clearly highlighted in the literature review (chapter 3), specifically in the subsection *Peak and off-peak*. The genesis of this thesis research is closely tied to the timing of a respondent's travel. This study examines how a traveller weighs factors such as the departure time. The focus is on peak hours, so a distinction is made accordingly. To ensure that respondents are indeed peak-hour travellers, the first part of the survey inquires about how often the respondent travels during peak hours on weekdays. The focus is on weekdays rather than weekends because travel patterns differ between weekends and weekdays (internal communication NS, 2024). Generally, NS divides time into half-hour intervals. The morning peak hours last from 06:30 a.m. to 09:00 a.m., resulting in five different time blocks within which someone can travel. In a previous study by A. Mastebroek, it was investigated to what extent a traveller is willing to depart half an hour earlier or later than usual. The conclusion of the study was that respondents were willing to travel just before or just after peak hours to obtain greater discounts. Based on A. Mastebroek's study, there is reason to believe that some travellers are willing to depart earlier or later than usual if it results in a financial benefit. Therefore, this current research also adds two time slots at the edges of peak hours. Ultimately, respondents in this study can choose from seven different time slots. These seven time blocks run from 06:00 a.m. to 09:30 a.m.

4.1.2. Constructing the choice sets

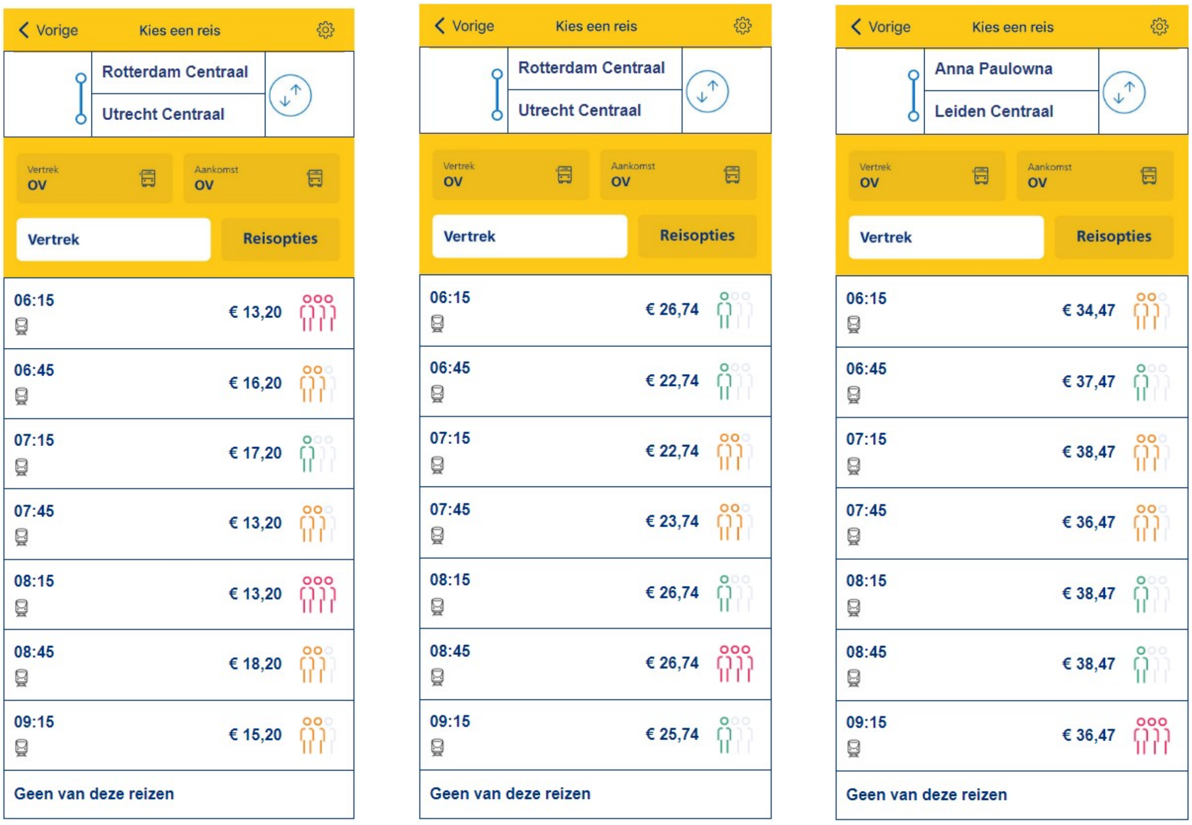
The choice sets were generated using the software Ngene. For each alternative, a level is chosen for the attributes. The software ensures that alternatives and choice sets are formed in such a way that no correlation arises between attributes and attribute levels. A rising price and increasing crowdedness result in a decrease in the utility of an alternative. If alternatives only vary in terms of time and crowdedness, a correlation arises if both crowdedness and price increase or decrease simultaneously. Such a relationship must be avoided because otherwise, it is impossible to determine which factor is causing a change in behaviour. This is indicated by Iles and Rose (2014) in their research.

In the first part of the survey, the respondent's usual departure time is asked. This departure time is not the same for every respondent. For example, if a respondent's most frequent journey always takes place at 07:00 a.m., it is not meaningful to present only two time slots in a choice task, such as those falling at 08:30 a.m. or 09:00 a.m. The respondent has no familiarity with these time slots and may be inclined to choose the opt-out option. Therefore, it was decided to present seven alternatives to the respondent when making a choice. This ensures that each time slot appears once in each choice task. If the respondent chooses the opt-out option in such a choice task, it indicates much more than in the previously mentioned example where the respondent can only choose between two alternative times. Price and crowdedness are varied across seven alternatives.

With a factorial design, it was ensured that the correlation between attribute levels is zero. However, there may still be a correlation between the alternatives themselves in terms of attributes and attribute levels. Ngene captures this as well, keeping this correlation low. In total, the Ngene design contains 36 choice tasks. According to Oehlmann et al. (2017), the optimal number of choice tasks per respondent lies between 10 and 15. To reduce the number of choice tasks, the 36 choice tasks are divided into three blocks, ensuring that each respondent completes twelve choice tasks. Appendix B shows what the respondents' choice tasks look like.

4.1.3. Presentation of choice alternatives

The choice tasks that the respondent encounters are derived from the NS travel planner app, designed to ensure that the respondent's stated choices mirror those they would make in real life. Figure 4.2 has been included for clarification. In this illustration, three distinct choice tasks are depicted. Figure 4.2a corresponds to a journey between Rotterdam Centraal and Utrecht Centraal, where the respondent travels in second class. The base price of a train ticket stands at €12.20. This choice task is rooted in set 30 of the choice sets, presented in appendix B. The second instance, figure 4.2b, mirrors the same journey as the first example, but the traveller opts for first class, evidenced by the higher price compared to the first example. Example 2 aligns with choice set 23 of appendix B. The final example, figure 4.2c, showcases a trip from Anna Paulowna to Leiden Centraal, with the respondent travelling in first class. Figure 4.2c is grounded in choice set 8 of appendix B. The varying prices of all three trips suggest that the choice tasks closely mirror real-life scenarios for the respondent.



(a) Example 1 **(b)** Example 2 **(c)** Example 3

Figure 4.2: Illustration choicetasks

4.2. Survey structure and distribution

The survey has been programmed by an external research agency. All questions have been devised by the author of this thesis. The questions were submitted to the external, and the external agency has programmed the survey questions and shared the results as a raw data file with the researcher. The structure of the survey is briefly explained in the following sections. Additionally, a section provides a brief discussion on the distribution of the survey.

4.2.1. Distribution

The respondents of the survey are approached via email by an external research agency, known as MWM2. This external market research agency is managing the NS Panel on behalf of NS. According to NS, this panel represents all train passengers in the Netherlands. Anyone can become a member of this panel by signing up online. There is no financial incentive to complete a survey; panel members do not receive compensation for participating in a questionnaire. However, prizes such as vouchers are occasionally raffled among the participants. The external market research agency ensures that 1200 respondents are found for the survey. Respondents are filtered based on various questions during the survey completion process. Firstly, respondents must be over 18 years old. If a respondent indicates being younger than 18 years old, they are redirected to the end of the survey. The questionnaire also includes a question about the respondent's travel frequency. If a respondent indicates during the survey that they travel less than 4 times a month during weekday rush hours, they are also directed to the end of the questionnaire. Finally, respondents are asked whether they pay for the journey themselves. The research agency attempts to maintain a 50/50 ratio within the sample. Therefore, at least half of the respondents partially or fully pay for the journey themselves. When the panel members receive an email, they receive information about the questionnaire. They are informed that the questionnaire is part of a graduation project by a student from TU Delft. Information about the length of the survey is also provided, estimated at 8 minutes. Additionally, a privacy statement is shared so that the respondent knows that the data is treated confidentially.

4.2.2. Content of the Survey

The questionnaire is divided into four distinct sections: questions about socio-economic and socio-demographic factors, questions about travel behaviour, a stated choice experiment, and a question related to the counterfactual check.

Personal Characteristics: in the first section of the questionnaire, respondents are asked about their personal characteristics. Specifically, questions cover gender, age, level of education, occupation, income, household composition, and other relevant factors. Justification for these questions can be found in chapter 3.

Travel Characteristics: the second section of the questionnaire addresses the respondent's travel behaviour. Respondents are asked how many weekdays they travel during the morning peak on a monthly basis, which indicates their travel frequency. Additionally, questions cover travel motives, the departure and arrival stations, and whether they travel first or second class. These questions provide insight into the respondent's travel distance and ticket price. This section also inquires about the mode of transport used by the respondent.

Stated Choice Experiment: in this section of the survey, the respondent participates in a stated choice experiment, which has been detailed in the preceding paragraphs. Each respondent is required to make a choice between different travel options 12 times. The 36 choice tasks are divided into 3 blocks. The external research agency ensures that there is an approximately equal number of respondents for each block to maintain the orthogonal design.

Status Quo Bias: in the final section of the questionnaire, all respondents are presented with the following information: *NS needs to deploy additional trains on Tuesdays and Thursdays during the morning peak hours to ensure there are enough seats for passengers. These additional trains are fully utilised for approximately 2-4 hours on those days. Outside peak hours, more than 7 out of 10 seats remain empty, so not all carriages are needed. However, it is not feasible to idle the extra trains and staff during off-peak hours. The costs for additional trains and staff are covered by train passengers.* Subsequently, half of the respondents is presented with the a statement (status quo) and asked how fair they find it. They then see another statement and are asked how fair they find it. The other half of the respondents also sees both statements, but in the reverse order. This group is also asked to rate the fairness of each scenario.

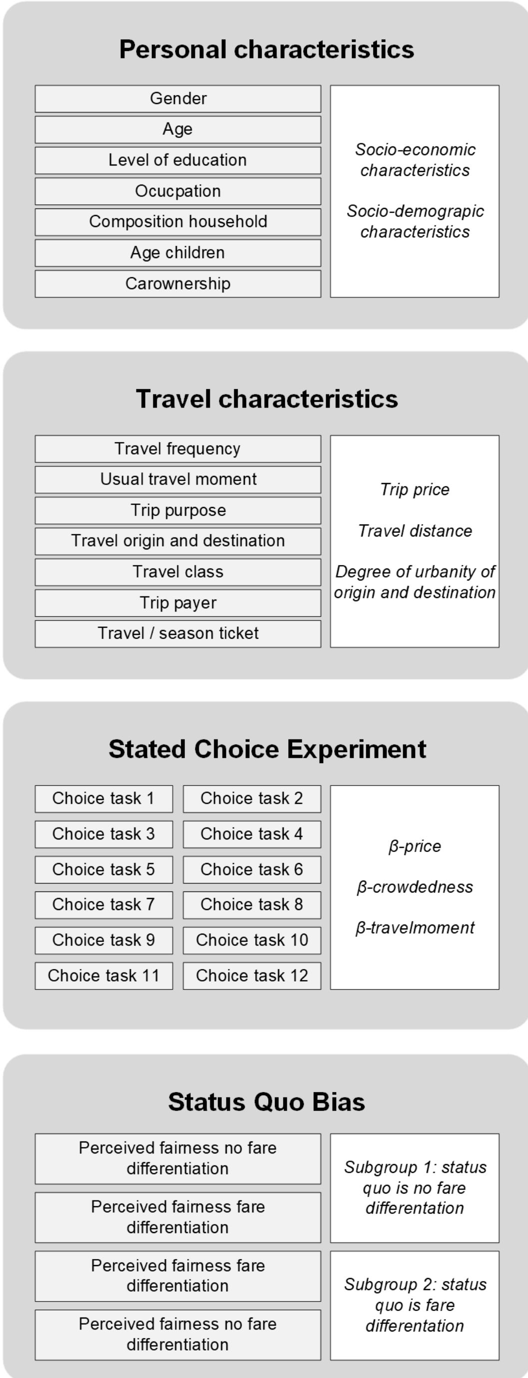


Figure 4.3: Research design

5
Data exploration

5.1. Data preparation

The data files obtained after the survey was completed are not yet ready for use in the analysis. The data is first cleaned. Additionally, some information is added based on the data. The following sections discuss what was involved in cleaning the data and what was part of the data preparation.

A portion of the respondents' answers is categorical, indicating differentiation in responses without measurable distance between them. The questions and their corresponding answers are of nominal scale. Therefore, nominal questions are dummy-coded (Hu et al., 2022). Dummy coding transforms a nominal variable into an interval variable. The dummy parameter is estimated relative to a reference point, which is one of the categories associated with a question. For each dummy variable, one of the answers serves as the reference point. It is crucial that the reference answers are logically chosen because the other dummy parameters are estimated around this reference point. For instance, if 'student' is chosen as the reference point for occupation, it would be counter-intuitive to select the highest income for 'income' as reference, since students often do not have high incomes. In this study, 'student' has been maintained as the reference point. Subsequently, for all other nominal variables, a reference point has been chosen based on the answer most frequently chosen by students. Appendix C graphically depicts the most frequently chosen answers by students. Additionally, this appendix clarifies how the nominal variables have been dummy-coded.

- Gender: In the response group, 57.9% of the participants identified as male and 40.9% as female. A total of 17 respondents chose not to disclose their gender or identified as other than male or female. These respondents were removed from the dataset because the group contained fewer than 30 people. Finally, male was coded as 0 and female as 1.
- Age and age categories: Not all respondents provided their exact age in the survey. These respondents were directed to a question asking for their age category. Most respondents answered this question. However, a dozen respondents did not answer the categorical question either. These respondents were removed from the dataset.

  To use age as a continuous variable, an integer value must be assigned to respondents who did not provide their exact age. This was done based on the mean, median, and mode of the age category selected by the respondent. A detailed explanation of this process is included in table C.1 of appendix C.
- Education: This variable has become a dummy variable. Four categories were distinguished: low-educated, medium-educated, high-educated, and other. Medium-educated is used as the reference category. Some respondents chose not to answer this question. An overview of the dummy coding can be found in appendix C, table C.2.
- Occupation: This variable has become a dummy variable. Five categories were distinguished: students, employees, entrepreneurs, people without labour income, and other. The students

category is used as the reference category.Some respondents chose not to answer this question. An overview of the dummy coding can be found in appendix C, table C.3.

- Income: This variable has become a dummy variable. Six categories were distinguished: very low income, low income, medium income, high income, very high income, and other. The very low income is used as the reference category. Some respondents chose not to answer this question. An overview of the dummy coding can be found in appendix C, table C.4.
- Household: This variable has become a dummy variable. Five categories were distinguished: single without children, single with children, together or maried with children, together or maried without children, and other. The single without children category is used as a reference. Some respondents chose not to answer this question. An overview of the dummy coding can be found in appendix C, table C.5.
- Age oldest/youngest child: This variable has become a dummy variable. Four categories were distinguished: kinds children younger than 4 years, children between 4 and 15 years, children aged 16 years and older, and other. The 'other' category is used as a reference. Some respondents chose not to answer this question or do not have any children. An overview of the dummy coding can be found in appendix C, table C.6 and table C.7.
- Car availability: The first way this variable was included in the analysis is as a continuous variable. Not every respondent (5) chose to answer this question and instead selected 'would rather not say'. To be able to work with a continuous variable, these respondents were removed from the dataset. One respondent indicated having 99 cars at their disposal. This number was corrected to 2. It may be more or fewer cars, but this adjustment does not distort the analysis.

  The car availability variable has also been dummy coded. This means categories were created based on the variable. The categories are simple: a respondent either has or does not have access to a car. A value of 0 indicates the respondent does not have access to a car, while 1 indicates the respondent has one or more cars available.
- Travel frequency: This variable can be used as a continuous variable in the analysis. Respondents' answers can range from 0 to 6. The difference between each answer is three trips; therefore, this variable can be considered a ratio variable.

  From this variable, a dummy variable has also been created. Two categories are defined: whether someone travels more or less than fifteen times per month by train.
- Travel moment: The respondent has indicated their usual departure time, which is a number between 1 and 7. For example, if someone always travels around 06:15, their usual departure time is 1, and if they travel at 09:15, it is 7. All other numbers correspond to half-hour intervals between 06:15 and 09:15. The departure time of a respondent is part of the utility function. This is modelled by adding an extra column in which a respondent scores either a zero or a one. If a respondent indicates that they always depart at time three, a one appears in this column at departure time 3, and the rest of the column is filled with zeros.

  An illustration of this can be found in Figure 5.1. This example shows a respondent who indicated always departing at 08:15, which corresponds to departure time 5. The following choice task is presented in table format. The table displays various attributes including price, crowding. For each choice option, the attribute level for that specific option is shown.

delta_price	crowdedness	travel_moment
1	3	0
4	2	0
5	1	0
1	2	0
1	3	1
6	2	0
3	2	0
-	-	-

Figure 5.1: Illustration attribuut values

- Trip purpose: This variable has become a dummy variable. Four categories were distinguished: business purposes, educational purposes, private purposes, and other. Some respondents chose not to answer this question. An overview of the dummy coding can be found in appendix C, table C.8.
- Urbanity origin and destination: In the survey, questions were included about the departure and destination stations of the traveller. These stations are located in specific places where the level of urbanisation is also known. As revealed in the literature review (chapter 3), the level of urbanisation is an indicator of a respondent's train usage. Higher levels of urbanisation often correlate with increased use of public transport. The level of urbanisation was determined using Python as follows: each station was linked to a locality using a dataset from the Statistics Netherlands (Centraal Bureau voor de Statistiek, 2023). This locality was then linked to the district where it is situated. The CBS dataset also includes the level of urbanisation per district, all based on data from the year 2023. Urbanisation level is measured based on the average address density in the vicinity. Five categories are distinguished, ranging from non-urban to very strongly urbanised. A non-urban area has an average address density of 500 addresses per km^2 or less, while a very strongly urbanised area has an average address density of 2500 addresses per km^2 or more.
- Class: This variable has become a dummy variable. Two categories were distinguished: travelling first class (dummy 0) or travelling second class (dummy 1).
- Payer: This variable has become a dummy variable. Four categories were distinguished: respondents who fully self-pay, respondents who do not self-pay, respondents who partially pay, and other. An overview of the dummy coding can be found in appendix C, table C.9.
- Card type: This coding is more complex than the other codings explained above. An overview of the dummy coding can be found in appendix C, table C.10. The card type can be divided into a single ticket or an NS subscription. The survey includes four types of subscriptions, including NS Reizen op Saldo and NS Flex. These subscriptions share several propositions (see appendix A). These propositions also exhibit several similarities.

  The first group of propositions includes Dal Voordeel and Dal Vrij. These propositions offer passengers 40% or 100% discount during off-peak hours. Traveling during peak hours is not advantageous for passengers with these propositions.

The following propositions can also be combined: Altijd Voordeel, Altijd Vrij, and Traject Vrij. For these propositions, passengers receive a discount of 40% to 100% outside of peak hours and 20%, 40%, or 100% during peak hours. For these travellers, travelling during peak hours is more advantageous compared to those who have chosen an off-peak proposition.

The propositions available to business travellers are divided into the categories Voordeel and Vrij. This distinction has been made in the dummy coding. For student cards in the data, only students with a weekly subscription were found, so there is no need to make a distinction.

Finally, there is also an 'other' option, meaning that someone does not choose any type of card. This option was chosen by 223 respondents, which constitutes a significant portion. For these respondents, it is unknown which card type they use for travel.

5.2. Data cleaning

The survey was conducted among respondents from May 28 to June 1 2024. In total, the survey was fully completed by 1419 people. One respondent had their starting station in Germany, and another had their destination station in Germany. These two respondents were excluded from the dataset. After all variables were checked and prepared for further analysis (see section 5.1), 1388 respondents remained out of the initial 1419.

It took respondents an average of 20 minutes to complete the survey. Initially, it was indicated that the survey would take approximately 8-10 minutes, so the average duration is twice as long. However, before concluding that the survey is too lengthy, it is necessary to identify any outliers that might skew the average. This was done using an Interquartile Range approach, detailed further in appendix C. Excluding these outliers, the average time to complete the survey is 6.37 minutes. It is possible that respondents who took longer to complete the survey may have opened it and filled it out at a later time.

Another aspect that was checked is whether respondents provided fictitious departure and destination stations. Appendix B includes a diagram showing how respondents could indicate their departure and destination stations. For instance, if respondents were not inclined to share their actual departure and destination stations in the survey, they might have randomly chosen stations that appeared on their screen at that moment. The stations which are presented when the respondent has not scrolled through the list of stations (figure B.1) are 's-Hertogenbosch, 's-Hertogenbosch Oost, 't Harde, Aalten, Abcoude, Aken, Aken West, Akkrum, Alkmaar, and Alkmaar Noord. Stations located in Germany have already been removed from the dataset and are no longer found in the records. For the other mentioned stations, it was checked whether they were entered as departure or destination stations.

One respondent was found who had 's-Hertogenbosch as the destination station and 's-Hertogenbosch Oost as the departure station. This respondent completed the survey in just over 2 minutes and selected options ranging from 06:15 to 08:15. Based on this, it could be assumed that the respondent quickly filled out the survey without making serious choices. On the other hand, the respondent did vary its bias status, suggesting he might have completed the survey seriously. It is challenging to make a definitive judgment about this respondent's answers based on the data. However, because it concerns only one respondent, it was decided not to exclude this respondent from the survey.

In section 4.1.2, it was explained that a total of 36 choice tasks have been created. Respondents are not required to complete all 36 tasks; instead, these tasks are divided into three groups, requiring each respondent to complete 12 tasks. An important consideration is to maintain equal numbers of blocks, ensuring orthogonality throughout the entire choice experiment. Prior to data cleaning, the distribution across the three blocks was 473, 472, and 474 respectively. Hence, the blocks were nearly perfectly balanced. However, post data cleaning, this distribution has altered. Thereafter, the distribution across the three blocks was 463, 464, and 461 respectively. This slight variance is not anticipated to impact data reliability adversely.

5.3. Descriptive statistics

In this section, descriptive statistics are presented using various tables and graphs. Part of the descriptive statistics involves comparing the sample with the population. In this case, the population is defined as the morning peak population. The composition is based on the 'NS traveller and trip survey'. The NS traveller and trip survey did not pose identical questions as the survey used to estimate parameters (the survey referenced in this study). The response options presented in the trip and traveller survey are sometimes more extensive than those in the current study. Therefore, the NS data has yet to undergo analysis and filtering.

At the start of the NS survey, nearly 90,000 records were in the dataset. From this group, individuals identifying with genders other than male or female were filtered out. Subsequently, only respondents aged 18 years and older were retained. Filtering then focused on travel frequency, excluding respondents who travelled less than once a week. Next, those not travelling during crowded hyper-peak periods were removed. Among the remaining respondents, those with multiple transport tickets were also excluded. Finally, respondents whose journeys partly occurred outside the Netherlands, particularly in Germany, and trips without specified stations were filtered out. After all these filtering steps, 6,277 respondents from the travel and ridership survey remain, who are compared with the sample respondents.

The records of the travellers have all been assigned two weighting variables. The first weighting variable is a figure that ensures the record is weighted according to personal characteristics. The second variable weights the respondent according to trip characteristics. This weighting creates an untainted representation of the ratio of travellers in the morning peak population. The weighted dataset has been internally verified by NS (by M. de Bruyn[1]) and marked as representative.

5.3.1. Sociodemographic and socioeconomic characteristics

In this section, the sociodemographic and socioeconomic variables considered include gender, age, education, occupation, income, household composition, age of children, and car ownership. Table 5.1 provides the characteristics of the respondents. It is immediately apparent from the table that men are overrepresented in the sample. The income and car ownership status of the population remain unknown. The other characteristics are elaborated upon in greater detail below. A graphical representation of the distribution of these personal characteristics is presented in figure C.4.

- Age: the mode for age in the sample is 55-64 years old. Compared to the population of morning peak travellers, this is not accurate. In the population, it is evident that the majority of travellers are between 18 and 44 years old. Thus, the sample is not representative of the population in terms of age. Relative to the population, there are insufficient young people and an excess of elderly individuals. It is known that individuals in the NS panel are generally older, and the age distribution is left skewed (M. de Bruyn, personal communication). This skewed representation is corrected by the class model, but only if age category is a significant covariate.
- Education: the mode for educational level within the sample is high. It is clear that this group is predominant in the sample, indicating that a significant portion of survey respondents are highly educated. This finding is consistent with the journeys and passenger research of NS, where highly educated individuals are also prominently represented. However, the sample exhibits fewer individuals with lower education levels and more with higher education levels compared to the population, resulting in a skewed representation. Consequently, the sample contains a higher proportion of highly educated individuals relative to those with lower education levels, in contrast to the population.

  The literature does not provide a definitive answer regarding the impact of education on public transport usage. One study suggests a higher level of education correlates with increased train usage (Zhao and Yuan, 2023), while another study presents an opposite finding (Dėdelė et al., 2020). Therefore, it is not feasible to determine in advance the influence of this factor.

[1]Sr Consultant Transportation Research at NS

- Occupation: the sample data indicates that the majority of respondents are employed. This aligns with the population as found in the NS study. However, the peak in the number of employees is higher in the sample than in the population. Additionally, it is noteworthy that the number of students in the sample is significantly lower than in the population. Generally, students do not pay for their own travel (appendix C), and thus may not respond to price changes. Therefore, it is crucial to account for this discrepancy.

  The sample also includes a substantial number of ’unemployed’ individuals. These individuals might be engaged in volunteer work, be homemakers, or be retired. Table 5.1 reveals that nearly half of the respondents in the sample are over 55 years old. It is possible that these individuals are retired, which could explain the peak in ’unemployed’ status.
- Composition household: The sample contains fewer singles and more partnered individuals, with or without children, compared to the general population. This aligns with expectations based on prior analyses. The student population is underrepresented, with most students identifying as single.

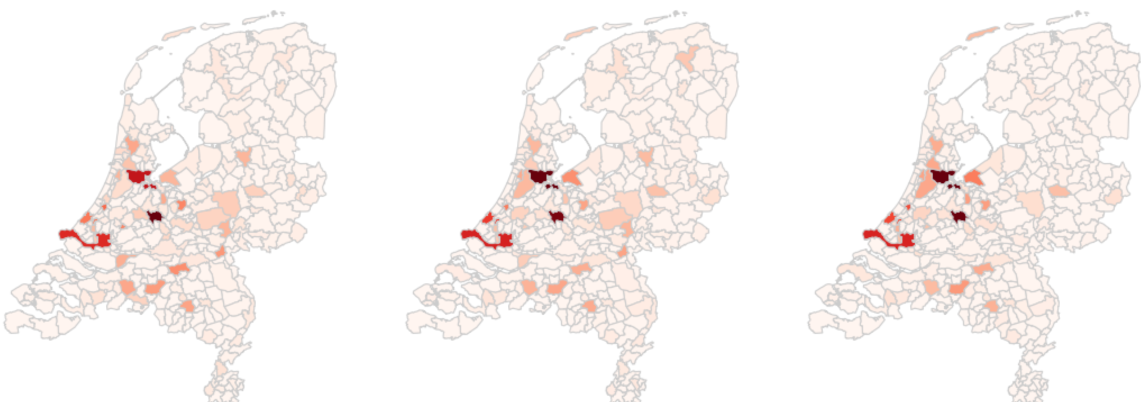
Table 5.1: Sociodemographic and socioeconomic characteristics of the sample

Characteristic	Categories	Frequency	Ratio... *in sample*	Ratio in population weighted... ...*by travellers*	...*by trips*
Gender	Man	813	58.6%	52.4%	51.3%
	Vrouw	575	41.4%	47.6%	48.7%
Age	18-24	97	7.0%	32.9%	26.6%
	25-34	195	14.0%	30.5%	29.6%
	35-44	159	11.5%	12.7%	14.4 %
	45-54	270	19.5%	11.6 %	14.3%
	55-64	447	32.2%	11.1%	13.0%
	65-74	187	13.5%	1.0%	1.8%
	75 +	33	2.4%	0.2%	0.3%
Education	Low	67	4.8%	10.4%	11.8%
	Middle	360	25.9%	24.7%	29.8%
	High	952	68.6%	63.6%	57.5%
	Else	9	0.6%	1.3%	0.9%
Occupation	Student	96	6.9%	24.3%	29.5%
	Employee	1085	78.2%	68.5%	65.7%
	Entrepreneur	75	5.4%	4.5%	3.0%
	Unemployed	127	9.1%	2.5%	1.5%
	Else	5	0.4%	0.2%	0.3%
Income	0-14.900	51	3.7%	-	-
	14.900-38.500	124	8.9%	-	-
	38.500-45.900	152	11.0%	-	-
	45.900-77.000	360	25.9%	-	-
	77.000+	467	33.6%	-	-
	wrns	234	16.9%	-	-
Household	Single	478	34.4%	48.7%	52.5%
	Single with child	20	1.4%	2.0%	1.8%
	Together with child	323	23.3%	17.8%	15.0%
	Together	553	39.8%	31.1%	30.4%
	Anders	14	2.0%	0.3%	0.3%
Age oldest	0-4	28	2.0%	4.5%	3.7%
	4-15	93	6.7%	3.5%	3.5%
	16+	213	15.3%	11.5%	9.2%
	wrns/none	1054	75.9%	80.5%	83.6%
Age youngest	0-4	26	1.9%	4.9%	3.9%
	4-15	97	7.0%	7.3%	6.6%
	16+	119	8.6%	7.2%	6.0%
	wrns/none	1146	82.6%	80.5%	83.6%
Carownership	0	475	34.2%	-	-
	1	705	50.8%	-	-
	2	176	12.7%	-	-
	3	26	1.9%	-	-
	3	5	0.4%	-	-
	5	1	0.1%	-	-

5.3.2. Travel characteristics

Table 5.2 provides a comprehensive overview of the various travel characteristics of the respondents. The precise travel times of the general population are not known. However, the population was pre-filtered based on travel time, ensuring that 100% of the population travels between 06:30 and 09:00. A graphical representation of the distribution of these travel characteristics is presented in appendix C.5.

- Travel frequency: It is challenging to make meaningful statements about this, due to unclear population figures. When weighted by travellers, it is evident that the majority of the population travels less than 16 times per month, whereas when weighted by trips, more than half of them travel by train 16 times or more per month. The sample indicates that almost 80% of travellers travel less than 16 times per month. This characteristic therefore remains ambiguous.
- Trip purpose: in the frequency table, it is observed that 85% of the travellers are commuting for work. Within this group, a significant portion are employed in salaried positions, while others are entrepreneurs. This large segment may not necessarily be a fully representative sample of the overall commuter population. In the population, this number appears to be lower. Upon examining the number of travellers journeying for educational purposes, it is evident that they are underrepresented in the sample compared to the population. It has previously been analysed that students are underrepresented in the sample, so this is not surprising.
- Card type: for these data, the same considerations apply as for travel frequency. The travel and passenger survey does not clearly indicate how each type of ticket is represented in the population. Therefore, comparing the sample with the population may be challenging. It is possible to request this data from NS, but the author of this thesis did not have access to that information. Consequently, little can be said about the type of ticket that would be of added value. What is noticeable, however, is that a relatively large proportion of tickets are off-peak discount tickets, even though these do not benefit the passenger during peak hours. It is possible that these individuals check in before 06:30 or after 09:00, as these time slots were also included as options in the survey.
- Urbanity origin and destination: in the sample, fewer individuals originate from extremely or strongly urbanized areas compared to the population, with a higher representation from moderately urbanized areas. Regarding destination, the sample and population exhibit a similar trend, indicating few notable differences between them. The maps in figure 5.2 illustrate the origins of the respondents. Darker shades indicate a higher number of respondents from those areas. Figure 5.2b shows the weighted origins of the population by traveller. Figure 5.2c displays the origins weighted by trips. Based on these figures, the sample appears to reasonably mirror the population. The sample aligns most closely with the population when weighted by travellers. Notably in the population, The Hague and Amsterdam, including the surrounding areas (Haarlemmermeer, Almere), are slightly underrepresented in the sample.



(a) Sample **(b)** Population weighted by travellers **(c)** Population weighted by trips

Figure 5.2: Heatmap of travel origin in sample and population

Table 5.2: Travel characteristics of the sample

Characteristic	**Categories**	**Frequency**	**Ratio...** *in sample*	**Ratio in population weighted...** *...by travellers*	*...by trips*
Travel frequency	<16 times/month	1098	79.1%	62.8%	42.0%
	>15 times/month	290	20.9%	37.2%	58.0%
Travel moment	07.45	274	19.7%	-	-
	07.15, 08.15	472	34.0%	-	-
	06.45, 08.45	291	21.0%	-	-
	06.15, 09.15	351	25.3%	-	-
Trip purpose	Business	1178	84.9%	74.3%	71.4%
	Education	95	6.8%	20.6%	25.5%
	Private	89	6.4%	4.9%	3.0%
	Else	26	1.9%	0.2%	0.1%
Urb. origin	Extremely	558	40.2%	42.2%	43.8%
	Strong	491	35.4%	36.9%	37.4%
	Moderately	187	13.5%	11.1%	10.0%
	Hardly	104	7.5%	7.5%	6.3%
	Not	48	3.5%	2.3%	2.6%
Urb. destination	Extremely	931	67.1%	63.9%	62.5%
	Hardly	351	25.3%	28.9%	29.7%
	Moderately	67	4.8%	4.0%	5.1%
	Hardly	26	1.9%	2.7%	2.2%
	Not	13	0.9%	0.5%	0.5%
Class	First class	221	15.9%	8.9%	4.5%
	Second class	1167	84.1%	91.1%	95.5%
Card type	Single ticket	6	0.4%	2.3%	1.1%
	Offpeak discount	342	24.6%	35.9%	19.1%
	Peak discount	195	14.0%	9.9%	22.8%
	Weekend discount	22	1.6%	2.4%	0.9%
	Travel on Balance	28	2.0%	0.0%	0.0%
	Business discount	113	8.1%	0.0%	0.0%
	Business free	377	27.2%	27.1%	26.3%
	Studentcard	84	6.1%	22.3%	29.8%
	Else	221	15.9%	0.0%	0.0%
Payer	Respondent	306	22.0%	-	-
	Third party	851	61.3%	-	-
	Partly respondent	206	14.8%	-	-
	Else	25	1.8%	-	-

6
Choice Model Estimation

As previously mentioned, an MNL model is a fundamental model for predicting people's choices. This generic model assumes homogeneity within the population. The principle is that everyone in the population has the same preferences and is equally sensitive to changes in attributes. In the MNL model, the attributes are examined without considering the various characteristics of the traveller population. This MNL model serves as the basis for the Latent Class Choice Model (LCCM). An LCCM is used to capture the heterogeneity of the sample and, indirectly, of the traveller population. While the MNL model assumes a single class, an LCCM distinguishes multiple classes.

6.1. Measurement instruments in the MNL and LCCM Models

To estimate and analyse both the single-class and multiple-class models, various instruments are employed. The utility function is the first instrument to be elaborated upon. Based on this function, the models are estimated. The second instrument utilized for both models is a transition matrix. The transition matrix is used to illustrate the journey a respondent chooses based on the estimated models. This section provides a detailed explanation of the utility function and the transition matrix.

6.1.1. Development of the utility function

The models (MNL and LCCM) utilise the utility function to calculate the utility of a specific choice option (see chapter 2). This utility function was developed iteratively by testing multiple options for the function. The function may be overly simplistic or potentially too complex. Based on certain criteria and transition matrices, the chosen utility function, which serves as the foundation for the models, are explained.

Goodness-of-Fit

The statistical criteria used for selecting a model include the Log-Likelihood, the ρ^2, the BIC, and the AIC. The Log-Likelihood indicates the explanatory power of the model. The closer the value of the Log-Likelihood is to 0, the better the model's predictive capability (Hauber et al., 2016). However, the Log-Likelihood value alone is insufficient for measuring Goodness-of-Fit. Another important indicator is McFadden's ρ^2. The higher this value, the better the Goodness-of-Fit. McFadden, the inventor of the MNL model and a Nobel Prize winner, suggested that a ρ^2 between 0.2 and 0.4 represents a very good fit of the model (Lee, 2013). Finally, the AIC and BIC are also indicators that can denote the Goodness-of-Fit of the model. Lower AIC and BIC values indicate better model performance and hence better Goodness-of-Fit. However, it should be noted that a more complex model inherently provides a lower BIC value. If a more complex model does not achieve a BIC improvement of at least 10, it is not considered superior to a less complex model, as a rule of thumb (Baier et al., 2019).

Parameter value and t-ratio

Parameter values can be interpreted as the amount of utility gained or lost with a 1-unit increase in the attribute. For each parameter, the t-value is also provided. This value is used to determine if a parameter is significantly different from zero. That is to say, if there were no relationship between the parameter and the choice made by the respondent, what is the likelihood that the observed value for this parameter would be found? If the t-value falls outside the range of $-1.96 < t$-value < 1.96, the probability of finding this value if there were no relationship between the parameter and the respondent's choice is 5% or less. If this is the case, the parameter is considered significant.

Estimating different functions

The indicators for the goodness-of-fit for each utility function are summarised in table 6.1. The detailed utility functions are provided in appendix D. The utility function was developed as follows:

1. The initial utility function tested estimates three parameters: β_{Δ_price}, β_{crowd}, and β_{travel_moment}. This function is presented in equation D.1. All parameters were found to be significant.
2. Subsequently, an interaction effect for price was included. As indicated in chapter 4, respondents saw trip prices in the survey that were based on the actual cost of their trip. These trip prices varied around the original cost of their journey. This interaction effect is incorporated in the subsequent utility function, with prices shown to respondents pivoted around the original trip price. The rationale behind this is that a change in trip price has a greater impact if the original price is low. For instance, an individual paying €50.00 for a trip is less sensitive to an absolute price change of €4.00 than someone whose trip initially costs €5.00. Therefore, the formula must reflect that a higher trip price results in a lower $\beta_{price\_interaction}$. For utility function D.2, all parameters are significant. With each additional parameter (in this case, one), the improvement in the BIC parameter is 15, which exceeds the threshold of 10.
3. Next, all parameters from the second equation were examined for the presence of a quadratic relationship. A quadratic relationship might exist when the utility decrease or increase for a respondent becomes increasingly steep or shallow with an increase in a parameter. For travel moment, a quadratic relationship cannot be estimated because the value in this column is either 0 or 1. It is either not possible to square the value for travel moment, or the square is the same as the non-quadratic value. All parameters are significant. However, the BIC value decreases by only 5.50 points, indicating that increasing the model's complexity does not provide sufficient additional information. Therefore, it was decided not to use quadratic components in the utility function for all parameters.
4. A utility function was then tested (based on equation 2) where a quadratic relationship was added only for the crowd parameter (and not for price or price interaction). This utility function achieved the lowest BIC value up to that point and each additional parameter significantly contributed to the BIC value (-15.36). At this stage, this utility function performed the best.
5. In the next utility function tested, equation 2 served as the basis with a quadratic parameter for Δ_price added. However, the BIC value increases compared to the other functions found.
6. The same applies when only a quadratic relationship is added to equation 2 for the indirect price parameter. The addition of this quadratic component results in a higher BIC value, indicating that the extra complexity does not provide additional information.
7. Finally, three equations were tested where two of the three basic parameters (see equation 1) have a quadratic relationship. For each combination, the extra parameters bring the Log-Likelihood closer to 0, but the BIC value increases, and the extra parameters do not provide additional information.

A total of nine utility functions were examined to determine which function best fits the criteria. The final utility function is detailed in equation D.4. This function represents a derivation of the linear and quadratic relationships. The rationale behind this derivation is that it allows for a more concise notation of the utility function as a whole. This iterative process has resulted in the following utility function:

$$V_i = (\beta_{p\_diff} + \frac{\beta_{p\_inter}}{base\_price}) \times \Delta price_i + (\beta_c \times crowd_i) + (\beta_{cQ} \times crowd_i^2) + (\beta_m \times moment_i) \tag{6.1}$$

In the choice tasks presented to the respondents, they always had the option to opt out. This means they could choose not to travel by train that day if it was too expensive or too crowded at the time they wanted to travel. They also indicated that they did not find a better travel option at a different time in the morning. Therefore, this opt-out option has a different utility function, as it is not associated with price, crowding, or time. To account for this, an alternative specific constant (ASC) was created. This utility function is quite simple, as it only involves an alternative specific constant. The utility function for the opt-out option is as follows:

$$V_{optout} = \delta_{optout} \tag{6.2}$$

In table 6.1, the scores of the utility functions across various goodness-of-fit criteria are presented. Additionally, a column has been included to show the increment in the BIC due to the extra parameters introduced. The final utility function demonstrates the lowest BIC value and contributes the most to the BIC value per parameter.

Table 6.1: Comparison Goodness-of-Fit for the utility functions

Utility function	Log-Likelihood	ρ^2	AIC	BIC	ΔBIC/Δparameter
D.1	-19037.23	0.4503	38082.46	38113.35	-
D.2	-19020.89	0.4508	38051.79	38090.39	-22.96
D.3	-18995.88	0.4515	38007.76	38069.53	-5.50
D.4	-19008.35	0.4512	38028.70	38075.03	-15.36
D.5	-19019.97	0.4508	38051.94	38098.26	7.87
D.6	-19018.61	0.4509	38049.22	38095.54	5.15
D.7	-19007.00	0.4512	38027.99	38082.04	7.01
D.8	-19006.22	0.4512	38026.45	38080.49	5.46
D.9	-19009.58	0.4511	38033.16	38087.20	12.17

Multicollinearity

Within the stated choice models employed in this thesis, multicollinearity may arise among the various independent variables. Multicollinearity refers to the linear relationship among two or more variables, which poses a significant data issue potentially undermining the reliability of the model parameter estimates (Alin, 2010). In simpler terms, when independent variables are so highly correlated, it becomes challenging for the model to determine which variable is causing the effect.

The independent parameters $\beta_{price\_difference}$ and β_{crowd} were programmed using Ngene software to ensure that their correlation consistently remains close to zero across all options. The question now is whether a correlation exists among the newly introduced parameters: $\frac{\Delta price_i}{base\_price}$, $crowd_i^2$, and $moment_i$. The correlation between the linear and quadratic parameters of crowd is likely to be very high, as the crowd parameter is squared. However, this correlation is not problematic since it concerns two components of the same variable (E. Molin, personal communication, December 6, 2018).

One method to detect multicollinearity is by computing a correlation matrix. A correlation matrix displays the extent to which the independent variables are correlated with each other. If this correlation is sufficiently high, it suggests the presence of multicollinearity. According to Hensher et al. (2005), a commonly accepted threshold for avoiding multicollinearity is a correlation level of 0.8.

The correlation matrix revealed that all correlations between the various variables remain below 0.70, indicating that the independent variables can be included in the utility function as distinct variables. All price interaction variables ($\frac{\Delta \text{price}_i}{\text{base\_price}}$ for $i \in [1, 7]$) are correlated with each other, but the correlation remains below 0.70. So none of the found correlations were concerning, thus multicollinearity is not present. The highest correlation observed (0.67) is between $\frac{\Delta \text{price}_1}{\text{base\_price}}$ and $\frac{\Delta \text{price}_6}{\text{base\_price}}$. This means that the utility function can be used without risk of model overfitting. A correlation matrix is provided in appendix D.2.

6.1.2. Transition matrices

A transition matrix describes the probability of transitioning between states in a stochastic process. It indicates the likelihood that an entity moves from state A to state B. Such a matrix has been constructed for the survey data. The first column specifies the usual departure time chosen by the respondent. Each subsequent row details how frequently a respondent has selected a particular departure time in the survey. Thus, the matrix represents the proportion of times a respondent selects a specific departure time, given the respondent's initial departure time.

Table 6.2: Transition matrix survey data

		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	80,32%	7,57%	3,06%	1,04%	0,50%	0,18%	0,23%	7,12%
	06:45	11,86%	69,30%	11,86%	3,10%	0,68%	0,51%	0,21%	2,47%
	07:15	1,25%	10,61%	69,17%	14,30%	2,21%	0,59%	0,13%	1,75%
	07:45	0,52%	1,19%	14,02%	68,00%	12,71%	1,55%	0,58%	1,43%
	08:15	0,23%	0,38%	0,99%	17,88%	65,53%	11,11%	1,60%	2,28%
	08:45	0,35%	0,26%	0,70%	2,28%	21,49%	61,58%	10,96%	2,37%
	09:15	0,40%	0,85%	1,51%	2,21%	6,33%	14,41%	59,69%	14,61%

The table demonstrates for example that 80.32% of passengers who typically depart at 06:15 still chooses the 06:15 departure time, under the circumstances that were presented in the stated choice experiment. There are numerous factors that could influence a passenger's decision to deviate from their usual departure time. In the survey, variables such as fare and crowdedness were varied. Consequently, it is not feasible to assert that, for instance, a change in fare directly leads to a behavioural adjustment. *The presented transition matrix is employed in the analysis as a reference point to compare the predictions that are made by the MNL model and the LCCM.*

6.2. Multinomial Logit Model

In this section, the results of the multinomial logit (MNL) model are presented and discussed. The MNL model does not account for the individual differences among respondents, and thus the results provide a general overview of the preferences of the sample population.

6.2.1. Parameter values MNL

Table 6.3 presents the parameter values, along with the t-ratio (0), which indicates their significance. The final column displays the parameter ranges, i.e., the minimum and maximum possible values of the parameters. The influence of crowdedness has been found to be significant both linearly and quadratically. The linear and quadratic components cannot be considered separately, as they are intrinsically linked.

The signs of the parameter values are consistent with expectations. The price parameter has a negative sign, indicating that as the price increases, the utility of the trip decreases. The value of the interaction variable is not a discrete number, as the interaction varies among respondents. The average trip price for the respondents in the sample is approximately €13.19. However, the median is about €10.60 and the mode is approximately €4.90. Therefore, it is incorrect to select a discrete value for the interaction variable. Assuming the mode, the range for this variable is from -0.48 to -0.08. Compared to the standalone price component, this range is roughly half. Similarly, crowding has a negative sign, meaning that as crowding increases, the utility of the trip decreases. This is consistent with the literature discussed in section 3. The range of this parameter is a combination of the linear and quadratic components. This implies that respondents perceive the difference between a green indication and an orange indication as less significant than the difference between an orange indication and a red indication.

Table 6.3: Parameters MNL model, $\rho^2 = 0.4512$

	Parameter value	*t-ratio (0)*	*Parameter range*
β_{p_diff}	-0.1436	-13.632	[-0.8616 ; -0.1436]
β_{p_inter}	-0.4013	-5.754	$[\frac{-2.4078}{base\_price} ; \frac{-0.4013}{base\_price}]$
β_c	-0.2794	-2.914	[-1.929 ; -0.4006]
β_{cQ}	-0.1212	-5.018	[-1.929 ; -0.4006]
β_m	2.9802	142.619	[0.000 ; 2.9802]
δ_{optout}	-1.7055	-18.365	[-]

The relative contribution of each parameter can be found in figure 6.1. This table shows that the contribution of the travel moment is relatively significant compared to the other parameters. This is particularly evident when considering that the value of the interactive price parameter is lower than currently displayed, as this figure is still divided by the original fare price. If the original price of the traveller's journey is greater than 1, the contribution of β_{p_inter} decreases. The minimum measurable price is the fare for one unit (for example, from 's-Hertogenbosch-Oost to 's-Hertogenbosch), which is €2.60. Thus, in the model, the contribution of β_{p_inter} is never be the extremes of the range.

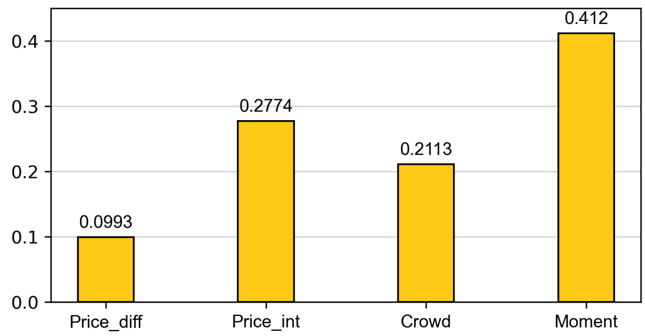


Figure 6.1: Relative importance attributes

6.2.2. Transition matrix Multinomial Logit Model

The transition matrix derived from this model is presented in table 6.4. For each respondent, the probability of choosing a specific time slot was calculated. For all respondents who typically depart at the same time, the average probability was computed.

The transition matrix associated with the MNL model is constructed based on these averages. Each respondent's usual departure time was identified, and for all respondents departing at the same time, the MNL model calculated the probability of choosing each potential departure time. Consequently, a probability value was generated for each respondent, indicating the likelihood of selecting a particular travel time. For all respondents departing at time i, the average probability of choosing departure time j was then computed. The figures in the transition matrix (table 6.4) are thus averages of the respondents' actual choices. Since the average is not always the most accurate measure, the median and mode were also considered. Notably, the diagonal of the MNL matrix aligns closest with survey values when averages are used, whereas the mode provides better predictive accuracy outside the diagonal. However, since the row sums of a transition matrix must equal 100%, the table presents only the average values.

For respondents indicating a departure at 06:15, the MNL model predicts that on average, 69.01% will choose to depart at 06:15. Survey data reveals a higher percentage, specifically 80.32%. For respondents who typically travel during the hyperpeak, the MNL model predicts that 68.04% will choose a journey at their usual time. Survey data indicates this percentage is 68.00%, demonstrating the MNL model's near-accurate prediction.

Table 6.4: Transition matrix MNL model

MEAN		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	69,01%	4,37%	4,51%	4,69%	4,53%	4,24%	4,61%	4,04%
	06:45	4,39%	68,35%	4,56%	4,83%	4,44%	4,77%	4,63%	4,03%
	07:15	4,53%	4,59%	68,01%	4,54%	4,62%	4,82%	4,80%	4,08%
	07:45	4,80%	4,56%	4,66%	68,04%	4,78%	4,32%	4,53%	4,31%
	08:15	4,25%	4,37%	4,55%	4,96%	67,94%	5,19%	4,45%	4,28%
	08:45	4,32%	4,63%	4,84%	4,30%	5,05%	67,89%	4,62%	4,33%
	09:15	4,77%	4,62%	4,99%	4,24%	4,56%	4,41%	68,30%	4,12%

When the MNL matrix is compared with the survey matrix, it is evident that around the hyperpeak, the model provides the best predictions (on the diagonal), and as time moves forward, the accuracy of the predictions diminishes in comparison to the survey matrix. Table 6.5 provides a clear summary of the differences (in percentage points) between the average predictions made by the MNL model and the actual choices. Red indicates that the MNL model underestimates, while blue indicates that the MNL model overestimates relative to the survey data. It is apparent from table 6.5 that the diagonal is the easiest for the MNL model to predict, while areas around the diagonal are the most challenging.

Table 6.5: Difference in percentage points between survey data and MNL predictions

DIFFERENCE		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	-11,31	-3,19	1,44	3,66	4,03	4,06	4,38	-3,08
	06:45	-7,47	-0,95	-7,31	1,72	3,76	4,26	4,42	1,56
	07:15	3,27	-6,02	-1,16	-9,75	2,42	4,23	4,66	2,34
	07:45	4,29	3,37	-9,36	0,04	-7,94	2,77	3,95	2,88
	08:15	4,02	3,99	3,56	-12,92	2,41	-5,92	2,85	2,00
	08:45	3,97	4,37	4,14	2,02	-16,44	6,31	-6,34	1,97
	09:15	4,37	3,77	3,48	2,03	-1,76	-10,00	8,61	-10,49

For the MNL model, the percentage of predictions that precisely match the respondents' actual choices has also been calculated. In 68.1% of the predictions, the MNL model assigns the highest probability to the option that the respondents actually chose. In 24.3% of the cases, the model assigns the highest probability to the option that deviates by half an hour (earlier or later) from the option chosen by the respondents. Thus, the prediction made by the MNL model is correct, or deviates by a maximum of half an hour from the actual choice provided by the respondent, in 92.4% of the cases.

6.3. Latent Class Choice Model

This section details the development of the LCCM. The first subsection describes the methodology used to determine the number of classes. The subsequent subsection explains which covariates are included in the analysis and the rationale behind their selection. The following section presents the estimated parameters, accompanied by figures illustrating the relative contribution of the parameters. Subsequently, the transition matrix for the combination of the four classes is presented. An additional valuable component of these sections is an overview of the Willingness-to-Pay (WtP), indicating what respondents are prepared to pay to depart at their preferred departure time.

6.3.1. Determining the amount of classes

The number of classes that best fits the data is determined without considering potential covariates. This recommendation comes from Bertrand and Hafner (2012). Earlier in this chapter, the measurements for determining goodness-of-fit was explained. An additional criterion has been added, namely class size. If a class becomes too small, it is not meaningful to add this extra class to the model. As a rule of thumb, a class size of at least 30 individuals is advocated, according to Paetz et al. (2019).

Table 6.6: Comparison Goodness-of-Fit for the LCCM

Classes	Log-Likelihood	ρ^2	AIC	BIC	Parameters	Smallest class
1 (MNL)	-19008.35	0.4512	38028.70	38075.03	6	1388
2	-16227.21	0.5315	32480.43	32580.79	13	626
3	-15230.06	0.5603	30500.13	30654.54	20	80
4	-14641.46	0.5773	29336.92	29545.37	27	80
5	-14523.80	0.5807	29115.59	29378.09	34	20

The above table indicates that an MNL model has the highest BIC value. This outcome was anticipated beforehand, because it is known that adding extra classes will always lower the BIC value. Adding a second class reduces the BIC and increases the value of ρ^2. The Log-Likelihood also decreases when the additional class is included. This pattern continues with the addition of a third, fourth, and fifth class to the model. However, including a fifth class results in the smallest class having fewer than 30 members. This violates the selection criterion requiring each class to have at least 30 individuals. Therefore, based on this analysis, the conclusion is to proceed with four classes. Another criterion to consider in conducting this analysis is the runtime which is needed to do the analysis. The researcher's device must be compatible enough to successfully execute a run with four classes. Without covariates, this proves feasible.

6.3.2. Determining the covariates

The device used for the analyses was unable to calculate the influence and interaction of all covariates simultaneously for four classes. The model provides a value for the parameter estimate but cannot report the standard error or t-ratio. The t-ratio is crucial for determining whether a parameter is significantly influential. Therefore, to account for all covariates, the number of classes must be reduced for a proper analysis.

When the model is estimated with three classes, the device still cannot compute the standard error and significance of the parameters. Consequently, a two-class model, incorporating all covariates, was estimated. In this case, the device successfully found an optimum and calculated the standard error and t-ratio for the covariates for each class. However, out of the 43 estimated covariate parameters, only two are significant. The covariates 'vertrek_0615' and 'pay_full' are significant, indicating that if someone departs at 06:15 and/or pays fully for the trip, their class assignment can be inferred. Beyond these, there is no basis for classifying respondents, besides a certain constant which is only applicable to the sample.

The log-likelihood of this model is -16173.49, ρ^2 is 0.5330, and the BIC value is 32881.61. This represents an improvement over the two-class model without covariates. However, it is not an improvement compared to a three- or four-class model without covariates. Due to the limited value added by a two-class model with all covariates, a four-class model with meaningful covariates was sought. Ultimately, only covariates that enrich the four-class model were included. The two-class model, including all covariates, is presented in tabular form in appendix E, where the t-ratio for each estimated parameter is also provided.

Separately testing covariates

To determine which covariates can be included in a four-class model, each covariate was initially added separately to the model. This approach means that the classification of respondents into the four classes is based on an independent variable delta (applicable only to the sample) in conjunction with a covariate. Table 6.7 illustrates the effect of each covariate on the goodness-of-fit criteria. The final column indicates the extent to which the BIC value changes with the addition of each parameter. A positive value signifies that the BIC value has not improved with the addition of the parameter, suggesting that no extra information is gained. Conversely, a negative value indicates that the BIC value has decreased due to the inclusion of the covariate in the model. For three variables, the value is reported as 'NA', indicating that the model was unable to find an optimum where both the standard error and significance for each parameter could be calculated.

Table 6.7: Addition of covariates

Covariate	Log-Likelihood	ρ^2	BIC	Parameters	$\triangle$BIC/$\triangle$parameter
Base	-14641.46	0.5773	29545.37	27	ref.
Urbanity origin	-14637.89	0.5774	29567.40	30	7.34
Travel class	-14640.68	0.5773	29572.98	30	9.20
Travel distance	-14641.43	0.5636	30518.06	30	324.23
Gender	-14608.41	0.5782	29574.47	30	9.70
Age	-14638.47	0.5774	29508.43	30	-12.31
Carownership	-14638.47	0.5774	29567.55	30	7.39
Travel moment	-14526.14	0.5806	29489.71	45	-3.09
Travel frequency	-14637.32	0.5774	29566.25	30	6.96
Occupation	NA	NA	NA	NA	NA
Payer	-14595.95	0.5786	29541.84	36	-0.39
Income	-14626.95	0.5777	29662.16	42	7.79
Trip Purpose	-14596.59	0.5786	29543.11	36	-0.25
Level of Education	NA	NA	NA	NA	NA
Comp. Household	-14630.52	0.5776	29640.07	39	7.89
Card type	NA	NA	NA	NA	NA

Handling possible interaction between covariates

Many covariates, in isolation, do not have a significant impact on predicting which class a respondent falls into. The first covariate that adds value to the model is age. By considering a respondent's age, it is partially possible to assign them to a specific class. Similarly, the time of travel for a respondent provides some insight into which class they might belong to. The Bayesian Information Criterion (BIC) value decreases when this covariate is included in the model. The same is true for the covariate 'payer'; knowing who pays for the trip partially helps in assigning respondents to a particular class. Additionally, 'trip purpose' could be a valuable predictor for classifying respondents.

Although some covariates, in isolation, increase the BIC value (indicating a deterioration in the model), this does not necessarily mean that these covariates are poor predictors for class assignment. For example, data show that ’travel distance’ alone does not add value to the four-class model. However, it is possible that a combination of specific covariates (such as travel distance and car ownership) might provide significant information. For instance, it could be that a ’long-distance traveller without a car’ can be assigned to one of the four classes, whereas knowing merely whether a respondent owns a car or not is insufficient for class assignment.

Despite being aware of these potential interaction effects, the decision was made not to estimate all possible interactions. Testing all possible combinations of covariates to identify potential interactions would require running the model 66 times. This would only determine whether two covariates interact with each other. In theory, significant information might only be added when three covariates are combined, making the analysis excessively complex. Therefore, it was decided to include only those covariates in the model that are known to provide valuable information on their own. These include age, travel moment, payer, and trip purpose.

Final decision about covariates

The covariates age, travel moment, payer, and trip purpose were all four included in one model, to decide whether they were still significant. Each covariate’s significance was assessed to determine its contribution to the model. It was found that all covariates except for age significantly contributed. Consequently, a revised four-class model was run again, but excluding age and incorporating only the covariates travel moment, payer, and trip purpose. In this iteration, travel purpose was also found not to be a significant contributor. Thus, travel purpose was removed from the model, leading to a subsequent run with only travel moment and payer as covariates.

In this final model, both of the covariates significantly influenced the class allocation. The Log-Likelihood of this model is -14508.96. Furthermore, the final BIC score is 29542.82, which is lower compared to a four-class model without covariates, suggesting that the model with two covariates is superior to a four-class model without covariates. Lastly, the value of ρ^2 is 0.5811, which is higher than that of the four-class model without covariates.

Given that the four-class model with the inclusion of the covariates ’travel moment’ and ’payer’ performs better across all goodness-of-fit criteria compared to a four-class model without covariates, it has been decided to proceed with the further analysis using the four-class model incorporating ’travel moment’ and ’payer’ as covariates.

6.3.3. Parameter values LCCM

The first notable observation in table 6.8 is that β_c and β_{cQ} are only significant for the second class identified in the LCCM. The parameters related to crowdedness are not significant for three out of the four classes. In the sample, these three classes represent approximately 66% of the respondents, who show no significant sensitivity to crowdedness. In contrast, around 34% of respondents in the sample are sensitive to crowdedness on the train.

The second observation is that the third class is the only one to assign a positive value to the opt-out option, indicating that they do not view the opt-out option negatively. The class membership model shows that these respondents mainly depart at 09:15. This explains their positive valuation of the opt-out option, as travellers departing at 09:15 seem more inclined to choose the opt-out option, which for them likely means ’departing at 09:45’.

Although the first class has the highest value for β_m, this does not necessarily mean that this class is the least responsive to changes in the price of a trip. The importance a respondent places on departing at their usual time depends on the values of $\beta_{p_{diff}}$ and $\beta_{p_{inter}}$. For example, if the value of $\beta_{p_{diff}}$ were equal to that of β_m, the utility of the respondent’s standard trip would decrease to zero with just a 1 unit increase in price. To determine the value of the departure time for each class, the Willingness-to-Pay has been calculated, as described in section 6.3.4.

Table 6.8: Estimates parameters LCCM with four classes, $\rho^2 = 0.5811$

	Class 1		Class 2		Class 3		Class 4	
	Est.	*t-ratio (0)*	*Est.*	*t-ratio (0)*	*Est.*	*t-ratio (0)*	*Est.*	*t-ratio (0)*
β_{p_diff}	-0.147	-2.305	-0.094	-4.319	-0.195	-4.242	-0.182	-7.409
β_{p_inter}	-0.551	-1.428	-0.973	-6.046	-1.049	-3.479	-0.769	-4.369
β_c	0.344	0.588	0.674	3.851	-0.362	0.681	-0.289	-1.520
β_{cQ}	-0.215	-1.498	-0.588	-12.223	-0.119	-0.873	-0.049	-1.029
β_m	6.146	46.456	2.980	42.744	3.369	23.422	0.638	7.147
δ_{optout}	-1.487	-2.325	-3.580	-16.318	1.665	3.426	-3.401	-15.253
Class membership								
α_{constant}	0.000	-	0.177	1.211	-3.620	-6.769	-0.965	-4.734
$\gamma_{tr\_moment\_0615}$	0.000	-	-1.783	-6.374	1.005	1.738	-1.499	-4.263
$\gamma_{t\_moment\_0645}$	0.000	-	-0.637	-2.816	-0.273	-0.349	-0.093	-0.343
$\gamma_{tr\_moment\_0715}$	0.000	-	-0.262	-1.276	0.120	0.168	0.011	0.042
$\gamma_{tr\_moment\_0815}$	0.000	-	0.144	0.687	0.501	0.725	-0.042	-0.146
$\gamma_{tr\_moment\_0845}$	0.000	-	0.431	0.514	-0.076	-0.066	0.274	0.732
$\gamma_{tr\_moment\_0915}$	0.000	-	-0.834	-2.716	2.487	4.381	0.065	0.212
γ_{pay_full}	0.000	-	0.364	-0.806	1.201	3.663	0.589	2.809
γ_{pay_part}	0.000	-	0.065	0.331	0.811	1.995	0.487	2.099
γ_{pay_else}	0.000	-	0.857	1.589	1.467	1.639	1.080	1.720
Class weight	**42.7%**		**34.1%**		**5.9%**		**17.3%**	

Classmembership

The first class serves as the reference class, meaning that all other classes are compared to it. The second class identified in the analysis is characterised by three personal characteristics that can be used as predictors for class membership. If a person usually travels at 06:15 or 06:45, they are less likely to be in the second class than in the first class. This also applies to a standard departure time of 09:15. In summary, individuals who depart before 07:00 or after 09:00 are more likely to be in the first class than in the second class.

The third class is associated with four parameters that can predict respondents' class membership. The first parameter is a constant ($\alpha_{constant} = -3.620$), which applies only to the sample and cannot be generalised to the population. For the sample, this constant suggests that respondents are less likely to be in the third class than in the first class. Another parameter used to predict class membership is the usual departure time. If someone typically departs at 09:15, they are more likely to be in the third class than in the first class. The same applies to the variables pay_full and pay_part; if an individual (partially) pays for the trip themselves, they are more likely to be in the third class than in the first class.

Finally, the fourth class also has a constant and three personal characteristics that can serve as predictors for class membership. The constant found here is also specific to the sample (similar to the third class). Furthermore, if someone usually departs at 06:15, they are less likely to be in the fourth class than in the first class. For the other parameters, the relationship is reversed: if an individual (partially) pays for their trip, they are more likely to be in the fourth class than in the first class.

An individual who usually departs at 07:45 and does not pay for their trip has a 1.1% probability of being classified in the third class and a 15.8% probability of being classified in the fourth class. If this person were to pay for their trip, the probability of being classified in the third class would increase to 3.2%, and the probability of being classified in the fourth class would rise to 24.7%.

An individual who does not pay for their trip and usually departs at 07:45 has a 41.5% probability of being placed in the second class and a 15.8% probability of being placed in the fourth class. In contrast, someone who usually departs at 06:15 has a 13.1% probability of being placed in the second class and a 6.6% probability of being placed in the fourth class.

6.3.4. Relative contribution parameters and Willingness-to-Pay

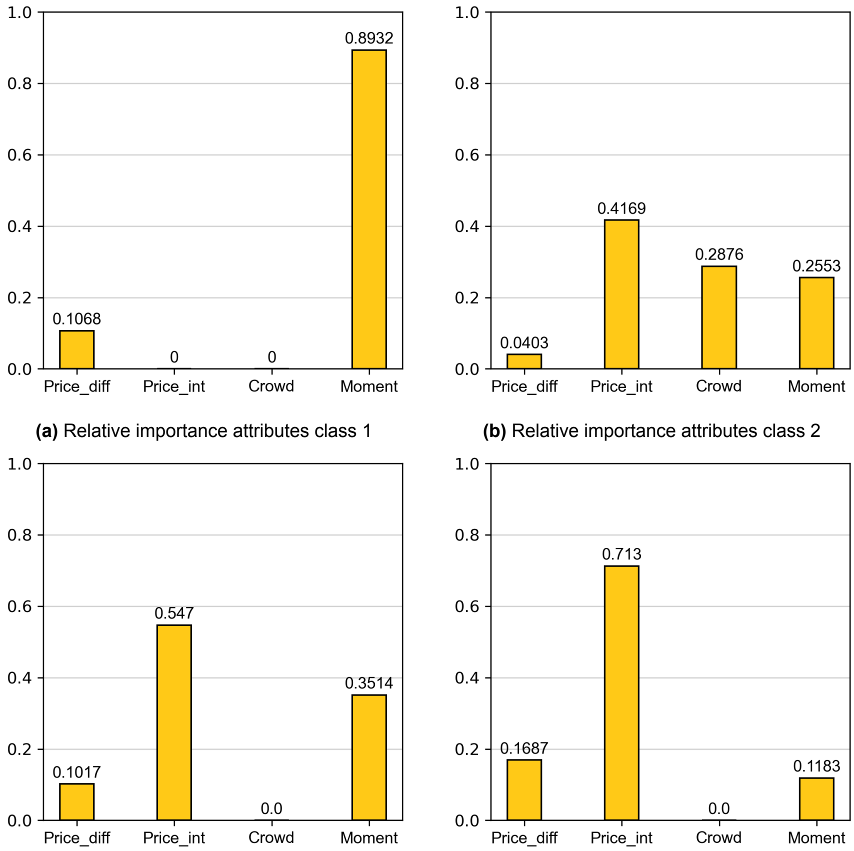
This section describes and graphically illustrates in figure 6.2 the relative contribution of various parameters in relation to one another. It also presents the Willingness-to-Pay (WtP) for departing at the respondent's standard departure time, expressed in euros. The Willingness-to-Pay indicates that if the trip price and crowdedness for all travel times remain zero, and the fare for the standard journey increases by the amount of the Willingness-to-Pay, then the respondent will be indifferent to their travel time choice, as earlier or later departure times will offer equal utility. The WtP is calculated by dividing the value of β_m by the sum of β_{p_diff} and β_{p_inter}. The value of β_{p_inter} is associated with the fare for the respondent. Consequently, it is not always possible to assign a specific value to the departure time, but it can be expressed as a function of the base fare.

The first class can be discussed relatively briefly, as it is not particularly complex. For this class, only the direct price parameter and the travel time contribute to the utility of a trip (see figure 6.2a). Travel time cannot be influenced, but the fare is an attribute that can be used to target this group of travellers. The attribute value of travel time is relatively high for this traveller, specifically 6.146. The attribute for fare change is -0.147. The total maximal contribution of the travel moment to the utility of a trip is 89%. The so-called Willingness-to-Pay for travel time for this traveller can be calculated using the formula $\frac{6.146}{-0.147}$, which equals €41.81. Only if the fare for the usual departure time of this traveller were to increase by €41.81 would the utility for the traveller's regular journey be reduced to zero. This class clearly indicates how it can be influenced, but it seems unrealistic that a ticket price would rise by €41.80.

The second class is influenced by changes in price as well as the crowding on the train. As illustrated in figure 6.2b, a change in price has a relatively small impact on the utility of the journey. The price parameter for the interaction with the standard fare also affects the utility of the journey. However, this impact is much smaller than shown in the figure, since the number should be divided by the original trip price. Travelmoment is of important value to the respondent and it is carefully weighed against the fare increase and the crowding on the train. The total maximal contribution of the travel moment to the utility of a trip is at least 25%. The β-value of travelmoment is 2.980. To express the value of the travel time in monetary terms, the travel time parameter must be divided by the price parameters. A price increase has both a direct and indirect effect, which cannot be considered independently of each other. Therefore, the value of the travel time, expressed in euros, is given by $\frac{2.980}{-0.094+\frac{-0.973}{base\_price}}$. This remains somewhat unclear; hence, figure 6.3 has been provided, which graphically depicts the Willingness-to-Pay for the various classes. At a trip price of €12.20, the WtP is approximately €17.00.

The third class is influenced by price and tends to adhere to the standard departure time. For this class, it is particularly noticeable that the interactive price parameter has a significant impact on the choices made by individuals. As with the second class, it is not possible to specify a concrete value for the Willingness-to-Pay (WtP), as this must account for the interactive price parameter. The Willingness-to-Pay is given by the formula $\frac{3.369}{-0.195+\frac{-1.049}{base\_price}}$. Similarly, figure 6.3 provides a clearer depiction of the WtP for this class. At a trip price of €12.20, the WtP is approximately €12.00.

Finally, it is observed that the fourth class exhibits a similar distribution between the direct price parameter and the interactive price parameter as the third class. However, the ratio of the relative contribution of the travel moment to the direct price parameter differs. For respondents in the fourth class, the travel moment is less significant than for respondents in the third class. Thus, this group is also quite attached to the usual departure time. As this group is also sensitive to the interactive price parameter, it is not possible to specify a concrete value for the Willingness-to-Pay. Figure 6.3 provides a clear depiction of the Willingness-to-Pay for these respondents. At a trip price of €12.20, the WtP is approximately €2.60.



(a) Relative importance attributes class 1

(b) Relative importance attributes class 2

(c) Relative importance attributes class 3

(d) Relative importance attributes class 4

Figure 6.2: Relative importance of the attributes per class

Willingness-to-Pay overview

From figure 6.3, it is evident which class is most sensitive to price and which class is less sensitive. As previously mentioned in this section, the Willingness-to-Pay (WtP) for three out of the four classes depends on the base fare of a train journey. The base fare is represented on the x-axis of figure 6.3, ranging up to a maximum of €25.00. A declining line in the figure indicates a higher WtP. The lower the y-value of the function, the higher the WtP of the respondent. The figure shows that travellers exhibit a higher WtP as the base fare increases.

For classes 2 through 4, the WtP increases as the base fare rises. At a base fare of €25.00, the WtP for the second class is above €20.00, approximately €14.00 for the third class, and around €3.00 for the fourth class. When considering only the impact of price, this figure clearly indicates that the fourth class has the lowest WtP, and thus the lowest willingness to pay to depart at the usual departure time. This appears to contradict table 6.8, which shows that the third class is particularly sensitive to price. However, because the value of the travel moment for class 4 is so small, the impact of the interactive price parameter is much stronger for the fourth class, resulting in the fourth class reacting most strongly to price changes.

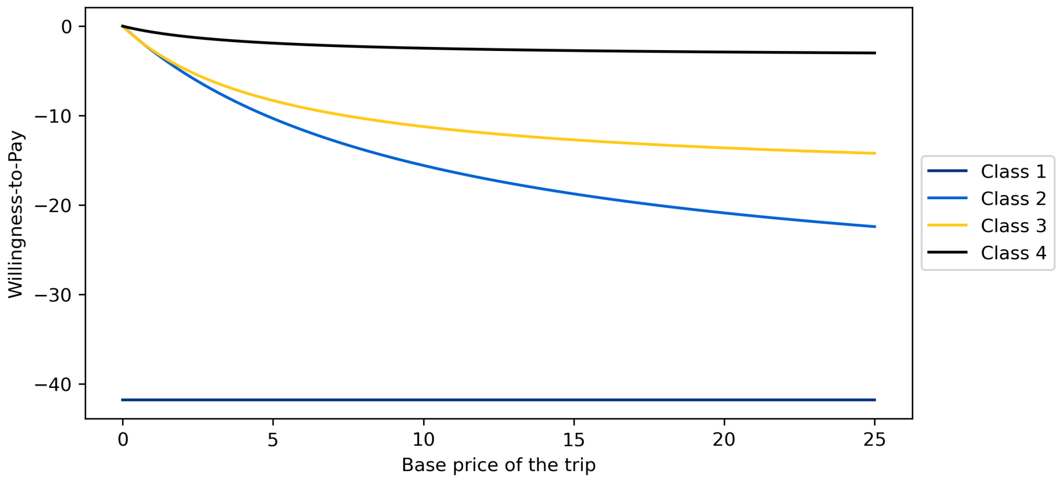


Figure 6.3: Willingness-to-Pay per class relative to the base price of a trip

6.3.5. Transition matrix Latent Class Choice Model

In this subsection, the transition matrix for the LCCM is presented. The transition matrix has been constructed as follows. For each respondent, the probability of ending up in a particular class was calculated based on the known covariates of the respondents. For instance, a respondent who indicated a departure time of 09:15 is significantly more likely to fall into the third or fourth class rather than the first class in comparison with someone who travels usually at 07:45. In this manner, the class into which each respondent is expected to fall was determined.

For each class, the probability of a respondent choosing a specific travel option, given the various circumstances, was calculated. This aligns with how choice probabilities are determined in the MNL model. Thus, for each class, the probability of a respondent selecting a particular travel option is known. To compute the final probability that a respondent will choose a specific travel option, the probability of the respondent being in a class is multiplied by the probability of selecting a travel option given that the respondent is in that class. The resulting probabilities are summed. Consequently, the final outcome provides the probability that a respondent will opt for a particular choice option.

Table 6.9: Transition matrix Latent Class Choice Model

MEAN		**Chosen departure time**							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	86,10%	2,06%	2,14%	2,14%	2,06%	2,00%	2,21%	1,28%
	06:45	4,49%	70,69%	4,68%	4,88%	4,54%	4,84%	4,85%	1,02%
	07:15	4,96%	5,06%	68,75%	4,79%	4,95%	5,22%	5,27%	0,99%
	07:45	5,19%	4,81%	5,21%	68,51%	5,23%	4,75%	5,18%	1,11%
	08:15	4,58%	4,79%	5,00%	5,35%	68,67%	5,74%	4,77%	1,10%
	08:45	4,66%	5,18%	5,43%	4,79%	5,63%	67,88%	5,28%	1,17%
	09:15	4,39%	4,35%	4,57%	4,11%	4,34%	4,24%	65,17%	8,83%

The final transition matrix is displayed in figure 6.9. It is evident that the values along the diagonal of the matrix are all estimated to be higher than those actually selected by the respondents (see figure 6.2). On either side of the diagonal, the model tends to underestimate the actual choices made by the respondents. The LCCM model correctly predicts 68.22% of the choices. Furthermore, in 24.31% of cases, the model's predictions are off by only half an hour from the actual choices made by the respondents, resulting in 92.53% of predictions being either correct or deviating by at most half an hour from the respondents' actual choices.

Table 6.10: Difference in percentage points between survey data and LCCM predictions

DIFFERENCE		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	5,78	-5,51	-0,92	1,11	1,57	1,82	1,99	-5,83
	06:45	-7,37	1,39	-7,18	1,77	3,86	4,33	4,64	-1,44
	07:15	3,70	-5,55	-0,42	-9,50	2,75	4,63	5,14	-0,75
	07:45	4,68	3,63	-8,81	0,50	-7,48	3,20	4,60	-0,32
	08:15	4,35	4,41	4,01	-12,53	3,14	-5,37	3,17	-1,18
	08:45	4,31	4,91	4,72	2,51	-15,87	6,30	-5,69	-1,20
	09:15	3,99	3,50	3,06	1,91	-1,98	-10,17	5,48	-5,78

In the currect section, the development of the LCCM and the results from the sample were thoroughly examined. The different parameter values per class were also discussed, revealing the willingness-to-pay for each class. The transition matrix (table 6.9) illustrates how the LCCM predicts for the entire sample. The next paragraph describes the LCCM's predictions for the behaviour of the identified classes in the choice experiments conducted in the survey.

6.4. Class profiles and transition matrices per class

In the previous section, the sample as a whole was analysed, whereas this section focuses on the behaviour of each class individually. Each class has been assigned a label that reflects its behaviour.

Class 1: The Rigid Traveller

The previous sections have established that first-class passengers are unaffected by crowdedness, responding only to direct price increases. This respondent, in particular, places such high value on their journey's utility that they would pay an additional €41.80 above the usual fare to maintain their preferred departure time. First-class has been selected as the reference for comparison with other classes. The transition matrix shows a probability of over 98% that this respondent will choose their usual departure time, regardless of crowdedness or price. This traveller can be classified as a 'Rigid Traveller,' as neither price nor crowdedness influences their choice of an alternative time.

Table 6.11: Transition matrix of the Rigid Traveller

MEAN		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	98,58%	0,22%	0,22%	0,22%	0,22%	0,23%	0,22%	0,08%
	06:45	0,23%	98,57%	0,22%	0,22%	0,23%	0,22%	0,22%	0,08%
	07:15	0,23%	0,22%	98,57%	0,22%	0,23%	0,23%	0,23%	0,08%
	07:45	0,22%	0,22%	0,22%	98,57%	0,22%	0,23%	0,23%	0,08%
	08:15	0,22%	0,23%	0,22%	0,22%	98,57%	0,23%	0,22%	0,08%
	08:45	0,23%	0,22%	0,23%	0,23%	0,23%	98,56%	0,23%	0,08%
	09:15	0,22%	0,22%	0,23%	0,23%	0,23%	0,23%	98,57%	0,08%

Class 2: The Semi-Flexible Peak Traveller

The previous paragraph has demonstrated that travellers in the second group make a careful trade-off between fare, congestion, and the standard departure time. Travellers within this class are likely to travel between 07:00 and 09:00 (table 6.8), indicating that they are peak-hour travellers. Despite travelling during peak times, this group is not willing to pay as much as the first group to depart at the standard travel time. Nevertheless, this group is prepared to pay a relatively substantial amount to depart at the usual departure time. This willingness is contingent upon the standard fare; for instance, on a journey priced at €12.20 (Rotterdam Centraal - Utrecht Centraal, second class), this group values departing at the usual time at €17.00. The transit matrix reveals that the probability that this class opts for their most frequent travel time is around 60%. This also indicates that individuals in this class are peak-hour travellers who carefully weigh fare, congestion, and the standard departure time. Consequently, this group is referred to as the 'Semi-Flexible Peak Traveller'.

MEAN		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	60,84%	6,15%	6,61%	6,79%	6,02%	5,49%	7,21%	0,89%
	06:45	5,62%	60,13%	6,44%	7,26%	5,76%	6,98%	6,98%	0,84%
	07:15	6,34%	6,65%	59,90%	6,02%	6,28%	6,95%	7,05%	0,81%
	07:45	6,91%	6,00%	6,99%	59,54%	6,97%	5,74%	6,82%	1,02%
	08:15	5,59%	5,88%	6,53%	7,44%	59,38%	8,27%	5,89%	1,02%
	08:45	5,32%	6,75%	7,25%	5,74%	7,75%	59,33%	6,90%	0,96%
	09:15	6,96%	6,75%	7,80%	5,25%	6,34%	5,82%	60,21%	0,87%

Table 6.12: Transition matrix of the Semi-Flexible Peak Traveller

Class 3: The Off-Peak Traveller

In the previous paragraph, it was made clear that the third class within the LCCM is a group that weighs price and departure time but does not consider crowdedness. Notably, it has been observed that this group rates the opt-out option positively. This indicates that this group is inclined to opt out of all available choices. The class membership model reveals that this group primarily consists of individuals who travel after the morning peak, around 09:15. It has also become apparent that these individuals are required to pay fully or partially for their journey. If someone's standard departure time is 09:15, and both this journey and the one at 08:15 become more expensive, it is logical that this traveller would prefer to travel at 09:45 rather than at 08:45 or 09:15, particularly since they are paying for the journey themselves. Thus, the opt-out option is likely to receive a positive evaluation. The Willingness-to-Pay for a journey costing €12.20 (Rotterdam Centraal - Utrecht Centraal, second class) is lower than that for first and second class, approximately €12.00. According to the transition matrix, the probability that this respondent opts for the opt-out option in about 30%. Furthermore, the transition matrix shows that the probability that the usual departure time is chosen is around 55%. Given that this group travels late, is not strongly tied to the usual departure time, and relatively frequently opts for travel outside the peak hours, this class is designated as the 'Off-Peak Traveller'.

MEAN		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	57,49%	2,23%	2,23%	2,19%	2,21%	2,27%	2,14%	29,23%
	06:45	2,29%	56,85%	2,20%	2,21%	2,29%	2,19%	2,26%	29,70%
	07:15	2,23%	2,16%	55,79%	2,17%	2,27%	2,24%	2,33%	30,81%
	07:45	2,19%	2,17%	2,12%	54,36%	2,15%	2,25%	2,26%	32,49%
	08:15	2,14%	2,25%	2,19%	2,15%	54,13%	2,24%	2,22%	32,66%
	08:45	2,29%	2,09%	2,26%	2,23%	2,21%	53,61%	2,20%	33,11%
	09:15	2,17%	2,24%	2,29%	2,23%	2,27%	2,24%	56,18%	30,39%

Table 6.13: Transition matrix of the Off-Peak Traveller

Class 4: The Price-Sensitive Traveller

From the previous paragraph, it has been established that this class is solely sensitive to price adjustments and not to potential crowdedness on the train. Compared to other classes, price is a significant factor for these passengers in contrast to the departure time. The class membership model indicates that this class comprises travellers who depart later than 06:15, thus travelling during peak hours. Moreover, the class membership model also reveals that these individuals are likely to pay for their journey either fully or partially themselves. While there are fewer self-paying passengers in this class compared to the third class, there are still more than in the first class. The Willingness-to-Pay (WtP) for this class is the lowest among all classes. For a journey costing €12.20, the WtP is €2.60. This means that with a standard fare of €12.20, the utility for the most typical journey of passengers in this class would be zero if the price increases by €2.60. Other classes exhibit relatively higher WtP scores compared to this last class. This is clearly illustrated by the transition matrix. Whereas the diagonals of the transition matrices for other classes were reasonably dark (indicating that respondents often choose their usual departure time), the transition matrix for the fourth class shows that respondents frequently switched their departure time. The probability that this class opts for the usual travel time is around 23%; due to the price fluctuations introduced in the choice experiment, respondents have relatively often chosen a different travel time than their usual one. Therefore, respondents in this class are easily influenced by price adjustments and quickly opt for an alternative travel time. Hence, this class is designated as the 'Price-Sensitive Traveller'.

MEAN		**Chosen departure time**							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	23,78%	12,39%	12,68%	12,45%	12,64%	12,64%	12,65%	0,77%
	06:45	12,68%	23,32%	12,59%	12,51%	12,74%	12,66%	12,72%	0,77%
	07:15	12,63%	12,53%	23,31%	12,45%	12,75%	12,75%	12,78%	0,80%
	07:45	12,64%	12,57%	12,55%	23,12%	12,71%	12,79%	12,76%	0,85%
	08:15	12,34%	12,84%	12,55%	12,47%	23,46%	12,83%	12,66%	0,85%
	08:45	12,74%	12,41%	12,74%	12,49%	12,73%	23,32%	12,71%	0,86%
	09:15	12,62%	12,51%	12,69%	12,50%	12,72%	12,67%	23,50%	0,79%

Table 6.14: Transition matrix of the Price-Sensitive Traveller

6.5. Status quo bias

6.5.1. From current system to new system

As previously explained in chapter 4, a question was added to the survey to investigate status quo bias. The concept of status quo bias, detailed in chapter 3 examines whether people tend to favour the alternative that represents the current situation. In the survey, 697 individuals were presented with the following statement: *NS needs to deploy additional trains on Tuesdays and Thursdays during the morning peak hours to ensure there are enough seats for passengers. These additional trains are fully utilised for approximately 2-4 hours on those days. Outside peak hours, more than 7 out of 10 seats remain empty, so not all carriages are needed. However, it is not feasible to idle the extra trains and staff during off-peak hours. The costs for additional trains and staff are covered by train passengers.*

These respondents are asked to imagine that in their current situation, they only have to pay for a journey based on the distance they travel. They were asked to assess this fare structure in terms of fairness. The following question was posed to them: *Imagine the currect fare system is as follows: the price for a train journey is calculated based on the distance travelled. The price for a particular route is the same during peak hours and off-peak hours. The extra costs incurred for additional trains and staff during peak hours are distributed among all train passengers. How fair do you think this is?* Respondents were able to indicate on a seven-point Likert scale whether they found this fair. On average, this statement scored 4.27 among the first group of respondents, indicating that they generally find it more fair than unfair (4 = neither fair nor unfair).

Next, the following statement is presented to this group of respondents, who can also evaluate this statement on a 7-point Likert scale: *Imagine the fare system from the first statement is replaced by a new fare system as follows: the price for a train journey is calculated based on the distance travelled and the time of travel. The price for a particular route is higher during peak hours than during off-peak hours. The extra costs incurred for additional trains and staff during peak hours are distributed among peak-hour passengers. As a result, 20% of journeys become more expensive than before because they fall during peak hours. 80% of journeys become cheaper than before because they fall outside peak hours.* On average, this respondent group rates the second statement at 4.20, indicating they generally perceive it as more fair than unfair.

The mean difference between the perceived fairness of the two statements is 0.070, with a standard deviation of the paired differences of 3.053. The two-sided p-value, which is 0.035, falls below the 0.05 threshold. This suggests that the observed difference between the two statements is not due to chance; rather, it indicates that, on average, respondents have consciously deemed tariff differentiation to be less fair compared to the absence of tariff differentiation.

6.5.2. From new system to current system

The other group of respondents (691 individuals) viewed the same opening statement as the first group. Subsequently, this subgroup was also asked about their perception of fairness. However, this subgroup was asked to imagine that the new fare structure (based on distance and quality) is the current situation. The following was asked to the respondents: *Imagine the currect fare system is as follows: the price for a train journey is calculated based on the distance travelled and the time of travel. The price for a particular route is higher during peak hours than during off-peak hours. The extra costs incurred for additional trains and staff during peak hours are distributed among peak-hour passengers. How fair do you think this is?* The respondents, on average, rated this as 4.26, indicating they consider it rather fair than unfair.

Next, the subgroup of respondents was shown the following: *Imagine the fare system from the first statement is replaced by a new fare system as follows: the price for a train journey is calculated based on the distance travelled. The price for a particular route is the same during peak hours and off-peak hours. The extra costs incurred for additional trains and staff during peak hours are distributed among all train passengers. As a result, 20% of journeys become cheaper than before because they fall during peak hours. 80% of journeys become more expensive than before because they fall outside peak hours.* Respondents also evaluated this statement, giving it an average score of 3.26 in terms of fairness.

The mean difference between the perceived fairness of the two statements is 0.997, with a standard deviation of the paired differences of 2.764. The two-sided p-value is less than 0.001, which is below the threshold of 0.05. This suggests that the observed difference between the two statements is not due to chance; rather, respondents, on average, have consciously chosen that they perceive rate differentiation as fairer than no rate differentiation.

Overview status quo bias

From the preceding analysis, it is apparent that the respondents' current status quo significantly affects their perception of fairness concerning the implementation of new policies. The first group rates 'no fare differentiation' at 4.27, while the second group rates it at 3.26. The value for the independent t-test is significant, with a two-sided p-value of less than 0.001. This indicates that the difference between the groups is not due to chance but rather that the status quo has influenced the evaluation of the statements. For the tariff system where fare differentiation is applied, the first group rates it at 4.20, and the second group rates it at 4.26. Again, the difference is significant, as the two-sided p-value of the independent t-test is 0.044, which is below the 0.05 threshold. This further suggests that the status quo plays a role in the evaluation process. Table 6.15 provides a clear summary of the values obtained.

Table 6.15: Overview Status Quo Bias

	No Fare Differentiation	*Fare Differentiation*	Paired t-test
Subgroup 1	4.27	4.20	0.035
Subgroup 2	3.26	4.26	<0.001
Independent t-test	<0.001	0.044	

This overview illustrates that the two different subgroups have distinct perceptions regarding the two tariffing methods. The first subgroup, which assumes that the standard situation does not involve tariff differentiation, considers tariff differentiation less fair than what they perceive as the current situation. It should be noted that the difference is minimal, only 0.07 points. In contrast, the second subgroup finds tariff differentiation one full point fairer than no tariff differentiation.

7

Application of the analysis

In this chapter, a practical application is developed, grounded on the data and analysis from chapter 6. A transition matrix for the entire sample is estimated to predict the behaviour of the sample. The anticipated behaviour under fare differentiation is also presented for each class.

7.1. Effect of the implementation of fare differentiation

Sample versus population

In this section, the potential impact of tariff differentiation on the sample is described. It is crucial to emphasise that the effect observed in the *sample* may not necessarily reflect the impact on the peak-hour *population*. The likelihood of this discrepancy arises because a specific constant used for class allocation is applicable only to the sample and not to the overall population. This constant partially determines the class into which a respondent is categorised. The sample consists of four distinct classes, as outlined in table 6.8. For instance, approximately 42.7% of the sample can be classified into the first class. However, the proportions found in the sample do not necessarily align with those of the classes within the actual peak-hour population. The population may be distributed differently across classes compared to the sample, and therefore, the relationships identified in this chapter cannot be directly applied to the population.

Base trip price

The predictions regarding the behaviour of the sample are based on the findings from the LCCM. As shown in table 6.8, the sensitivity to price for certain classes is partially dependent on the respondent's initial fare. The predictions which are described in this chapter are based on respondents of the survey, and hence the personal characteristics of the respondents of the survey.

To measure the impact of fare differentiation, the base trip price is standardised across all respondents. The selected base fare for each respondent is €12.20. This base fare was chosen because the highest crowdedness occurs on routes between cities in the Randstad. A journey between Rotterdam and Utrecht costs €12.20, a journey between Utrecht and Amsterdam costs €8.80, and a journey between Rotterdam and Amsterdam costs €17.90. The median fare in this case is €12.20, which has been chosen as the standard fare for all respondents. The standard departure time of respondents from the survey remains unchanged. Additionally, no alterations have been made regarding who pays. Consequently, the method for classifying respondents remains unchanged.

Parameter values of $\triangle$Price and Crowdedness

To accurately predict the impact of fare differentiation, it is crucial that the values for $\triangle$Price and the level of crowdedness align with reality. These parameter values are used to make predictions that reflect actual conditions, and it would therefore be illogical to select random values for these parameters.

Chapter 6 demonstrates the predictive power of the LCCM, and in chapter 7, the LCCM is employed to make predictions.

Table 7.1 outlines how crowdedness has been modelled and what price adjustments have been applied for different time slots within the morning peak period. These price adjustments reflect the potential adjustments which will hold when fare differentiation is applied. The level of crowdedness has been determined based on internal data from NS, corresponding to the levels observed during the morning peak hours in recent years. The peak in crowdedness occurs between 07:00 and 08:30, with the highest peak period between 07:30-08:00 often referred to as the 'hyperpeak'. The half-hours adjacent to this are known as the 'shoulder peak'. The prices which would be applicable in case of fare differentiation has been set according to a presentation given by T. Smit during a technical briefing to a committee of the Ministry of Infrastructure and Water Management (direct, 2023).

Table 7.1: Attribute values fare differentiation

Travel moment	*06:15*	*06:45*	*07:15*	*07:45*	*08:15*	*08:45*	*06:15*
$\triangle$*Price*	-€0.50	+€0.50	+€1.50	+€2.50	+€1.50	+€0.50	-€0.50
Crowdedness	1	2	3	3	3	2	1

Reference situation and new situation

To evaluate the effectiveness of fare differentiation, two scenarios are compared. The first is the reference scenario, where fare differentiation is not applied. Only crowdedness is modelled as shown in table 7.1, and $\triangle$Price is zero. This scenario represents the current real-world fare structure and crowdedness. Subsequently, the LCCM is used to predict how the sample would behave if fare differentiation were implemented. Unlike the reference scenario, the second scenario does involve fare increases and decreases at different times. During the hyperpeak, travelling becomes more expensive, while the cost decreases for those who travel earlier or later than the hyperpeak. Table 7.1 illustrates how prices vary across different time periods.

In the following paragraph, the effect on the sample is presented. Preceding this, a grey box provides essential instructions on how to interpret the tables. It is crucial to read this box as it offers a clear and necessary explanation of how to interpret the tables of paragraph 7.1.1.

How to read the tables of section 7.1.1

The tables presented in section 7.1.1 illustrate the differences between the reference scenario and the new scenario. It is crucial to interpret these tables correctly. This information box has been added to provide a clear explanation of how the figures should be interpreted.

Each cell presents the extent to which the new scenario deviates from the previous one. This deviation is expressed as a percentage of growth or decline relative to the reference scenario. A positive figure indicates that the number of people choosing a particular travel time has increased, while a negative figure signifies that fewer people will choose that specific travel time.

It is important to understand the precise implications of these figures. The most practical approach is to read the tables column by column. To illustrate this, consider the following example:

- Assume there are 100 people who typically depart at 07:45. In the reference scenario, 53% of these individuals actually choose to travel at 07:45. This results in 53 people opting for the 07:45 departure time. Upon the implementation of peak pricing, this number decreases by 9%, as shown in table 7.2. This means that of the 53 people, approximately 48 would continue to travel at 07:45, while 6 would choose a different departure time. A 9% decrease thus results in a reduction of 6 people during the hyperpeak.
- Now, suppose there are also 100 individuals whose standard departure time is 06:45. In the reference scenario, 3.1% of these individuals opt for the 07:45 departure time, equating to 3 people. When peak pricing is applied, this number decreases by 37%, as shown in table 7.2. For 3 people, this means that approximately 2 would continue to travel at 07:45, while 1 would choose another departure time. A 37% decrease, therefore, leads to a reduction of 1 person during the hyperpeak.
- If there were no additional figures to consider, it could be concluded that the total number of travellers during the hyperpeak decreases by 6+1 individuals, resulting in a reduction of 7 people. Proportionally, this represents 7 out of 56 (53+3) individuals, which equates to 13%.

This demonstrates that **the effect of fare differentiation on the entire hyperpeak is at least as significant as the smallest effect measured in the 07:45 column.** This holds true regardless of circumstances, and it is where the most meaningful insights can be drawn. Therefore, when analysing and studying the tables, one should look for the smallest effect measured in the 07:45 column. This represents the minimum impact that fare differentiation will have on overall crowdedness during the hyperpeak.

7.1.1. Effect on the sample

The effect of fare differentiation is evident across the entire sample. The outer edges of the peak period (so travelling before 06:30 or after 09:00) become more attractive, while the hyperpeak, specifically travelling at 07:45, becomes less appealing. The shoulder peak will also see a significant decrease in crowdedness, as the number of travellers diminishes across all time slots. Conversely, the outer edges of the peak period are expected to experience increased crowdedness. For each standard departure time, more travellers will now choose to travel at the outer edges of the peak period due to the lower cost.

Among travellers whose standard departure time is 07:45, the proportion choosing this habitual departure time decreases by 8.4%. Those 07:45 travellers who no longer opt for their standard departure time predominantly select an off-peak travel option, which is €0.50 cents cheaper. A very small proportion will choose the opt-out option. Notably, among those who typically depart at 09:15, fewer now choose the opt-out option. Implementing fare differentiation would, therefore, have the effect of reducing crowdedness by at least 8.4% during the hyperpeak in the sample.

Table 7.2: Effect of implementation of fare differentiation on whole sample

IMPACT FARE DIFFERENTIATION		**Chosen departure time**							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	1,1%	-4,5%	-23,3%	-39,3%	-23,3%	-4,5%	16,1%	-5,8%
	06:45	23,2%	-0,7%	-19,0%	-36,2%	-19,0%	1,5%	23,2%	12,6%
	07:15	15,0%	-1,8%	-5,0%	-34,2%	-17,1%	-1,8%	15,0%	16,6%
	07:45	17,9%	0,8%	-14,7%	-8,4%	-14,7%	0,8%	17,9%	27,2%
	08:15	15,0%	-1,8%	-17,1%	-34,2%	-5,0%	-1,8%	15,0%	16,4%
	08:45	20,7%	0,7%	-19,0%	-36,2%	-19,0%	-1,3%	20,7%	11,8%
	09:15	19,1%	-4,9%	-25,3%	-41,7%	-25,3%	-4,9%	4,0%	-6,6%

7.1.2. Effect on the four classes

The implementation of fare differentiation across the entire sample is expected to reduce crowdedness during the hyperpeak. The sample comprises four distinct classes, as outlined in table 6.8. Approximately 42.7% of the individuals in the sample can be categorised into the first class. However, the proportions observed within the sample do not necessarily align with the distribution of these classes within the actual peak-time population. Consequently, this subsection analyses behaviour at the class level. If it is later determined that, for example, the entire peak-time population mirrors the composition of a specific class, such as the Semi-Flexible Peak Traveller, the analysis of these individual classes can provide insights into how the peak-time population might behave.

Effect of fare differentiation on the Rigid Traveller

The Rigid Traveller is minimally affected by the introduction of fare differentiation. Of the individuals who typically depart at 07:45, 98.7% continue to choose the 07:45 time slot in the reference situation. With the introduction of fare differentiation, this proportion of Rigid Travellers decreases by 0.5%. This implies that 98.2% of the 07:45 travellers still stick to their standard departure time. Hence, the implementation of fare differentiation has a negligible impact on the Rigid Traveller. This outcome is expected, as chapter 6 already indicated that the Rigid Traveller is scarcely influenced by price increases. Furthermore, section 6.4 demonstrated that despite fluctuations in price and crowdedness, this class continues to travel at their usual departure time.

Table 7.3: Effect of fare differentiation on the Rigid Traveller

IMPACT FARE DIFFERENTIATION		**Chosen departure time**							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	0,2%	-13,4%	-25,3%	-35,5%	-25,3%	-13,4%	0,2%	-6,9%
	06:45	15,9%	0,0%	-13,6%	-25,4%	-13,6%	0,0%	15,9%	7,7%
	07:15	33,9%	15,6%	-0,2%	-13,8%	-0,2%	15,6%	33,9%	24,4%
	07:45	54,7%	33,5%	15,3%	-0,5%	15,3%	33,5%	54,7%	43,7%
	08:15	33,9%	15,6%	-0,2%	-13,8%	-0,2%	15,6%	33,9%	24,4%
	08:45	15,9%	0,0%	-13,6%	-25,4%	-13,6%	0,0%	15,9%	7,7%
	09:15	0,2%	-13,4%	-25,3%	-35,5%	-25,3%	-13,4%	0,2%	-6,9%

Effect of fare differentiation on the Semi-Flexible Peak Traveller

The Semi-Flexible Peak Traveller weighs crowdedness, fare, and the standard departure time against each other. For instance, a highly crowded train results in fewer Semi-Flexible Peak Travellers boarding, but a higher fare also decreases their representation. This is illustrated in table 7.4, which shows that in the new scenario, passengers are willing to deviate from their standard departure time. For instance, among travellers who typically depart at 07:45, the proportion choosing this time decreases by 33%.

Almost all of these travellers shift to the edges of the peak period, where the fare drops by €0.50. Some opt for the alternative option. Among Semi-Flexible Peak Travellers, no one chooses a departure time where the fare is higher than in the reference scenario. For example, a traveller might find €2.50 above the standard fare too expensive, but €0.50 extra acceptable. In such cases, the traveller would choose either 06:45 or 08:45. However, this is not observed. In every instance where the fare increases, fewer people travel, and those who do almost entirely shift to off-peak times.

Table 7.4: Effect of fare differentiation on the Semi-flexible Peak Traveller

IMPACT FARE DIFFERENTIATION		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	0,7%	-15,4%	-28,9%	-40,2%	-28,9%	-15,4%	0,7%	-7,7%
	06:45	14,4%	-3,8%	-19,1%	-32,0%	-19,1%	-3,8%	14,4%	4,9%
	07:15	10,7%	-6,9%	-21,8%	-34,2%	-21,8%	-6,9%	10,7%	1,5%
	07:45	13,4%	-4,7%	-19,9%	-32,6%	-19,9%	-4,7%	13,4%	4,0%
	08:15	10,7%	-6,9%	-21,8%	-34,2%	-21,8%	-6,9%	10,7%	1,5%
	08:45	14,4%	-3,8%	-19,1%	-32,0%	-19,1%	-3,8%	14,4%	4,9%
	09:15	0,7%	-15,4%	-28,9%	-40,2%	-28,9%	-15,4%	0,7%	-7,7%

Effect of fare differentiation on the Off-Peak Traveller

If everyone behaved as the Off-Peak Traveller, it would result in reduced crowdedness during the hyperpeak periods. It should first be noted that individuals who typically depart at 07:45 are unlikely to be included in this category. Nevertheless, it is interesting to analyse the behavioural implications if everyone were to be classified as Off-Peak Travellers.

It is evident that the crowdedness during the hyperpeaks would be reduced by definition. Individuals who normally depart during these hyperpeak periods would begin to disperse to hours outside of these peaks. Relatively, most of these individuals would shift to travel during the periods on the fringes outside of the peak hours, although some would also choose to travel during the shoulder peaks. Additionally, a significant portion would opt for the opt-out option. Compared to the Rigid Traveller and the Semi-Flexible Peak Traveller, the Off-Peak Traveller exhibits distinct behaviour. It is unprecedented that travellers would distribute themselves across the shoulder peaks when fare differentiation is applied.

Conversely, it is observed that people are drawn to the outer edges of the peak periods. Individuals who, in the reference situation, opted for the opt-out option now, in some cases, choose travel times just outside the peak periods, such as 06:15 or 09:15. This choice is made because these times are €0.50 cheaper. The model considers a time window from 06:00 to 09:30. It does not account for the fact that the price remains €0.50 cheaper for any departure time after 09:30. Therefore, a cheaper outer edge of the peak period might not attract additional travellers.

Table 7.5: Effect of fare differentiation on the Off-Peak Traveller

IMPACT FARE DIFFERENTIATION		Chosen departure time							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	6,9%	-19,3%	-39,1%	-54,0%	-39,1%	-19,3%	6,9%	-7,1%
	06:45	30,8%	-1,3%	-25,5%	-43,8%	-25,5%	-1,3%	30,8%	13,6%
	07:15	57,2%	18,7%	-10,4%	-32,4%	-10,4%	18,7%	57,2%	36,6%
	07:45	85,6%	40,1%	5,7%	-20,2%	5,7%	40,1%	85,6%	61,2%
	08:15	57,2%	18,7%	-10,4%	-32,4%	-10,4%	18,7%	57,2%	36,6%
	08:45	30,8%	-1,3%	-25,5%	-43,8%	-25,5%	-1,3%	30,8%	13,6%
	09:15	6,9%	-19,3%	-39,1%	-54,0%	-39,1%	-19,3%	6,9%	-7,1%

Effect of fare differentiation on the Price-Sensitive Traveller

As discussed in previous sections and chapters, it has become evident that the Price-Sensitive Traveller is not particularly attached to their usual travel time. Even a relatively small change in price can prompt this traveller to alter their departure time, as demonstrated in section 6.4. When tariff differentiation is applied, this traveller also shows a high degree of responsiveness to price adjustments. It is apparent that the hyperpeak periods will become less crowded as a result. Additionally, it is clear that the shoulder peak periods will experience reduced crowdedness. Similar to the Off-Peak Traveller, the Price-Sensitive Traveller will shift their travel to the edges of the peak periods to a small extent, and a significant portion will travel during the quieter periods around 06:15 and 09:15. Furthermore, there is an increase in the number of opt-out travellers. Therefore, the Price-Sensitive Traveller is notably influenced by price and can be discouraged from travelling during certain times by increasing costs. If all travellers behaved like this group, the hyperpeak periods would see a substantial reduction in crowdedness.

Table 7.6: Effect of fare differentiation on the Price-Sensitive Traveller

IMPACT FARE DIFFERENTIATION		**Chosen departure time**							
		06:15	06:45	07:15	07:45	08:15	08:45	09:15	optout
Usual departure time	06:15	28,0%	0,2%	-21,6%	-38,6%	-21,6%	0,2%	28,0%	13,3%
	06:45	32,2%	3,4%	-19,0%	-36,6%	-19,0%	3,4%	32,2%	16,9%
	07:15	35,6%	6,1%	-16,9%	-35,0%	-16,9%	6,1%	35,6%	20,0%
	07:45	38,4%	8,3%	-15,2%	-33,6%	-15,2%	8,3%	38,4%	22,5%
	08:15	35,6%	6,1%	-16,9%	-35,0%	-16,9%	6,1%	35,6%	20,0%
	08:45	32,2%	3,4%	-19,0%	-36,6%	-19,0%	3,4%	32,2%	16,9%
	09:15	28,0%	0,2%	-21,6%	-38,6%	-21,6%	0,2%	28,0%	13,3%

8

Discussion of the results

In this chapter, the findings of this thesis are compared with the existing literature. These results may either corroborate, contradict, or extend the current literature. The contributions of this thesis to the existing body of knowledge are also discussed in this chapter.

8.1. Heterogeneity of Dutch Train Travellers

The thesis discusses the heterogeneity among train passengers in the Netherlands. This specific characterization of Dutch train passengers is not previously found in the literature. The thesis distinguishes passengers based on their typical departure time and payment profile—i.e., who pays for the train journey. The main findings, which have not been previously identified in the literature regarding passenger heterogeneity, are as follows:

- Off-peak passengers who check in before the morning peak (i.e., before 06:30) respond significantly less to price changes compared to those who check in after the morning peak (i.e., after 09:00). While existing literature treats off-peak passengers uniformly, this thesis demonstrates that distinctions should be made based on the departure time during off-peak hours to assess price sensitivity.
- The payment profile (whether a passenger pays for their journey themselves) is a covariate that can determine the category in which a passenger is classified. Self-paying passengers are more likely to be classified into a price-sensitive category compared to those who do not pay for their journey themselves.

Peak and Peak-Off Travellers

Various sources have demonstrated that classifying travellers based on travel time is feasible. Kholodov et al. (2021) found that individuals travelling outside peak periods are more sensitive to price changes compared to those travelling during peak times. Their study categorises travellers into two groups: peak and off-peak, providing a relatively broad definition of departure times. Similarly, Paulley et al. (2006) did not distinguish specific departure times but examined the differences between peak and off-peak travellers. Their research also found that off-peak travellers are more sensitive to price increases than peak travellers. Hensher et al. (2008a) confirms these findings, noting that off-peak travellers are generally more sensitive to price changes than peak travellers. Hensher (2008a) highlights that off-peak travellers primarily engage in leisure, shopping, and personal trips, which are more flexible regarding destination and timing. De Grange et al. (2013) makes a more specific distinction by categorising travellers into narrower time slots: those travelling between 06:00-07:00 and those between 07:00-08:00. Although both time slots partially fall within the peak period, this categorisation remains less specific compared to the approach adopted in this thesis.

This thesis contributes to the literature by not only classifying passengers based on peak and off-peak periods, but by providing a more granular categorisation using half-hour intervals. As shown in table

6.8, passengers departing before the peak period are classified differently compared to those travelling immediately after the peak begins (06:30 to 07:00). Additionally, passengers travelling at the start of the peak period (06:30 to 07:00) are categorised differently from those travelling during the hyperpeak (07:30 to 08:00). Such a detailed classification of train passengers in the Netherlands has not been previously documented in the literature.

Travellers departing before 06:30, that is, before the peak period begins, are classified based on this thesis into either the first category (The Rigid Traveller) or the third category (The Off-Peak Traveller). If these travellers fall into the first category, they are not sensitive to price adjustments. But if they are classified into the third category, they are sensitive to price changes. Within the sample, the likelihood of someone being a Rigid Traveller (first category) is 78%, provided they do not pay for their trip and typically depart before 06:15. By checking in before the official peak period, they qualify not as peak travellers, but as off-peak travellers. According to Kholodov et al. (2021), Paulley et al. (2006), and Hensher et al. (2008a), such an off-peak traveller would be more sensitive to price changes compared to a peak traveller. However, this does not appear to be the case. The early traveller is likely not sensitive to price changes (see table 7.3). The hypothesis is that these individuals check in early because they have a relatively long journey and cannot afford to depart later. This aligns with the finding of Kholodov et al. (2021) that those travelling longer distances are less sensitive to price increases.

For individuals departing before 07:00 who do not personally cover their travel costs, there is a likelihood of approximately 52% that they will be classified into the first category of travellers, who are not sensitive to price increases. This suggests that early peak travellers are likely not responsive to fare changes. Travellers departing between 07:00 and 09:00 have a 42% chance of being classified into either the first category or the second category of travellers. The first category, termed the Rigid Traveller, has a Willingness-to-Pay (WtP) exceeding €40.00, while the second category, the Semi-Flexible Peak Traveller, has a WtP of approximately €17.00. The third and fourth categories have WtPs of €12.00 and €2.60, respectively. This indicates that peak travellers between 07:00 and 09:00 are relatively insensitive to price changes.

When people travel after 09:00, they are relatively likely to be classified as Off-Peak Travellers, who are sensitive to price adjustments. This group has a Willingness-to-Pay (WtP) of approximately €12.00 for a journey costing €12.20, indicating higher price sensitivity compared to travellers in the first or second categories. Notably, this off-peak traveller is likely to be more sensitive to a price increase than an off-peak traveller who departs before the peak period begins.

The generic findings of Kholodov et al. (2021), Paulley et al. (2006), and Hensher et al. (2008a) are partially corroborated by this thesis. Off-peak travellers who travel after the morning hyperpeak are indeed more sensitive to price adjustments than peak travellers, as also found in the cited literature. However, the novel contribution of this thesis is that off-peak travellers who start their journey before the morning hyperpeak exhibit different price sensitivities compared to off-peak travellers who travel after the hyperpeak. This distinction has not been previously identified and should be considered a main takeaway of the thesis. The key finding regarding the heterogeneity of Dutch train travellers based on departure time is that a distinction must be made between off-peak travellers who travel before the hyperpeak and those who travel after it.

Payment Profile of Travellers

This thesis demonstrates that travel behaviour can partly be explained by whether a traveller pays for a trip themselves. Although this indicator is not explicitly mentioned in the literature, it is intuitive that a traveller who does not pay for a trip personally is less sensitive to price changes compared to someone who pays partially or fully. The findings indicate that a traveller who pays (at least partially) is more likely to be classified in the third or fourth category than one who does not pay. The third and fourth categories, identified in this thesis, have the lowest Willingness-to-Pay (WtP). Specifically, the fourth category shows a very low Willingness-to-Pay and is thus highly sensitive to price.

Alternative ways to classify travellers

In previous literature, travelers have been categorised based on specific characteristics. For instance, Ding et al. (2023) identified that travelers could be classified according to travel frequency. Those who travel less are more price-sensitive and thus more affected by price increases. This correlation was not observed in this thesis, as incorporating this information into the model did not improve its performance. The BIC value of the model with travel frequency as a covariate was higher than that of the model without it. Consequently, this information was excluded from the analysis, and no relationship between travel frequency and the heterogeneity of train passengers in the Netherlands was found.

Age has been used to categorise travellers in various studies. According to McCollom and Pratt (2004), older individuals are less sensitive to price adjustments compared to younger people. Campisit et al. (2022) and Abe (2021) also use respondents' age for categorisation. In this thesis, age initially appeared to be a factor for classification when considered alone as a covariate in the model. However, further analysis revealed that when 'trip purpose' was included, age lost its significance. This indicates that once trip purpose is considered, age becomes irrelevant for categorising travellers due to its correlation with trip purpose. Hensher et al. (2008a) found that trip purpose could be a factor for categorisation, but with the inclusion of travel time and payment profile, trip purpose also became insignificant. As noted by Hensher et al. (2008a), trip purpose often correlates with departure time: peak travellers typically travel for work or education, while off-peak travellers tend to travel for leisure. Ultimately, age and trip purpose were found to be insignificant in a model analysing standard departure time and payment profile.

The level of urbanity and travel distance are theoretically factors that can be used to categorise travellers. However, different correlations are reported in the literature. For instance, Paulley et al. (2006) found that greater travel distance results in lower price elasticity, while Wardman et al. (2014a) found that price elasticity increases with travel distance. Paulley et al. (2006) explain this by noting that the cost per extra kilometre decreases as the journey lengthens. This pricing strategy is also used by NS: the longer the distance, the cheaper the travel cost per kilometre. This leads to lower price elasticity with increasing distance. Conversely, Wardman et al. (2014a) argue that longer distances often occur between urban and rural areas, where travellers might opt for car travel instead of train travel. Thus, a fare increase for train journeys could lead to a shift towards alternative transport modes. This thesis found no significant relationship between travel distance and price elasticity. Adding travel distance to the LCCM only worsened the model's performance, leading the researcher to exclude this information. The same applies to the level of urbanity. Although several sources suggest that urbanity may influence travellers' price elasticity (Hörcher and Tirachini, 2021; Dargay et al., 1999; Wardman, 2014b; 2013), this was not observed in this thesis. Including urbanity in the model resulted in increased complexity and a deterioration in model performance, hence this information was excluded from the analysis.

8.2. Effect of fare differentiation and crowdedness

This subsection discusses the findings of this thesis regarding the effects of fare differentiation and the influence of crowdedness on respondents' travel behaviour, compared to existing literature. The main takeaways from this analysis are as follows:

- People experience a smaller reduction in utility when moving from crowdedness level 1 to level 2 than when moving from level 2 to level 3. In short: people prefer travelling alone, tolerate sitting next to someone less, but find standing strongly unpleasant.
- In this sample, the number of passengers checking in during the hyperpeak decreases by 8.4% when peak pricing is applied, provided the usual trip price does not exceed €12.20.
- If more than 88% of the peak population consists of Rigid Travellers, fare differentiation fails to achieve the desired effect when the average trip price during the hyperpeak exceeds €12.20.

Discomfort crowdedness

In addition to fare differentiation, Paulley et al. (2006) identify service quality as another factor influencing the demand for public transport. One aspect of service quality is whether or not passengers can sit during their train journey. It does not hold true for all travellers that crowdedness directly affects their perception of service quality. Tirachini et al. (2017) found that some individuals are sensitive to crowdedness, while others are less affected. Their study indicated that young, high-income men are somewhat less sensitive to crowdedness compared to older people, those with lower incomes, and women, who are more affected. This thesis identifies a segment of travellers who are sensitive to crowdedness: the Semi-Flexible Peak Travellers. This group weighs the fare, travel time, and crowdedness against each other. However, this thesis did not find significant socio-demographic or socio-economic predictors, such as gender, income, or age, that could reliably indicate sensitivity to crowdedness. What is established in this thesis is that crowdedness-sensitive travellers are predominantly peak-hour travellers, specifically travelling between 07:00 and 09:00. Further details about this traveller group's composition remain unknown.

Wardman and Whelan (2011) found that the decrease in comfort is not entirely linear with the increase in crowdedness. They observed that individuals seated tend to dislike increased crowdedness (i.e., more people per square meter) more than those already standing. Passengers who are standing are less disturbed by increased crowdedness. Nevertheless, whether seated or standing, a more crowded trip consistently reduces the enjoyment of the journey. A similar finding is reported in this thesis. The Semi-Flexible Peak Traveller prefers to travel alone and dislikes sitting next to someone. When the train becomes more crowded and the Semi-Flexible Peak Traveller has to sit next to someone, it is experienced as unpleasant. This results in a small decrease in the utility function. However, if the crowdedness increases further, forcing the Semi-Flexible Peak Traveller to stand, the utility decreases significantly. The decrease in utility between 'sitting alone' and 'sitting next to someone' is much smaller than the decrease between 'sitting next to someone' and 'possibly having to stand'. Thus, the substantial drop in utility occurs when standing becomes necessary, rather than when seated next to someone. In general, the utility function decreases notably only when the Semi-Flexible Peak Traveller must stand. The impact of sitting alone versus sitting next to someone is relatively minor. It is unknown whether the perceived pleasantness of crowdedness varies with travel duration. Previous research has shown that passengers prefer longer journeys during peak times to ensure a seat (Tirachini et al., 2016. However, no such relationship was found in this thesis; travel distance is not a significant predictor of class preference.

Fare differentiation

The effect of fare differentiation on train travel behaviour in the Netherlands has not been as specifically addressed in previous literature as it is in this thesis. The literature often refers to a general figure for price elasticity of demand. For instance, Wardman (2022) conducted a meta-analysis on price elasticities in Great Britain, where price elasticity is calculated by comparing old and new prices. Similarly, Liu and Charles (2013) discuss how price elasticity can vary based on transit mode, location, and time frame, but do not link it to fare differentiation.

This study differs from previous research by examining the impact of a €2.50 price increase during the busiest peak moment when prices also rise around this period (an increase of €1.50 during the shoulder peak and €0.50 on the edges of the peak hours). If only the hyperpeak becomes more expensive, and not the shoulder peak, the effect on demand differs compared to when fares also increase around the hyperpeak.

The study of A. Mastebroek (personal communication) investigates whether passengers are willing to shift from the hyperpeak to the shoulder peak if fares are reduced in the latter period. Mastebroek found that the hyperpeak can decrease by 4.5% if passengers receive a discount of 40% around the hyperpeak, compared to the previous 20% discount. Previously, this level of discount was only available during off-peak hours. Thus, a €10.00 journey now costs €4.00 less instead of €2.00, resulting in a relative decrease in fare of 25%. The reduction in fare by 25% and the decrease in the peak by 4.5% indicates an elasticity of -0.23. These figures are only applicable to people who travel with an 'Altijd Vrij' subscription.

This thesis does not identify the demand elasticity for specific ticket types. The sample includes various ticket types, but under fare differentiation, prices increase by €2.50 during the hyperpeak. Compared to a fare of €12.20, this is a 20.5% rise. In the sample, the number of travellers during the hyperpeak drops by approximately 8.4%, resulting in a price elasticity of -0.41. This value is larger in absolute terms than the figure found by Mastebroek, for which several explanations can be offered. First, the sample composition differs from Mastebroek's. While Mastebroek focused solely on the impact on Altijd Vrij subscriptions, this thesis considers all types of subscriptions, including those where respondents receive no discount and pay the full fare, unlike the discounted Altijd Vrij subscriptions. Second, this thesis evaluates fare differentiation based on a standard fare of €12.20. If this base fare increases, the impact of fare differentiation diminishes, as people are less likely to react to price changes (see table 6.3). Finally, the sample used in this thesis may include a higher proportion of price-sensitive individuals compared to Mastebroek's, where fewer price-sensitive respondents were included. Sample composition significantly influences the price sensitivity observed.

The effectiveness of fare differentiation depends on the composition of the peak population and the base fare of a passenger's train journey. This thesis identifies four categories of travellers, with the first group being the least responsive to price changes, referred to as Rigid Travellers. If more than 88% of the peak population consists of Rigid Travellers, fare differentiation, as shown in table 7.1, will not achieve the desired 5% reduction in crowdedness during the hyperpeak when the base fare is €12.20. However, if the proportion of Rigid Travellers is below 88%, fare differentiation could potentially have the intended effect, depending on the composition of the other traveller groups. The three other groups are more responsive to peak charges.

8.3. Discussion Status Quo Bias

Chapter 3 discusses the status quo bias. Godefroid et al. (2023) found that the status quo bias significantly influences decision-making between options. This is illustrated by Lang et al. (2021), where one group of respondents was willing to pay 2.5 times more for a product than another group due to the status quo bias.

So far, limited empirical evidence exists on the role of status quo bias in implementing transport policies. Börjesson et al. (2016) conducted a study with two surveys: one before and one after the implementation of road pricing. They found that support for the road pricing policy was significantly higher after its implementation.

This thesis confirms that status quo bias affects respondents' perceptions of fairness regarding fare differentiation. Based on previous reports (Godefroid et al., 2023; Dean et al., 2017; Lang et al., 2021), the hypothesis was that respondents would perceive changes to their status quo—whether introducing or removing fare differentiation—as less fair. Respondents who experienced fare differentiation as the status quo viewed its removal as unfair, while those without fare differentiation found its introduction unfair. Both groups perceived the new situation as less fair than their current one. Hence, support for the implementation of a new fare system is potentially determined by the status quo bias.

The introduction suggested that one way to address resistance to a policy is through a counterfactual check: discussing the counterfactual with policy proponents (van Wee et al., 2023). This could potentially reduce resistance to fare differentiation.

The status quo bias in the context of fare differentiation has not been previously documented in the literature. This thesis contributes by highlighting respondents' fairness perceptions regarding fare differentiation in light of the status quo bias, adding empirical evidence of its role in transport policies.

9
Conclusion, limitations and recommendations

This study aims to provide a clearer understanding of how train passengers adjust their behaviour in response to peak-period pricing within a new fare system. The concept of status quo bias is also considered to enhance insight into fairness perceptions on this subject. This chapter addresses the various research questions. The limitations of this thesis are also described in this chapter. The chapter concludes with several specific recommendations for further research.

9.1. Conclusion

9.1.1. Answering the subquestions

In the first chapter of this thesis, the sub-questions were formulated. These sub-questions are addressed in this section. Rather than answering each question individually, the answers are structured by subsection. For clarity, the sub-questions are presented again below.

1. *What travel-related attributes influence travel behaviour of train travellers in the Netherlands*
2. *To what extend do these travel-related attributes influence the preferences of train travellers?*
3. *Which socio-demographic and socio-eonomic characteristics influence the preferences of train travellers in the Netherlands?*
4. *What is the role of the status quo bias on the perceived fairness of the implementation of fluctiations in ticket fares during peak hours?*

Travel related attributes and their influence on preferences

The first sub-question addresses which travel-related attributes influence the behaviour of train travellers in the Netherlands. This thesis initially finds that the price of a train journey significantly impacts the preference for a particular journey. An absolute increase in the price of a train journey is perceived negatively by travellers, leading to a diminished valuation of the journey. A portion of the travellers is primarily concerned with the absolute price increase, while another segment considers both the absolute and relative price increases. This indicates that travellers perceive a price increase as less severe when their original fare is already high. For instance, if their original fare is €50.00, a price increase of €2.50 is perceived as less burdensome compared to an increase when the original fare is €25.00. Across the entire sample, a price increase of €2.50 results in a reduction of approximately 8.4% in the number of people travelling during the hyperpeak, assuming a base fare of €12.20. The price elasticity of demand is therefore approximately -0.41. Thus, the first travel-related attribute is fare price, both in absolute and relative terms. A price increase of 10% in regards to the base trip price leads to a decrease in demand of 4.1%. It is noteworthy that price sensitivity decreases as the original fare increases. Conversely, individuals with a lower standard fare than €12.20 are more sensitive to price adjustments.

The second travel-related attribute is crowdedness. For some travellers, a crowded train environment is considered undesirable. This thesis identifies four distinct types of travellers, with only one of these types displaying sensitivity to crowdedness. The sensitivity to crowdedness follows a quadratic increase, indicating that the marginal decline in travel utility intensifies as crowdedness increases. In this study, crowdedness is measured across three levels. Crowdedness level 1 indicates that a traveller can be seated, while level 2 suggests a decreased likelihood of securing a seat, though it remains probable. The key distinction between levels 1 and 2 is that at level 1, there is no other passenger seated next to you, whereas at level 2, there is a possibility of another passenger sitting beside you. Crowdedness level 3 indicates a likelihood that the traveller will have to stand during the journey. For the group sensitive to crowdedness, level 1 is perceived positively, with travel utility increasing when crowdedness remains at this level. However, when crowdedness shifts to level 2, the travel utility decreases by approximately 1 point. To put this in perspective, a fare increase of €6.27 on a journey priced at €12.20 has an equivalent effect on utility as the shift from crowdedness level 1 to level 2. When crowdedness goes from level 2 to level 3, the travel utility further decreases by 2.18 points. This demonstrates that the impact of transitioning from level 1 to level 2 is less significant than the shift from level 2 to level 3. In comparison, a fare increase of €12.55 on a journey costing €12.20 has the same effect on travel utility as a shift in crowdedness from level 2 to level 3. For the group sensitive to crowdedness, this factor can significantly influence the perceived utility of the journey.

Finally, the thesis has found that travellers place varying degrees of importance on departing at their usual departure time. The respondents in the sample indicated the time at which they normally depart on an average weekday (Tuesday). Some travellers highly value departing at their regular time. The group most attached to their own departure time assigns a value of €41.81 to this preference, implying that the utility of their usual journey drops to zero only when the price increase for this departure time approaches €42.00. Other travellers place less importance on their usual departure time. For these individuals, the value they assign to their regular departure time is partially dependent on their original fare. The more expensive their journey typically is, the more they are willing to pay to depart at their preferred time. The group least attached to their usual departure time values it at approximately €3.51.

Personal characteristics that influence the preferences of train travellers

This thesis has demonstrated that the classification of travellers as peak or off-peak significantly impacts their preferences. Additionally, the timing of check-in for off-peak travellers—either before or after the morning hyperpeak—affects their preferences. Travellers can also be categorised as fully self-paying or partially/non-self-paying, which further influences their preferences. Other personal characteristics that might affect traveller preferences were not identified in this thesis.

The peak traveller whose payment status is unclear, whether self-paying or not, is the same traveller who considers the crowdedness of the train when evaluating a particular journey. This traveller weighs crowdedness against the fare and is attached to their usual departure time. Peak travellers who do pay fully or partially for their journey are not concerned with crowdedness but are sensitive to the fare. This group places little value on their usual departure time and reacts relatively strongly to a fare adjustment.

Late off-peak travellers are those who travel after the peak period has ended. Their usual departure time is after 09:00 in the morning. The majority of these travellers either pay fully or partially for their journey; their trips are not fully reimbursed. This makes the traveller sensitive to fare increases, though not as sensitive as the self-paying peak traveller. The late off-peak traveller is not particularly attached to their standard departure time and has no issue with choosing a journey that falls further outside the peak period, such as after 09:30.

Role of the status quo bias

The status quo has a significant impact on individuals' perceptions of the fairness of tariff differentiation. In the survey, respondents rated the fairness of different fare systems on a 7-point scale, where a score of 7 denotes a completely fair system and a score of 1 denotes a completely unfair system. The current fare system in the Netherlands is based solely on travel distance. The new tariff system under consideration includes a peak charge, where the fare is determined by both distance and travel time.

Respondents evaluated the fairness of both systems. Interestingly, half of the sample found the distance-based system (mean score: 4.27) fairer than the new system with a peak charge (mean score: 4.20), while the other half rated the new system (mean score: 4.27) as significantly fairer than the current system (mean score: 3.26). This indicates that perceptions of fairness vary significantly between the two groups, with one group favouring the existing system and the other favouring the new one. All average scores and the differences between groups are statistically significant.

The key distinction between these groups is their status quo: for one group, it is the distance-based system, while for the other, it is the new system with a peak charge. Those who consider the new system as their status quo view the current system as significantly less fair. Thus, an individual's status quo strongly influences their fairness assessment. Hence, support for the implementation of a new fare system is potentially determined by the status quo bias. Ultimately, both groups rate a new tariff system with peak pricing as more fair than unfair, indicating that the overall perception within the sample is that a new tariff system is fair.

9.1.2. Answering the main question

In this section, the main research question is addressed. The answer to this question is interwoven throughout the thesis, particularly in chapter 6, chapter 7 and chapter 8, where key insights are already presented. When referring to 'the application of fare differentiation/peak pricing' in this section, it implies that the price decreases by 50 cents at the edges of the peak period, while approaching the hyperpeak, prices increase by €1.00 every half hour. During the hyperpeak, this results in a price increase of €2.50. A detailed overview can also be found in table 7.1. In this section, the primary research question is addressed in detail. The primary research question is as follows:

What are various traveller profiles among train travellers in the Netherlands and are different travellers likely to alter their travel behaviour in response to fluctuations in ticket fares during peak hours?

In the sample, four distinct traveller profiles were identified. The first profile is that of the Rigid Traveller. The Rigid Traveller can be described as a traveller who is unaffected by price changes or crowdedness. This traveller will almost never alter their departure time due to a price increase or increased crowdedness. Only if the fare for their usual departure time rises by €41.81 will this traveller potentially choose a different travel time. Thus, the Willingness-to-Pay for this traveller is €41.81. The impact of peak charges on the Rigid Traveller is minimal to negligible, and virtually all Rigid Travellers will continue to depart at their usual time. The effect of fare differentiation will be that approximately 0.5% of travellers will choose a different travel time.

The second group that can be distinguished is the Semi-Flexible Peak Traveller. This traveller is influenced both by the crowdedness on the train and by the cost of the journey. They carefully weigh a price increase against the typical cost of their journey. The higher the original fare for the Semi-Flexible Peak Traveller, the less impact a fare increase has. The maximum Willingness-to-Pay for the traveller's usual departure time is €31.70, provided the original fare exceeds more than ten thousend euros, which is an unrealistic scenario. With a fare of €12.20, the Willingness-to-Pay for this traveller is approximately €17.15. Under a new fare structure that implements fare differentiation, approximately 33% of these travellers will shift away from the hyperpeak periods. The periods surrounding the hyperpeaks will also become less crowded. The majority of these travellers will opt for a relatively cheaper travel time, thus travelling outside the peak periods. A small proportion of this 33% will ultimately choose the opt-out option. Compared to the Rigid Traveller, there are significantly fewer Semi-Flexible Peak Travellers with a standard departure time before 07:00. Additionally, there are fewer Semi-Flexible Peak Travellers travelling after 09:00 compared to the Rigid Traveller.

The third profile is that of the Off-Peak Traveller. This traveller is influenced by price rather than crowdedness. Similar to the Semi-Flexible Peak Traveller, the Off-Peak Traveller carefully weighs a price increase against the usual cost of their journey. The higher the original fare for the Off-Peak Traveller, the less impact a fare increase has. For this profile, the maximum Willingness-to-Pay (WtP) for the usual departure time is €17.28. However, this maximum WtP is only reached if the original fare is exceptionally high. For a fare of €12.20, the WtP is €11.99. The effect of peak pricing is thus clearly evident among travellers with this profile. At least 21% of travellers in this profile will avoid the peak periods in case of peak pricing. Some of these individuals may travel during a different time within the peak, but most will opt for a journey outside peak hours. Additionally, it is possible that some may choose the opt-out option. Compared to the Rigid Traveller, the Off-Peak Traveller group includes a significantly higher proportion of individuals whose standard departure time is later than 09:00. Furthermore, a greater number of these travellers fully or partially self-fund their train journeys. Therefore, the Off-Peak Traveller primarily travels after 09:00, partially self-funds their journey, is influenced by price increases, and readily chooses the opt-out option.

The final profile is that of the Price-Sensitive Traveller. The name of this traveller class is quite indicative; these travellers are strongly influenced by the cost of a journey. The Price-Sensitive Traveller is not affected by crowdedness on the train. When the fare increases, the Price-Sensitive Traveller takes into account the original price of their journey. If the original fare is already high, a price increase has less impact compared to when the original fare is low. The maximum Willingness-to-Pay for the typical departure time of the Price-Sensitive Traveller is €3.51. This maximum Willingness-to-Pay is only reached with an unrealistically high base fare. For a journey priced at €12.20, the maximum Willingness-to-Pay is €2.60. This demonstrates once again that this traveller profile is highly sensitive to price. The introduction of peak pricing will therefore significantly impact the number of travellers with this profile travelling during peak times. With the implementation of a new fare system, the number of Price-Sensitive Travellers is expected to decrease by at least 35%. Some travellers will shift to travel at the edges of peak times or just outside peak periods. A smaller proportion will opt for the opt-out option. Compared to Rigid Travellers, there are fewer Price-Sensitive Travellers with a standard departure time between 06:00 and 06:30. More individuals will have to pay for their journey either entirely or partially out of pocket. However, compared to Off-Peak Travellers, the number of those paying for their journey is lower. Thus, the Price-Sensitive Traveller is one who travels from the beginning of the peak period and pays (partially) for their journey.

In addition to a quantitative response to the main question, the qualitative approach is also of interest. The small-scale study on status quo bias has revealed that respondents' perception of the status quo significantly influences their views on the fairness of a new fare system. The higher the degree of perceived fairness, the greater the Willingness-to-Pay of a traveller. Therefore, it is likely that individuals who view a new system as fairer than the old one will also exhibit a higher willingness to pay under the new system.

9.2. Recommendations for The Dutch Railways

In this section, a recommendation is made specifically for The Dutch Railways. This recommendation elaborates on whether this thesis can be utilised to support the justification for implementing a hyperpeak surcharge. The recommendation is based on the various traveller profiles and the analysis detailing the effect of a hyperpeak surcharge (see section 7.1.1).

In figure 9.1, the sample's response to the implementation of fare differentiation is illustrated. While table 7.2 already presents this information, figure 9.1 provides a clearer visual representation of how the sample's reaction has been calculated. It is known from the sample that approximately 42% of the individuals are Rigid Travellers. These travellers exhibit minimal responsiveness to peak pricing, meaning that approximately 42% of the sample will continue to travel during the hyperpeak.

To measure the overall effect of fare differentiation on the peak population, the proportion of each traveller type must be multiplied by the percentage of that specific traveller type that will cease travelling during the hyperpeak. The effectiveness of fare differentiation depends on the distribution of traveller types within the population. The Rigid Traveller group is the least responsive to fare differentiation. If more than 88% of the peak population consists of Rigid Travellers, it will be impossible to reduce the hyperpeak by 5%. If the peak population is composed of exactly 88% Rigid Travellers, the remaining 12% must consist of Price-Sensitive Travellers to achieve a 5% reduction in the hyperpeak.

Given that four distinct traveller profiles have been outlined, it is not feasible to specify the exact impact of fare differentiation. However, this thesis demonstrates that three out of the four traveller profiles respond favourably to peak pricing. It is also evident that the Semi-Flexible Peak Traveller consistently travels during peak times and not outside them. As previously mentioned, 32% of the Semi-Flexible Peak Travellers will shift away from the hyperpeak if peak pricing is implemented.

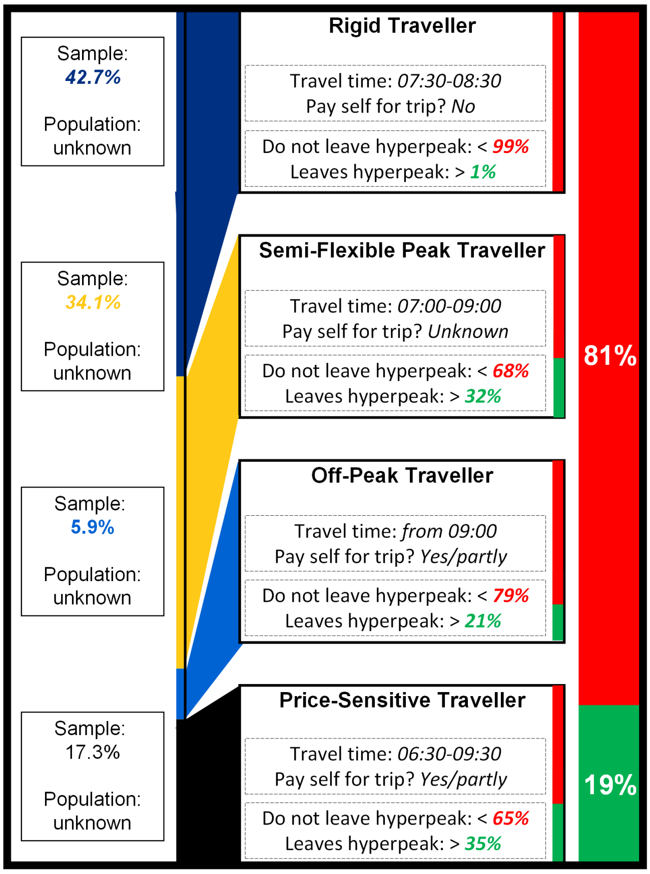


Figure 9.1: Illustration effect fare differentiation

There are numerous potential configurations of the four different traveller classes that could achieve the targeted 5% reduction in the hyperpeak. The specific composition of these configurations is beyond the scope of this thesis. It is up to NS to investigate the representation of different traveller groups within the population. Once NS has a clear understanding of this distribution, the impact of peak pricing can be accurately assessed. This thesis provides a foundation for further exploration into the implementation of fare differentiation.

9.3. Limitations

Covariates

One of the limitations of the model is the small number of covariates predicting class membership. The aim of an LCCM is for researchers to reasonably estimate which class a traveller will belong to using these covariates. The hypothesis of this thesis was that it would also succeed in predicting the group a respondent or traveller falls into, based on factors such as card type, income, trip purpose, and urbanicity level. This approach aims to correct the skewed distribution observed in the sample compared to the population (see chapter 5), ensuring each traveller and respondent is assigned to the correct class using statistical methods. However, few to none of the covariates have proven to be significant, thereby preventing the correction of this skewed distribution.

Bias of respondents

Another significant limitation to consider is that the individuals in the sample may be biased in a certain way. Those who join the NS panel do so voluntarily, and one reason for joining might be an inherent preference for travelling by train. This preference could be based on sustainability concerns, but it could also stem from comfort, convenience, or other personal reasons. Therefore, the people in the sample are likely to have a stronger than average preference for train travel. As a result, it is uncertain whether the choices made by the sample can be generalised to the entire population. For instance, a potential price increase might be perceived as less severe by members of the panel compared to non-panel members. The same applies to crowdedness. Suppose someone joins the NS panel for sustainability reasons; this person might be less affected by increased crowdedness than someone who uses the train without any particular reason. This existing bias in the NS panel could lead to a distorted view of travel behaviour. However, this does not necessarily pose a problem. The hypothesis suggests that the sample reacts less severely to price changes than the actual population. For NS, this is favourable, as NS hopes for a strong reaction from travellers if prices are raised.

Assumptions respondents

In the survey, respondents were asked to consider their own situation when completing the choice tasks. An explicit piece of text was included (see appendix B) emphasising that, for instance, a student with a week subscription may treat the price component in the choice task as if it is paid by the government (which it is). Similarly, if an employer covers travel costs, respondents should assume that the employer would pay any additional costs for the journey. This ensured that each respondent fully considered their own situation. The choice tasks also included two options that, according to official NS rules, do not fall within peak hours: 06:15 and 09:15. This might have caused some confusion among respondents. For example, someone with an off-peak discount subscription (in Dutch: Dal Voordeel) might have thought that the displayed prices at the outer edges of the peak period (06:15 and 09:15) should be multiplied by 0.6 (since such a subscription offers a 40% discount at these times). However, this would contradict the spirit of the choice experiment, as it would create a clear correlation between the departure time and the trip price. In the choice experiment, travelling further from the peak period would then result in a lower trip price. When designing the choice experiment, the price and crowdedness were varied to ensure no correlation between crowdedness, departure time, and trip price (see chapter 4). If respondents with an off-peak subscription believed that the price outside peak hours would be lower for them (due to their subscription), they might have chosen differently than they would in reality. This potential distortion might have occurred during the completion of the choice tasks.

Check-ins

This thesis presents another limitation. The analysis in chapter 7 examines the effect of fare differentiation on the number of passengers during the hyperpeak. The number of passengers during the hyperpeak is defined as: the number of passengers who typically depart between 07:30 and 08:00. This includes all respondents who check in between 07:30 and 08:00. If the sample is representative of the peak population, the number of check-ins during the hyperpeak is expected to decrease by 8.4%. Consequently, it is concluded in this thesis that the number of passengers during the hyperpeak also decreases by at least 8.4%. However, this is not necessarily accurate. Some passengers may have checked in before the hyperpeak began and could still be on the train during the hyperpeak. In such cases, while the number of check-ins during the hyperpeak may decrease by 8.4%, the total number of passengers on the train during the hyperpeak may not decrease by 8.4%. Although it is not entirely accurate to state that the hyperpeak decreases by 8.4%, it is evident that the number of passengers checking in before the hyperpeak also decreases when fare differentiation is applied. This occurs not only in the overall sample but also in the various identified classes (see chapter 7). Therefore, this limitation is relevant to mention but will not lead to any drastic conclusions beyond those already drawn.

Stated behaviour versus actual behaviour

Another drawback of the stated choice experiments is the potential discrepancy between stated behaviour and actual behaviour (Kroes and Sheldon, 1988). This means that respondents may choose differently when filling out a survey than when making a real choice. Van Essen (2018) mentions several reasons for this: respondents may try to influence policy by strategically completing the survey, they may give a politically correct answer, or the respondent may not recognize themselves in the situation and simply not know which alternative they would choose in real life. The latter cause can be addressed by bringing the choice tasks of a respondent as close to reality as possible. Therefore, in this study, the choice tasks are brought as close to reality as possible. The choice tasks for the respondent are based on the journey the respondent most frequently makes on weekdays. The survey inquires about the departure and arrival stations for the respondent's most frequent journey. It also inquires about which travel product and class the respondent uses. With this information, the cost of the train journey for the respondent is determined. This unique price is included in the choice tasks for each respondent. Based on the current fare of the respondent, the displayed fare in the choice tasks varied.

Leaving earlier or later

Finally, a limitation of the model is its simplification, as it does not examine whether a traveller opts for an earlier or later departure when deviating from their usual departure time. Initially, an attempt was made to address this by incorporating two additional attributes into the utility function: one for cases where a respondent chose an earlier departure and one for cases where a respondent chose a later departure. For example, if a traveller chose a departure time one hour earlier than their usual time, the 'earlier-departure attribute' in the utility function was assigned a value of 2 (representing a deviation of two half-hours), while the 'later-departure attribute' was assigned a value of zero, and vice versa. This approach was applied to all respondents and choice tasks. However, the issue that arose was that the 'earlier-departure attribute' and the 'later-departure attribute' were so highly correlated that multicollinearity occurred (see chapter 6).

To avoid this, the model was simplified by not calculating the magnitude of the deviation (i.e., the number of half-hours someone departs earlier or later) but by indicating only whether someone chose an earlier or later trip. If a traveller chose an earlier departure than their usual time, the 'earlier-departure attribute' was assigned a value of 1 and the 'later-departure attribute' a value of 0. Conversely, if a traveller chose a later departure, the 'earlier-departure attribute' was assigned a value of 0 and the 'later-departure attribute' a value of 1. If a traveller chose their usual departure time, both the 'earlier-departure attribute' and the 'later-departure attribute' were assigned a value of 0.

As a result, a correlation of -1 arose between six of the attributes. This occurred because, for someone departing at 07:15, travelling at 06:45 was always considered too early, resulting in the 'earlier-departure attribute' being 1. Conversely, travelling at 07:15 was never considered too late, as it was their usual departure time, so the 'later-departure attribute' was 0. Hence, multicollinearity was also present, because this issue held for six alternatives. The issue lead to the rejection of this analytical approach.

The researcher then decided not to distinguish specifically between earlier or later departures from the usual time. In hindsight, it is now understood that it would have been possible to differentiate between earlier and later departures by creating an *alternative specific constant* for six of the seven alternatives. However, this idea emerged too late to be incorporated into the thesis due to deadlines. The lack of differentiation between earlier and later departures remains a limitation of the thesis.

9.4. Further research

In this thesis, four distinct groups of travellers have been identified, each exhibiting unique travel behaviour. Some travellers can be influenced by price incentives, while others cannot. If the sample were representative of the population, the introduction of fare differentiation would ideally reduce the hyperpeak by 5%. However, as demonstrated in chapter 5, the sample does not fully represent the population. Specifically, the age of the peak population is significantly lower than that of the sample. Additionally, the sample contains a disproportionate number of individuals who are unemployed, a deficit of those travelling for educational purposes, and an overrepresentation of individuals with highly theoretical educational backgrounds. Therefore, the sample does not provide a representative picture of the actual peak population. While the four classes identified in this thesis may indeed be present within the peak population, the proportions observed in the sample are likely not reflective of those in the population. Consequently, further research could be initiated to determine the actual distribution of these groups within the population. Once the proportions of the different classes (Rigid-, Semi Flexible Peak-, Off-Peak-, and Price Sensitive Travellers) in the population are established, the true effect of fare differentiation can be accurately assessed.

This thesis investigates the effect of fare differentiation on the morning peak. Currently, a similar peak is observed in the afternoon data. This afternoon peak is generally slightly lower than the morning peak and is somewhat broader, with people spreading out more compared to the morning peak. The behaviour of individuals during the morning peak with fare differentiation does not necessarily mirror their behaviour during the afternoon peak. Research by Adnan et al. (2020) demonstrates that morning and afternoon peak behaviours are intertwined. Consequently, further research should be conducted to examine the behaviour of individuals during the afternoon peak with the introduction of fare differentiation. As previously mentioned, the allocation of the number of trains per day is determined by the highest peak expected that day. If, for instance, the morning peak decreases by 5% due to fare differentiation, but the afternoon peak remains unchanged, fare differentiation would still have limited utility. Although it is intuitive that the afternoon peak would also decrease with fare differentiation, concrete data is lacking. Therefore, it is recommended that further research be undertaken in this area.

As mentioned in the limitations, this thesis does not distinguish between departing earlier or later than a traveller's usual departure time. This limitation could be further investigated and addressed by adding alternative specific constants to the model. Although briefly considered by the author, time constraints prevented its inclusion in the thesis. Such an analysis could be performed for both the MNL model and the LCCM. By adding an alternative specific constant to six of the seven alternatives (with one alternative serving as a reference point), it would become clearer whether travellers are inclined to choose an earlier or later travel time than their usual departure time if the price of their usual trip increases.

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A

Season tickets Dutch Railways

Table A.1 illustrates the different subscription options available and the propositions associated with each subscription. The details of these propositions can be found in Table A.2.

	Dal voordeel	Altijd voordeel	Weekend vrij	Dalvrij	Keuzedagen	IC direct maandtoeslag	Traject vrij	Weekend voordeel	Altijd vrij	IC direct Altijd toelsag vrij	Trein vrij	OV vrij
On balance	x	x	x	x	x	x						
NS Flex	x	x	x	x			x	x	x	x		
Business travel	x						x			x	x	x

Table A.1: Season tickets and propositions

	Off-peak hours	Weekend	Public holidays	Travelling together	Peak hours	Fixed route	Train	All public transport
Dal voordeel	40%	40%	40%	40%				
Altijd voordeel	40%	40%	40%	40%	20%			
Weekend voordeel		40%	40%	40%				
Weekend vrij		100%	100%	40%				
Dal vrij	100%	100%	100%	40%				
Altijd vrij	100%	100%	100%	100%	40%			
Traject vrij	40%	40%	40%	40%		100%		
Trein vrij				40%			100%	
OV vrij				40%				100%

Table A.2: Propositions summarised

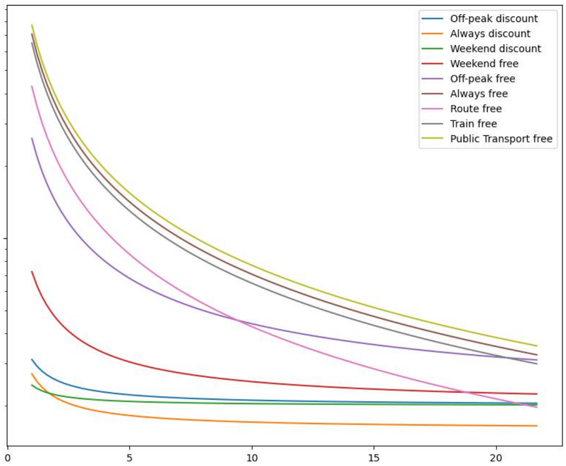
To examine potential subscription changes a respondent might consider, an overview has been created in figure A.1. **This overview illustrates the average cost per journey per month**. The x-axis represents the number of journeys made per month, while the y-axis shows the average price per journey. As the frequency of travel increases, the cost per journey decreases due to the distribution of fixed costs over more journeys.

The overview differentiates between the price per journey in the current fare structure and the new fare structure, as well as by ticket prices in the current system. Takeaways:

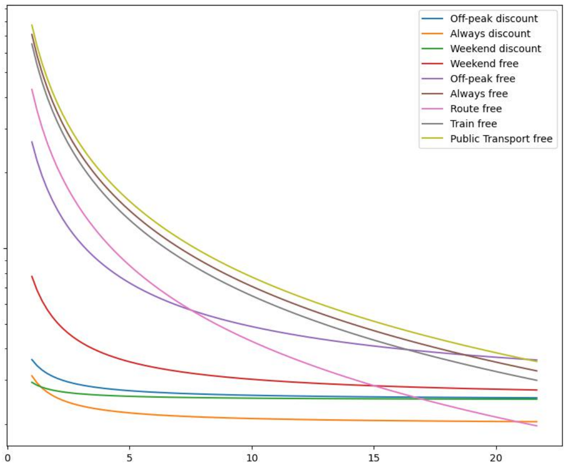
- If the cost of a single journey is €10, the respondent is unlikely to hold a season ticket. Conversely, if a respondent's single journey costs €50, they might opt for a season ticket depending on their monthly travel frequency.
- For respondents paying approximately €10 per single journey, it is practical to always choose the 'Altijd Voordeel' subscription. It is reasonable to assume that these respondents are already subscribed to 'Altijd Voordeel'.
- For those paying around €25 per single journey, the current situation is as follows: if a respondent travels less than 10 days per month by train, the 'Altijd Voordeel' subscription is most advantageous. If travel exceeds 10 days, the 'Traject Vrij' subscription is preferable. Assuming rational behaviour, respondents would adopt this approach. In the new fare structure, the situation is similar, with a threshold of about 9.5 days of train travel per week. Hence, it is likely that there will be no change in subscription choice.
- Lastly, for a respondent with an average single journey price of €50, the following applies: if they travel less than 5 days per month, the 'Altijd Voordeel' subscription is the most cost-effective. If they travel more than 5 days per month on a specific route, the 'Traject Vrij' subscription would be better. This holds true for both the current and potential new fare structures.

According to NS data (J. Traas[1], personal communication, April 2024), the 'Dal Voordeel' subscription holds the largest share with approximately 1.4 million subscriptions. The 'Weekend Voordeel' follows with 70,000 subscriptions. It can be inferred that the off-peak discount subscription primarily serves season ticket holders. Therefore, it is counterintuitive for season ticket holders to change their subscription in response to a new fare structure, as no new subscription appears more advantageous than the current options.

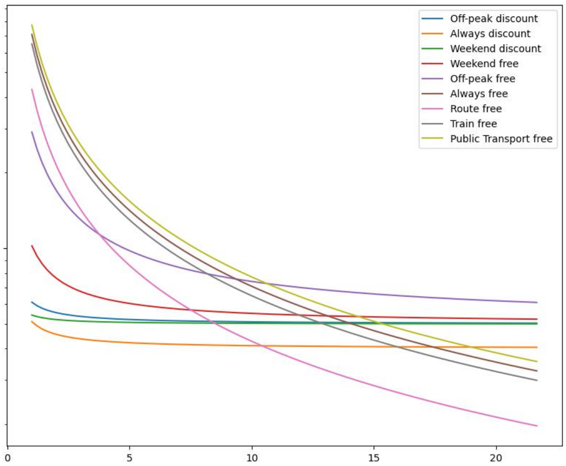
[1] Pricing Manager at NS



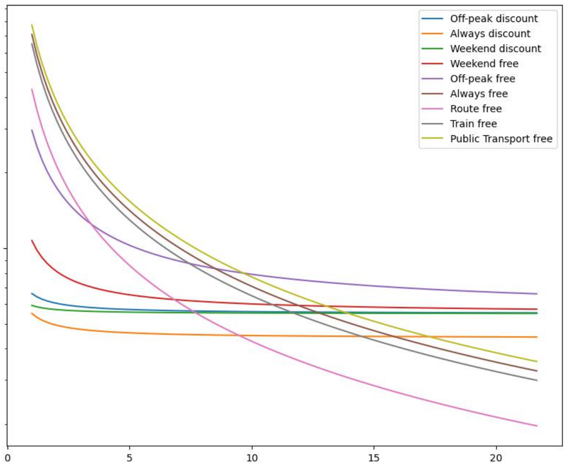
(a) Current fare system: ticket price €10,00



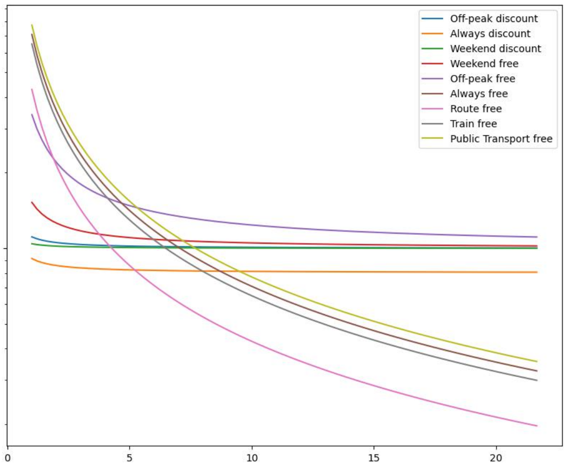
(b) New fare system: ticket price €12,50



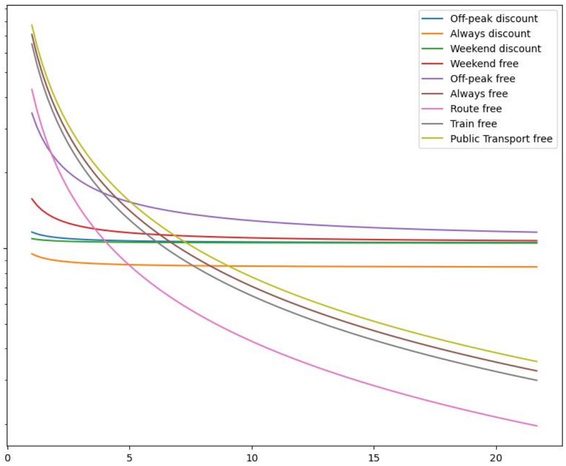
(c) Current fare system: ticket price €25,00



(d) New fare system: ticket price €27,50



(e) Current fare system: ticket price €50,00



(f) New fare system: ticket price €52,50

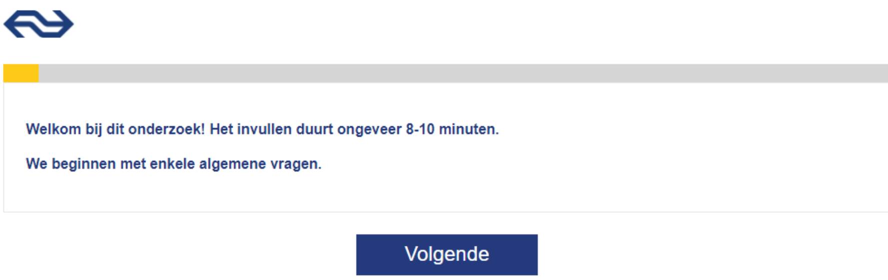
Figure A.1: Marginal costs per season ticket

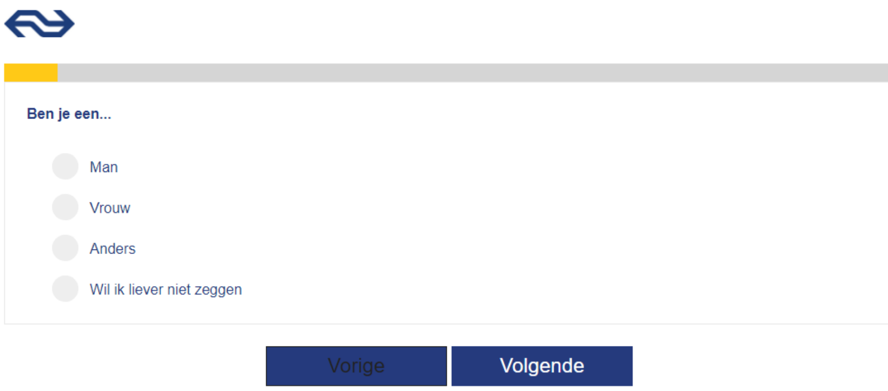
B

Construction of the choice sets

In this appendix, the survey and choice situations are presented. As shown in Figure B.2, seven choices are generated, each with a unique combination of attribute levels per choice. In the last column of the table, it can be seen that the 36 choice situations are divided into three different blocks, each containing twelve different choice sets.

B.1. Survey structure





Wat is je leeftijd?

jaar

Zeg ik liever niet

Vorige | Volgende

Wat is ongeveer het totale bruto inkomen per jaar in jouw huishouden?

Bruto jaarinkomen is het totale inkomen van jou en je eventuele partner voor belastingen + winst van alle betaalde banen, uitkeringen en pensioenen.

- Minder dan € 14.900
- € 14.900 - € 38.500
- € 38.500 - € 45.900
- € 45.900 - € 77.000
- Meer dan € 77.000
- Weet niet/zeg ik liever niet

Vorige | Volgende

Op hoeveel doordeweekse dagen reis je maandelijks met de trein tussen 06.00u en 09.29u in de ochtend?

- 1 – 3 keer per maand
- 4 – 6 keer per maand
- 7 – 9 keer per maand
- 10 – 12 keer per maand
- 13 – 15 keer per maand
- 16 – 18 keer per maand
- 19 – 21 keer per maand
- 22 – 24 keer per maand
- Geen van deze

Vorige | Volgende

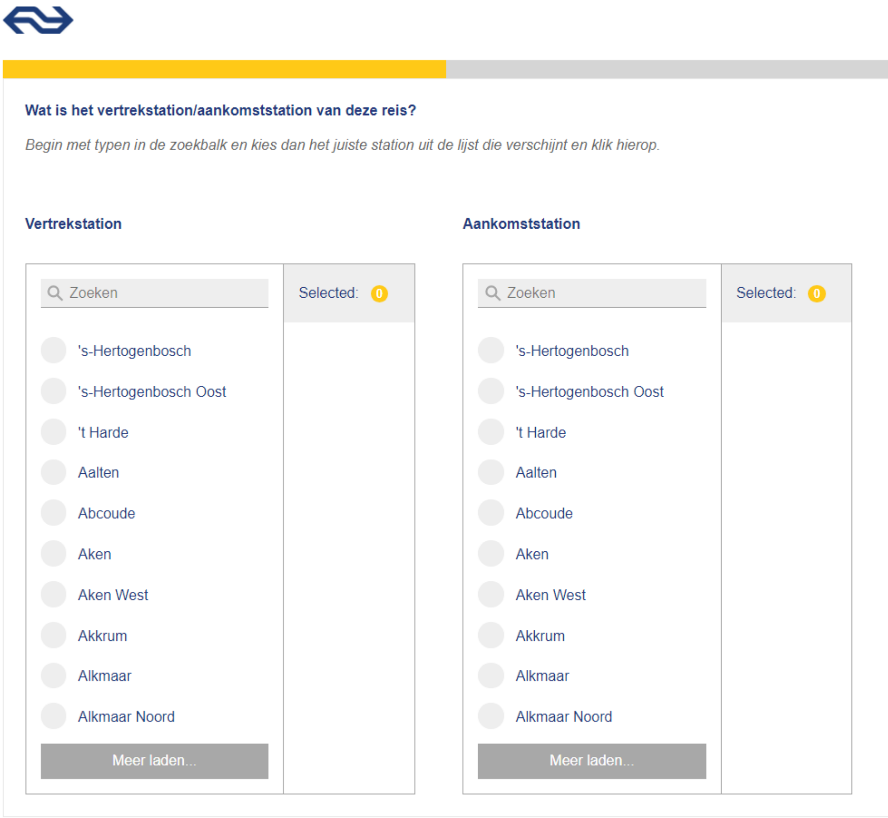
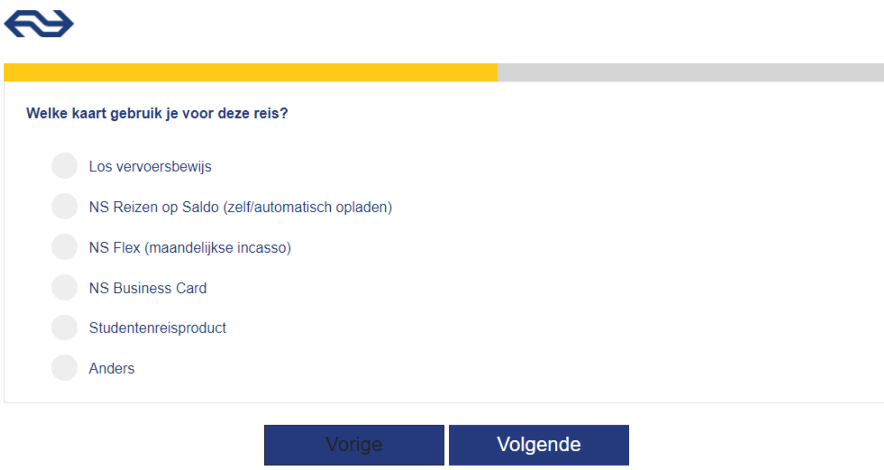
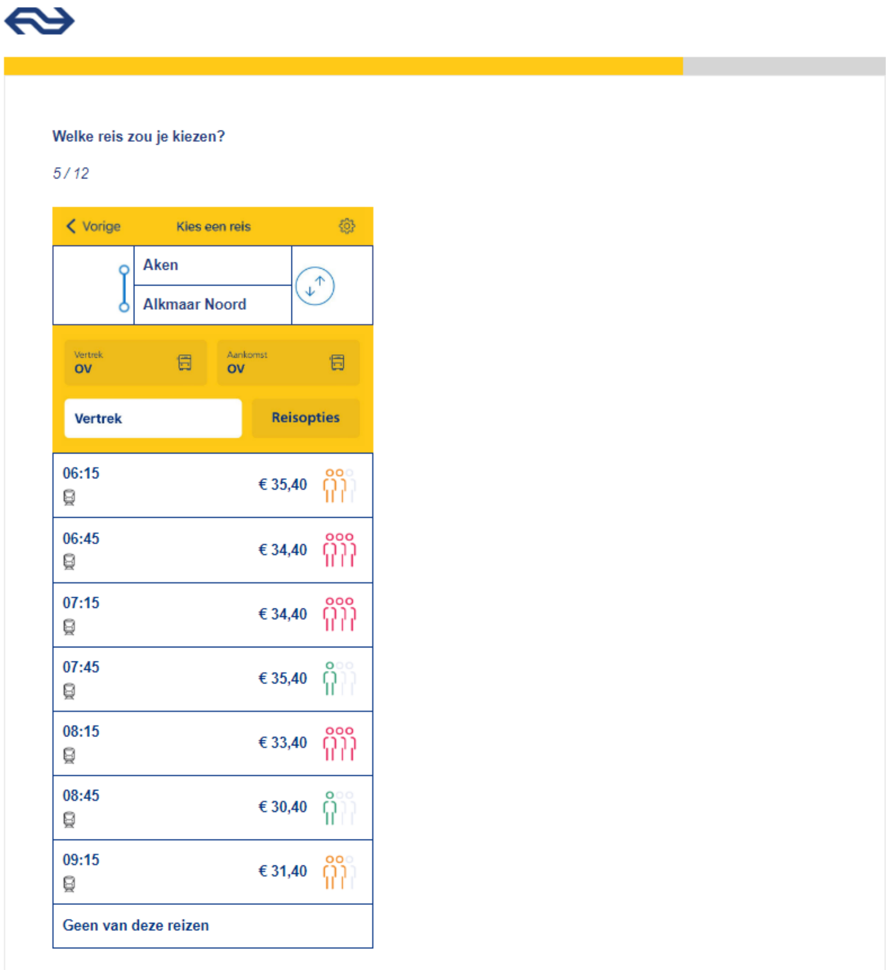


Figure B.1: Stations




In het volgende deel zal je worden gevraagd 12 keer een keuze te maken tussen verschillende reizen. De reizen verschillen ten opzichte van elkaar op het gebied van prijs, drukte en vertrektijd. Om drukte aan te geven, worden druktepoppetjes gebruikt. Een groen poppetje betekent dat er genoeg zitplaatsen zijn, twee oranje poppetjes betekent dat het gemiddeld druk is, maar er nog wel zitplaatsen beschikbaar zijn en drie rode poppetjes betekent dat er mogelijk geen zitplaatsen meer zijn. Ga ervan uit dat de keuzetaken gaan over de reis die je in gedachten hebt genomen bij het beantwoorden van de vorige vragen. De ritprijs die je ziet, is gebaseerd op de prijs van een los ticket voor jouw traject.
Houd tijdens het invullen altijd je eigen situatie in gedachten. Heb je bijvoorbeeld een 'Altijd Vrij' of een 'Traject Vrij' abonnement, dan geldt de getoonde ritprijs niet voor jou, omdat je dit hebt afgekocht met een abonnement. Je mag dan uitgaan van een ritprijs van €0,-. Reis je bijvoorbeeld met een 'Dal Voordeel' abonnement, dan gelden de getoonde prijzen wel voor jou. Als je voor jouw reis bijvoorbeeld een NS-business card gebruikt die wordt betaald door je werkgever mag je ervan uitgaan dat de getoonde ritprijs ook wordt betaald door je werkgever (dus is de ritprijs €0,-).
Vorige
Volgende


Welke reis zou je kiezen?
5 / 12
Vorige
Kies een reis
Aken
Alkmaar Noord
Vertrek
OV
Aankomst
OV
Vertrek
Reisopties
06:15
€ 35,40
06:45
€ 34,40
07:15
€ 34,40
07:45
€ 35,40
08:15
€ 33,40
08:45
€ 30,40
09:15
€ 31,40
Geen van deze reizen

NS moet extra treinen inzetten op dinsdag en donderdag tijdens de ochtendspits om ervoor te zorgen dat er genoeg zitplaatsen zijn voor de reizigers. Deze extra treinen worden op de betreffende dag ongeveer 2-4 uur volledig benut. Buiten de spitsuren om blijven meer dan 7 van de 10 stoelen leeg, dus niet alle coupes van de trein zijn nodig. Echter, het is niet mogelijk om tijdens de daluren de extra treinen en het personeel zomaar stil te zetten. De kosten voor extra treinen en personeel wordt betaald door treinreizigers.

Stel je voor dat het huidige tariefstelsel er als volgt uitziet: de prijs voor een treinreis wordt berekend op basis van de ***afstand*** *die iemand aflegt. De prijs voor een bepaald traject is tijdens spitsuren gelijk aan de prijs tijdens daluren. De extra kosten die gemaakt worden voor extra materieel en personeel tijdens spitsuren, worden verdeeld over* ***alle treinreizigers****.*

Hoe eerlijk vind je dit?

Helemaal oneerlijk	Redelijk oneerlijk	Een beetje oneerlijk	Niet oneerlijk/niet eerlijk	Een beetje eerlijk	Redelijk eerlijk	Helemaal eerlijk

Stel je voor dat het tariefstelsel uit het eerste statement wordt vervangen door een nieuw tariefstelsel dat er als volgt uitziet: de prijs voor een treinreis wordt berekend op basis van de ***afstand*** *die iemand aflegt en op basis van het* ***tijdstip*** *dat iemand reist. De prijs voor een bepaald traject is tijdens spitsuren duurder dan tijdens daluren. De extra kosten die gemaakt worden voor extra materieel en personeel tijdens spitsuren, worden verdeeld over de* ***spitsreizigers****. Als gevolg wordt 20% van de reizen duurder dan voorheen, omdat deze reizen in de spits vallen. 80% van de reizen wordt goedkoper dan voorheen, omdat deze reizen buiten de spits vallen.*

Hoe eerlijk zou je dit vinden?

Helemaal oneerlijk	Redelijk oneerlijk	Een beetje oneerlijk	Niet oneerlijk/niet eerlijk	Een beetje eerlijk	Redelijk eerlijk	Helemaal eerlijk

Volgende

B.2. Choice situations

Choice situation	a.price	a.drukte	b.price	b.drukte	c.price	c.drukte	d.price	d.drukte	e.price	e.drukte	f.price	f.drukte	g.price	g.drukte	Block
1	1	1	6	2	2	3	4	1	2	2	5	2	5	3	2
2	4	2	3	3	6	1	6	1	1	1	2	2	3	3	1
3	4	3	1	3	5	2	6	3	4	3	2	2	6	2	3
4	2	2	4	2	1	1	3	2	3	1	5	3	4	3	3
5	5	3	2	3	4	2	5	1	4	2	4	3	3	2	3
6	5	1	1	1	3	2	3	1	2	2	6	1	4	2	1
7	3	3	5	2	5	1	4	3	2	1	3	3	1	1	3
8	6	1	2	1	2	2	3	2	6	1	6	3	5	1	2
9	6	2	6	3	2	2	2	1	5	3	1	1	6	1	1
10	1	1	2	2	2	2	5	3	5	1	4	2	6	1	1
11	4	2	4	3	2	1	3	3	6	2	3	2	5	3	2
12	4	3	3	2	3	2	6	2	5	3	1	3	3	3	3
13	2	2	5	1	6	2	4	2	6	1	6	1	4	3	1
14	5	3	4	1	5	3	4	2	1	2	3	3	6	2	2
15	5	1	6	2	4	1	5	3	2	2	5	3	6	3	3
16	3	3	3	3	6	3	1	3	5	2	5	3	2	1	1
17	6	1	2	2	3	3	1	1	4	2	2	1	2	1	3
18	6	2	5	3	5	3	6	1	4	3	1	1	2	2	1
19	1	1	5	1	2	1	6	1	6	1	4	1	1	1	2
20	4	2	3	1	4	3	5	2	4	1	4	3	1	3	1
21	1	3	1	1	3	3	2	2	3	3	1	2	6	1	3
22	2	2	4	3	6	1	1	1	6	3	5	1	1	2	3
23	5	3	1	3	1	2	1	1	3	3	1	3	4	1	1
24	2	1	3	2	5	3	4	2	6	2	1	1	2	2	2
25	3	3	3	3	1	3	4	3	5	3	6	2	2	3	2
26	6	1	1	1	1	1	5	1	4	2	2	1	3	3	3
27	3	2	4	2	6	1	5	3	5	1	3	3	2	2	2
28	4	1	6	1	3	1	2	2	1	3	3	2	5	2	1
29	1	2	2	2	4	2	3	3	1	1	4	2	1	1	1
30	1	3	4	2	5	1	1	2	1	3	6	2	3	2	2
31	5	2	1	2	4	2	3	3	3	2	2	3	5	3	1
32	2	3	6	1	1	1	2	2	3	2	6	1	4	2	2
33	2	1	6	1	6	2	6	2	2	3	3	1	1	3	2
34	6	3	5	3	4	3	2	1	1	1	4	2	5	1	3
35	3	1	5	3	3	3	2	3	3	3	2	2	4	2	2
36	3	2	2	1	1	3	1	3	2	1	5	1	3	1	3

Figure B.2: Choice situations Ngene

C

Data cleaning and descriptive statistics

C.1. Data preparation

Reference dummy

In the following figure, the most frequently chosen answers by students and pupils are depicted. Frequency tables are utilised to select a reference answer per nominal question. Regarding education, students predominantly selected propaedeutic, bachelor's, or master's degrees. Since a significant majority of students have obtained at least a propaedeutic diploma, this has been chosen as the reference point. Concerning income, students indicated earning relatively little; thus, the lowest income category is chosen as the reference point. Students indicated predominantly not having children and being unmarried, residing primarily at home or with housemates. Therefore, answers indicating single status are chosen as the reference point. Regarding trip purpose, students commonly travel for educational purposes, which is straightforward. Hence, this is chosen as the reference point. Lastly, a large majority of students reported not paying for their own travel. Consequently, this is chosen as the reference point.

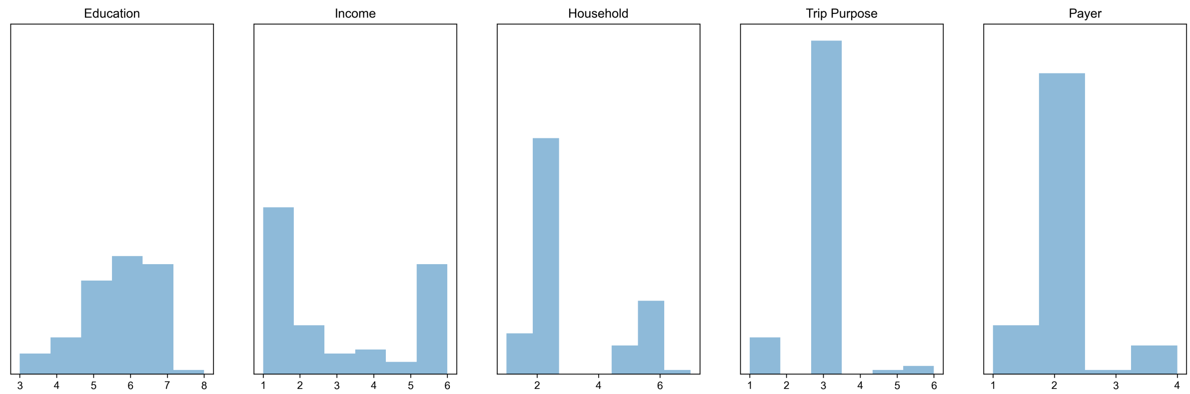


Figure C.1: Frequency table nominal variables for students

Missing age

Not all respondents provided their exact age; some preferred to indicate their age category instead. Table C.1 presents an overview of the mean, median, and mode for each age category. For the various categories, the chosen representative ages are 21, 29, 40, 51, 60, 67, and 77, respectively. These values have been incorporated into the dataset.

Table C.1: Average, median and mode of each age categorie

	18-24	**25-34**	**35-44**	**45-54**	**55-64**	**65-74**	**75+**
Average	21.38	29.35	39.65	50.17	59.74	68.01	77.48
Median	21	29	40	50.5	60	67	77
Mode	24	25	35	54	62	65	76

C.1.1. Dummy coding

Education

The variable 'education' is divided into four groups: low educated, medium educated, high educated, and 'else'. The low educated group includes respondents who indicated having no education, or up to the fourth year of vmbo, havo or vwo. The medium educated group consists of individuals with an mbo 2, 3, or 4 diploma, those with a havo or vwo diploma, and those with an hbo/wo propedeuse. The high educated group comprises individuals with an hbo/wo bachelor's or master's degree or higher. Lastly, some respondents selected the 'else' category.

Table C.2: Dummy education

	edu_low	*edu_high*	*edu_else*
None/basic	1	0	0
LBO/VMBO	1	0	0
MAVO/ (HAVO/VWO till fourth grade)	1	0	0
MBO 2,3,4	0	0	0
HAVO/VWO diploma	0	0	0
Propedeuse	0	0	0
HBO/WO bachelor	0	1	0
HBO/WO master	0	1	0
Else	0	0	1

Occupation

Pupils and students are classified under the category of education-following individuals. Employees remain a standalone category, as they are in paid employment. Entrepreneurs and freelancers are grouped together as self-employed individuals. Volunteers, househusbands and housewives, and retirees are classified in the final category, as it is assumed they no longer have income from employment. Additionally, an 'else' group is included for this category.

Table C.3: Dummy occupation

	occ_wage	*occ_entre*	*occ_none*	*occ_else*
Pupil	0	0	0	0
Student	0	0	0	0
Employee	1	0	0	0
Entrepreneur	0	1	0	0
Freelancer	0	1	0	0
Volunteer	0	0	1	0
Houseman/housewife	0	0	1	0
Retiree	0	0	1	0
Else	0	0	0	1

Income

A significant portion of respondents preferred not to disclose their income. Additionally, the other five categories have not been combined. Consequently, there are six categories for income in total.

Table C.4: Dummy income

	inc_low	*inc_med*	*inc_high*	*inc_very_high*	*inc_wrns*
0 - 14.900	0	0	0	0	0
14.900 - 38.500	1	0	0	0	0
38.500 - 45.900	0	1	0	0	0
45.900 - 77.000	0	0	1	0	0
77.000 - +	0	0	0	1	0
Would rather not say	0	0	0	0	1

Household

Respondents who indicated they are single, live with their parents, or reside in a household with multiple adults (students) are coded as 'single'. These individuals do not have responsibility for children and function as a single respondent. Respondents who selected 'else' are challenging to define, but it has been decided not to exclude them from the analysis. Therefore, they are coded as 'else'.

Table C.5: Dummy household

	hh_sc	*hh_tc*	*hh_t*	*hh_wrns*
Single	0	0	0	0
Living at parents	0	0	0	0
Single with children	1	0	0	0
Together with children	0	1	0	0
Together without children	0	0	1	0
Multiple adults	0	0	0	0
Else	0	0	0	1

Age oldest child

Table C.6: Dummy age oldest

	aoy	*aom*	*aoo*
Age oldest 0-4	1	0	0
Age oldest 4-15	0	1	0
Age oldest 16+	0	0	1
Else	0	0	0

Age youngest child

Table C.7: Dummy age youngest

	ayy	*aym*	*ayo*
Age youngest 0-4	1	0	0
Age youngest 4-15	0	1	0
Age youngest 16+	0	0	1
Else	0	0	0

Trip purpose

Table C.8: Dummy purpose

	pur_busi	*pur_priv*	*pur_else*
Work	1	0	0
Business	1	0	0
Education	0	0	0
Visit family/friends	0	1	0
Shopping/holiday	0	1	0
Else	0	0	1

Payer

The respondent had four options to choose from when indicating who pays for the most frequent journey: themselves, another party entirely, partially themselves, or 'else'. These four categories were also used in dummy coding.

Table C.9: Dummy payer

	pay_self	*pay_part*	*pay_else*
Self	1	0	0
Not self	0	0	0
Partly self	0	1	0
Else	0	0	1

Cardtype and proposition

This coding is more intricate compared to the other codings explained above. Ticket type can be divided into a single ticket or an NS subscription. The survey includes four types of subscriptions, such as NS Travel on Balance and NS Flex. These subscriptions mentioned earlier share a considerable number of propositions (see Appendix A). These propositions also exhibit similarities. The first group of propositions includes Off-Peak Discount and Off-Peak Free Travel. These propositions offer travellers 40% or 100% discount during off-peak hours. Travelling during peak periods is not advantageous for travellers with these propositions.

The following propositions can also be combined: Always Advantage, Always Free, and Route Free. These propositions offer discounts ranging from 40% to 100% outside peak periods and 20%, 40%, or 100% discounts during peak periods. For these travellers, travelling during peak periods is more advantageous than choosing an off-peak proposition.

Weekend Voordeel and Weekend Vrij are the other propositions that have been combined. For this proposition, full fare is charged both during and outside crowded peak periods on weekdays. Given that this study focuses on peak-time travel on weekdays, it can be concluded that there is no benefit to be gained for these travellers anywhere.

The propositions available to business travellers can be divided into the categories Advantage and Free. This distinction has been made during dummy coding. For student cards, the data only include students with a weekly subscription, so no distinction needs to be made.

Finally, there is also an 'other' option, meaning that someone chooses not to select any ticket type at all. This option was chosen by 223 respondents, which constitutes a significant portion. Therefore, for these respondents, it is unknown which ticket they are using for travel.

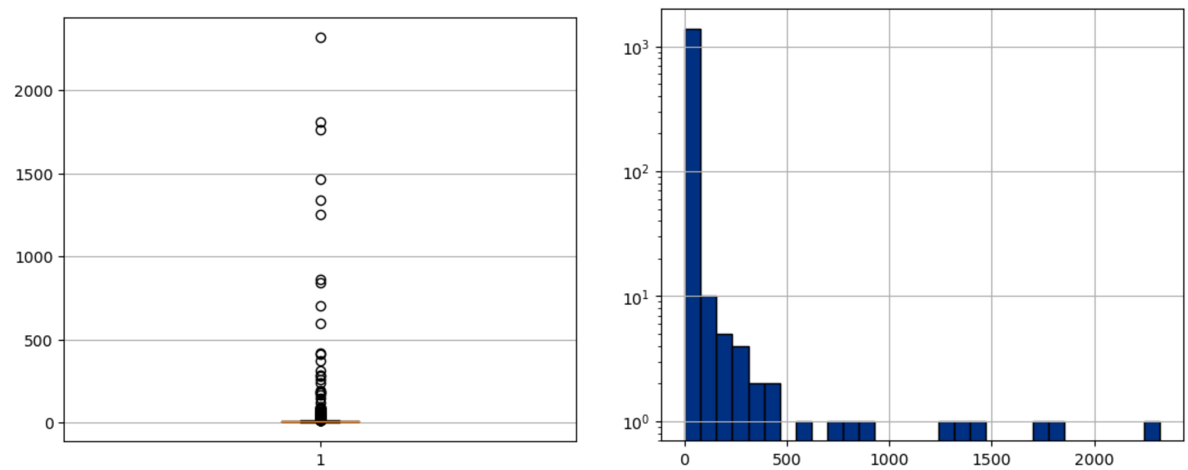
Table C.10: Dummy card and proposition

	op_disc	*p_disc*	*weekend*	*ros_else*	*b_disc*	*b_free*	*lvb*	*else*
Separate ticket	0	0	0	0	0	0	1	0
Travel on Balance Dal Voordeel	1	0	0	0	0	0	0	0
Travel on Balance Altijd Voordeel	0	1	0	0	0	0	0	0
Travel on Balance Weekend Vrij	0	0	1	0	0	0	0	0
Travel on Balance Dalvrij	1	0	0	0	0	0	0	0
Travel on Balance Else	0	0	0	1	0	0	0	0
NS Flex Traject Vrij	0	1	0	0	0	0	0	0
NS Flex Weekend Voordeel	0	0	1	0	0	0	0	0
NS Flex Dal Voordeel	1	0	0	0	0	0	0	0
NS Flex Altijd Voordeel	0	1	0	0	0	0	0	0
NS Flex Weekend Vrij	0	0	1	0	0	0	0	0
NS Flex Dal Vrij	1	0	0	0	0	0	0	0
NS Flex Altijd Vrij	0	1	0	0	0	0	0	0
NS Flex Else	1	0	0	0	0	0	0	0
NS Business Dal	0	0	0	0	1	0	0	0
NS Business Trein Vrij	0	0	0	0	0	1	0	0
NS Business Traject Vrij	0	0	0	0	0	1	0	0
NS Business OV Vrij	0	0	0	0	0	1	0	0
NS Business Else	0	0	0	0	1	0	0	0
Studentcard	0	0	0	0	0	0	1	0
Else	0	0	0	0	0	0	0	1

C.2. Data cleaning

Survey length

The average time taken to complete the survey is twice as high as estimated. Therefore, outliers have been identified using the Inter Quartile Range (IQR) approach and removed for calculating the mean. The boxplot displaying the duration time before outlier removal can be found in figure C.3a. The IQR approach works as follows: the data is divided into four equal parts, namely Q1, Q2, Q3, and Q4. Q1 represents the 25th percentile of the data, and Q3 represents the 75th percentile. The IQR is the difference between Q3 and Q1. Values that fall 1.5 times the IQR above or below the first or third percentile are considered outliers. The average time taken to complete the survey is approximately 20 minutes. According to the IQR approach, all values equal to or greater than 13.41 minutes are outliers. Figure C.3b displays a histogram showing the frequency distribution of values. The y-axis is logarithmically scaled to visualize the histograms for outliers as well.

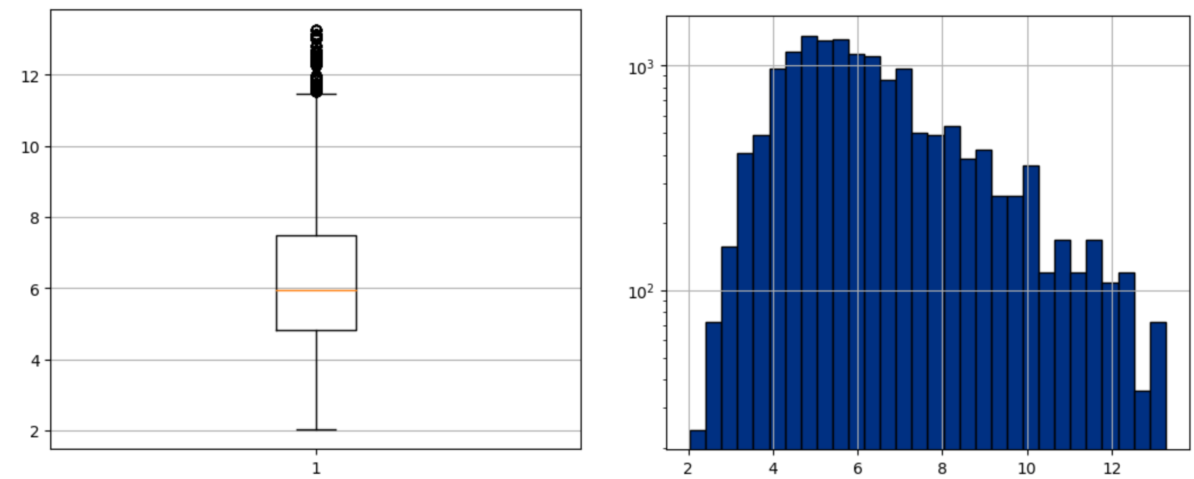


(a) Boxplot of duration after removal of outliers

(b) Histogram of duration after removal outliers

Figure C.2: Outliers graphical

The dataset contains 1560 records with outliers. Each respondent has 12 records, indicating that 130 individuals have an outlier in duration. Excluding these 130 respondents reduces the average filling time to 6.37 minutes. The updated plots can be found in figure C.3



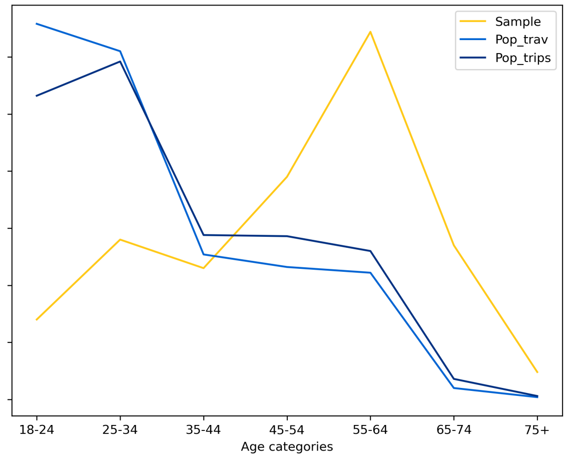
(a) Boxplot of duration after removal of outliers

(b) Histogram of duration after removal outliers

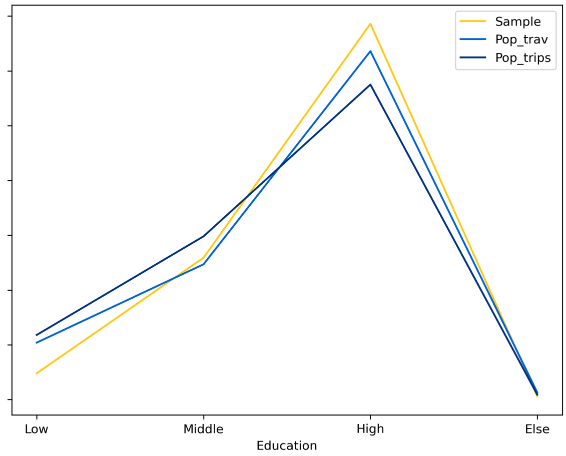
Figure C.3: Outliers graphical

C.3. Descriptive statistics

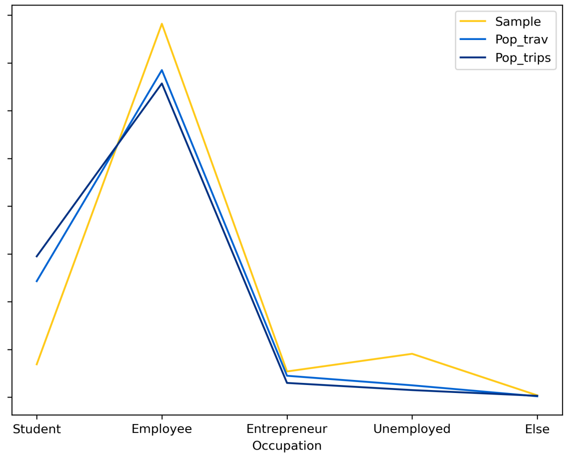
Comparison sample with population



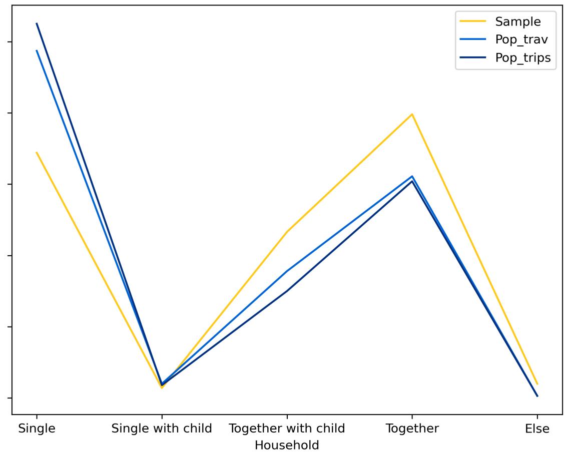
(a) Age in sample and population



(b) Level of education in sample and population

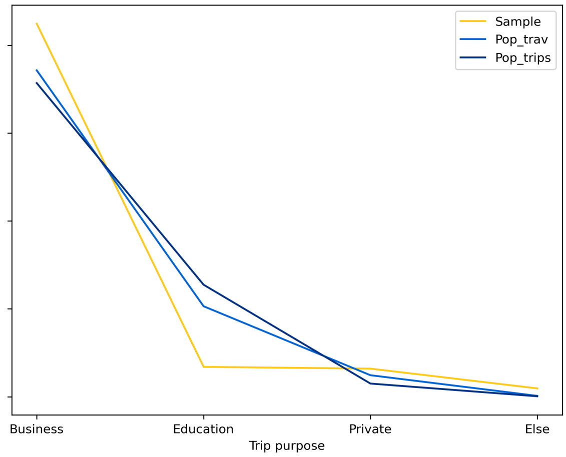


(c) Occupation in sample and population

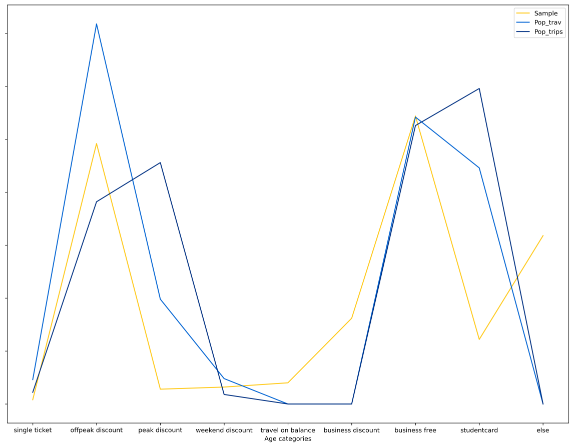


(d) Composition household in sample and population

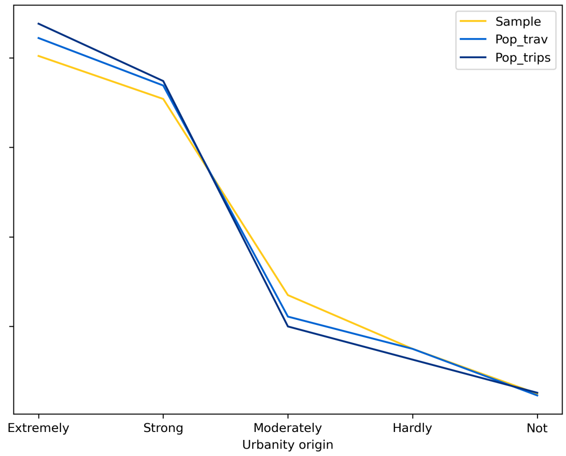
Figure C.4: Comparison of personal characteristics in sample and population



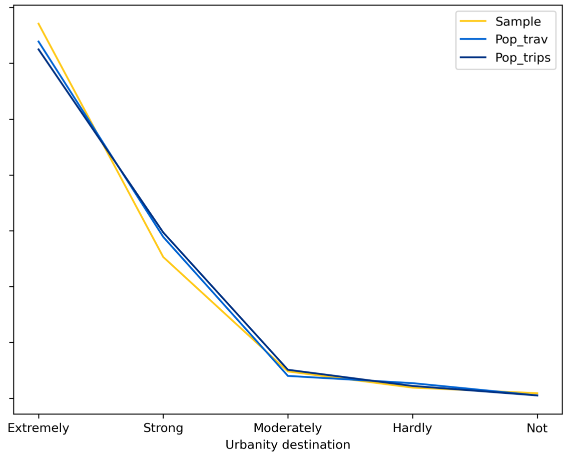
(a) Trip purpose in sample and population



(b) Card type in sample and population



(c) Urbanity origin in sample and population



(d) Urbanity destination in sample and population

Figure C.5: Comparison of travel characteristics in sample and population

D

Model specification

D.1. Tested utility functions

1. Three variables and no interaction effect

$$V_i = (\beta_{p\_diff} \times \Delta price_i) + (\beta_c \times crowd_i) + (\beta_m \times moment_i) \tag{D.1}$$

2. Three variables and with interaction effect

$$V_i = ((\beta_{p\_diff} + \frac{\beta_{p\_inter}}{base\_price}) \times \Delta price_i) + (\beta_c \times crowd_i) + (\beta_m \times moment_i) \tag{D.2}$$

3. Three variables and with interaction effect and quadratic components

$$\begin{aligned} V_i = ((\beta_{p\_diff} + \frac{\beta_{p\_inter}}{base\_price}) \times \Delta price_i) + (\beta_c \times crowd_i) + (\beta_m * moment_i) \\ +((\beta_{p\_diffQ} + \frac{\beta_{p\_interQ}}{base\_price}) \times \Delta price_i^2) + (\beta_{cQ} \times crowd_i^2) + (\beta_{mQ} \times moment_i^2) \end{aligned} \tag{D.3}$$

4. Three variables and with interaction effect and quadratic component for crowd

$$V_i = (\beta_{p\_diff} + \frac{\beta_{p\_inter}}{base\_price}) \times \Delta price_i + (\beta_c \times crowd_i) + (\beta_{cQ} \times crowd_i^2) + (\beta_m \times moment_i) \tag{D.4}$$

5. Three variables and with interaction effect and quadratic component for price

$$V_i = ((\beta_{p\_diff} + \frac{\beta_{p\_inter}}{base\_price}) \times \Delta price_i) + (\beta_{p\_diffQ} \times \Delta price_i^2) + (\beta_c \times crowd_i) + (\beta_m \times moment_i) \tag{D.5}$$

6. Three variables and with interaction effect and quadratic component for price interaction

$$V_i = ((\beta_{p\_diff} + \frac{\beta_{p\_inter}}{base\_price}) \times \Delta price_i) + (\frac{\beta_{p\_interQ}}{base\_price} \times \Delta price_i^2) + (\beta_c \times crowd_i) + (\beta_m \times moment_i) \tag{D.6}$$

D.2. Correlation Matrix

	p1	c1	m1	p2	c2	m2	p3	c3	m3	p4	c4	m4	p5	c5	m5	p6	c6	m6	p7	c7	m7	pi1	pi2	pi3	pi4	pi5	pi6	pi7	c1Q	c2Q	c3Q	c4Q	c5Q	c6Q	c7Q
p1	1,00																																		
c1	0,00	1,00																																	
m1	-0,01	-0,01	1,00																																
p2	-0,17	-0,14	0,02	1,00																															
c2	0,20	0,33	-0,01	0,00	1,00																														
m2	0,00	0,00	-0,16	0,00	0,00	1,00																													
p3	-0,08	0,14	0,00	0,15	0,16	0,00	1,00																												
c3	0,12	0,08	0,00	-0,20	0,08	0,00	0,00	1,00																											
m3	0,00	0,00	-0,19	0,00	0,00	-0,19	0,00	0,00	1,00																										
p4	0,02	-0,16	0,00	0,07	-0,08	0,00	0,23	-0,14	0,00	1,00																									
c4	-0,30	0,13	0,01	-0,06	0,00	0,00	0,08	0,00	0,00	0,00	1,00																								
m4	0,00	0,00	-0,19	0,00	0,00	-0,20	0,00	0,00	-0,23	0,00	0,00	1,00																							
p5	-0,02	-0,12	0,01	-0,11	0,14	0,00	-0,07	0,00	0,00	0,14	0,02	0,00	1,00																						
c5	0,10	0,17	0,00	0,06	0,29	0,00	0,00	0,13	0,00	-0,16	-0,12	0,00	0,00	1,00																					
m5	0,02	0,01	-0,17	-0,02	0,01	-0,18	0,00	0,00	-0,20	0,00	-0,01	-0,21	-0,01	0,00	1,00																				
p6	-0,30	-0,02	0,01	0,17	-0,26	0,00	-0,09	-0,16	0,00	-0,20	0,14	0,00	-0,04	-0,36	-0,01	1,00																			
c6	0,14	0,37	0,00	-0,16	0,17	0,00	0,08	-0,04	0,00	0,08	0,38	0,00	-0,14	-0,17	0,01	0,00	1,00																		
m6	0,00	0,00	-0,11	0,00	0,00	-0,11	0,00	0,00	-0,13	0,00	0,00	-0,13	0,00	0,00	-0,12	0,00	0,00	1,00																	
p7	0,24	0,02	0,00	-0,03	0,00	0,00	-0,30	0,04	0,00	-0,12	0,08	0,00	-0,15	0,14	0,00	-0,07	0,18	0,00	1,00																
c7	0,00	-0,12	0,01	0,18	-0,04	0,00	0,10	-0,21	0,00	0,46	0,04	0,00	0,00	0,13	-0,01	0,08	0,08	0,00	0,00	1,00															
m7	0,00	0,00	-0,14	0,00	0,00	-0,15	0,00	0,00	-0,17	0,00	0,00	-0,18	0,00	0,00	-0,16	0,00	0,00	-0,10	0,00	0,00	1,00														
pi1	0,55	0,00	-0,09	-0,10	0,11	-0,09	-0,05	0,06	-0,03	0,01	-0,16	0,08	-0,01	0,05	0,10	-0,16	0,08	0,06	0,13	0,00	-0,04	1,00													
pi2	-0,10	-0,07	-0,08	0,54	0,00	-0,08	0,08	-0,11	-0,03	0,04	-0,03	0,08	-0,06	0,03	0,08	0,10	-0,08	0,07	-0,02	0,10	-0,04	0,49	1,00												
pi3	-0,04	0,08	-0,09	0,08	0,09	-0,08	0,54	0,00	-0,03	0,12	0,04	0,08	-0,04	0,01	0,09	-0,05	0,05	0,06	-0,16	0,05	-0,04	0,53	0,63	1,00											
pi4	0,01	-0,08	-0,08	0,04	-0,04	-0,08	0,12	-0,08	-0,03	0,55	0,00	0,08	0,08	-0,08	0,09	-0,11	0,05	0,07	-0,07	0,25	-0,04	0,58	0,60	0,66	1,00										
pi5	-0,01	-0,06	-0,08	-0,06	0,08	-0,08	-0,04	-0,01	-0,03	0,08	0,01	0,08	0,54	0,00	0,09	-0,02	-0,08	0,07	-0,09	0,00	-0,04	0,56	0,52	0,54	0,63	1,00									
pi6	-0,16	-0,01	-0,08	0,10	-0,14	-0,08	-0,05	-0,09	-0,03	-0,11	0,07	0,08	-0,02	-0,19	0,09	0,54	0,00	0,07	-0,04	0,04	-0,04	0,44	0,65	0,53	0,48	0,55	1,00								
pi7	0,13	0,02	-0,09	-0,02	0,00	-0,08	-0,16	0,02	-0,03	-0,07	0,05	0,08	-0,09	0,08	0,10	-0,03	0,10	0,06	0,55	0,00	-0,04	0,67	0,56	0,44	0,52	0,50	0,54	1,00							
c1Q	0,00	0,99	-0,01	-0,14	0,31	0,00	0,11	0,10	0,00	-0,16	0,11	0,00	-0,14	0,21	0,01	-0,01	0,38	0,00	0,04	-0,15	0,00	0,00	-0,07	0,07	-0,08	-0,07	0,00	0,03	1,00						
c2Q	0,24	0,35	-0,01	0,00	0,99	0,00	0,15	0,10	0,00	-0,09	-0,04	0,00	0,15	0,32	0,01	-0,25	0,12	0,00	0,01	-0,05	0,00	0,13	0,00	0,08	-0,05	0,08	-0,13	0,00	0,33	1,00					
c3Q	0,10	0,08	0,00	-0,15	0,08	0,00	0,00	0,99	0,00	-0,16	0,00	0,00	-0,02	0,11	0,00	-0,15	-0,05	0,00	0,01	-0,19	0,00	0,05	-0,08	0,00	-0,09	-0,02	-0,08	0,01	0,10	0,10	1,00				
c4Q	-0,26	0,11	0,00	-0,08	0,08	0,00	0,07	0,00	0,00	0,00	0,99	0,00	0,03	-0,13	-0,01	0,12	0,36	0,00	0,07	0,01	0,00	-0,14	-0,04	0,04	0,00	0,01	0,07	0,04	0,10	0,04	0,00	1,00			
c5Q	0,06	0,19	0,00	0,07	0,30	0,00	0,01	0,11	0,00	-0,15	-0,11	0,00	0,00	0,99	0,00	-0,36	-0,17	0,00	0,11	0,09	0,00	0,03	0,04	0,01	-0,08	0,00	-0,19	0,06	0,22	0,33	0,10	-0,12	1,00		
c6Q	0,18	0,36	0,00	-0,16	0,12	0,00	0,09	-0,05	0,00	0,09	0,34	0,00	-0,09	-0,19	0,01	0,00	0,99	0,00	0,13	0,08	0,00	0,10	-0,08	0,05	0,05	-0,05	0,00	0,08	0,36	0,08	-0,06	0,32	-0,19	1,00	
c7Q	0,00	-0,13	0,00	0,16	-0,05	0,00	0,05	-0,19	0,00	0,46	0,05	0,00	0,01	0,07	-0,01	0,08	0,10	0,00	0,00	0,99	0,00	0,00	0,09	0,03	0,25	0,01	0,04	0,00	-0,17	-0,06	-0,19	0,02	0,04	0,10	1,00

Figure D.1: Correlation matrix independent variables utility function

E

Latent Class Choice Model Table

Table E.1: Estimates parameters LCCM with two classes

	Class 1		Class 2	
	Est.	*t-ratio (0)*	*Est.*	*t-ratio (0)*
β_{p_diff}	-0.106	-3.375	-0.179	-12.970
β_{p_inter}	-0.228	-1.037	-0.558	-5.884
β_c	1.361	4.542	-0.227	-1.794
β_{cQ}	-0.669	-8.710	-0.174	-5.189
β_m	5.409	53.143	1.639	43.883
δ_{optout}	-2.143	-5.745	-1.856	-16.414
Class membership				
$\alpha_{constant}$	0.000	-	0.173	0.388
$\gamma_{urbanity\_origin}$	0.000	-	-0.051	-0.882
γ_{class}	0.000	-	0.084	0.474
$\gamma_{travel\_distance}$	0.000	-	-0.001	-0.707
γ_{gender}	0.000	-	-0.121	-0.961
γ_{age}	0.000	-	0.003	0.580
$\gamma_{car\_ownership}$	0.000	-	0.263	1.814
$\gamma_{travel\_moment\_0615}$	0.000	-	-0.951	-4.063
$\gamma_{travel\_moment\_0645}$	0.000	-	-0.183	-0.876
$\gamma_{travel\_moment\_0715}$	0.000	-	-0.210	-1.104
$\gamma_{travel\_moment\_0815}$	0.000	-	0.151	0.758
$\gamma_{travel\_moment\_0845}$	0.000	-	0.186	0.711
$\gamma_{travel\_moment\_0915}$	0.000	-	0.498	1.883
$\gamma_{occupation\_employee}$	0.000	-	-0.977	-1.072
$\gamma_{occupation\_entrepreneur}$	0.000	-	-1.243	-1.318
$\gamma_{occupation\_unemployed}$	0.000	-	-1.619	-1.736
$\gamma_{occupation\_unknown}$	0.000	-	-1.783	-1.166
γ_{pay_full}	0.000	-	0.492	2.460
γ_{pay_part}	0.000	-	0.320	1.753
γ_{pay_else}	0.000	-	0.922	1.965
γ_{income_low}	0.000	-	-0.021	-0.049
γ_{income_mid}	0.000	-	-0.204	-0.480
γ_{income_high}	0.000	-	-0.234	-0.575
$\gamma_{income\_very\_high}$	0.000	-	-0.266	-0.646
γ_{income_wrns}	0.000	-	-0.337	-0.841

$\gamma_{purpose\_business}$	0.000	-	-0.125	-0.256
$\gamma_{purpose\_private}$	0.000	-	0.279	0.504
$\gamma_{purpose\_else}$	0.000	-	-0.718	-1.124
$\gamma_{education\_low}$	0.000	-	-0.158	-0.524
$\gamma_{education\_high}$	0.000	-	-0.041	-0.269
$\gamma_{education\_else}$	0.000	-	-0.206	-0.272
$\gamma_{household\_single\_children}$	0.000	-	-0.154	-0.309
$\gamma_{household\_together\_children}$	0.000	-	0.015	0.081
$\gamma_{household\_together}$	0.000	-	0.012	0.075
$\gamma_{household\_wrns}$	0.000	-	0.251	0.424
γ_{card_lvb}	0.000	-	0.352	0.274
$\gamma_{card\_offpeak\_discount}$	0.000	-	1.023	1.203
$\gamma_{card\_peak\_discount}$	0.000	-	0.437	0.506
$\gamma_{card\_weeknd\_discount}$	0.000	-	0.835	0.881
$\gamma_{card\_ros\_unknown}$	0.000	-	0.370	0.387
$\gamma_{card\_business\_offpeak\_discount}$	0.000	-	1.193	1.366
$\gamma_{card\_business\_always\_discount}$	0.000	-	0.527	0.617
$\gamma_{card\_unknown}$	0.000	-	0.690	0.802

F

Codes R-studio

F.1. Multinomial Logit Model

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

# Clear memory
rm(list = ls())

# Load Apollo library
library(apollo)

# Initialise code
apollo_initialise()

# Set core controls
apollo_control = list(
  modelName       = "MNL_thesis",
  modelDescr      = "MNL",
  indivID         = "respid",
  outputDirectory = "output",
  panelData = FALSE
)

setwd("~/TU Delft/EPA/Master Thesis/Data/resultaten_survey")
# Load data
database = read.csv('data_frame_final_csv_cov_dummy_nieuw.csv',sep = ',',header = TRUE)


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

# Define parameters
apollo_beta = c(
  b_price_single =0,
  b_price   = 0,
  b_crowd   = 0,
  b_crowdQ   = 0,
  b_moment = 0,
  d_optout = 0

)

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

# Validate inputs
```

```
apollo_inputs = apollo_validateInputs()

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

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

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

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

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
  V[["Optie1"]]  = (b_price_single * p1) + (b_price * p1 * (1/hprice)) +  (b_crowd * c1) + (b_moment * m1) + (b_crowdQ * c1*c1)
  V[["Optie2"]]  = (b_price_single * p2) + (b_price * p2 * (1/hprice)) +  (b_crowd * c2) + (b_moment * m2) + (b_crowdQ * c2*c2)
  V[["Optie3"]]  = (b_price_single * p3) + (b_price * p3 * (1/hprice)) +  (b_crowd * c3) + (b_moment * m3) + (b_crowdQ * c3*c3)
  V[["Optie4"]]  = (b_price_single * p4) + (b_price * p4 * (1/hprice)) +  (b_crowd * c4) + (b_moment * m4) + (b_crowdQ * c4*c4)
  V[["Optie5"]]  = (b_price_single * p5) + (b_price * p5 * (1/hprice)) +  (b_crowd * c5) + (b_moment * m5) + (b_crowdQ * c5*c5)
  V[["Optie6"]]  = (b_price_single * p6) + (b_price * p6 * (1/hprice)) +  (b_crowd * c6) + (b_moment * m6) + (b_crowdQ * c6*c6)
  V[["Optie7"]]  = (b_price_single * p7) + (b_price * p7 * (1/hprice)) +  (b_crowd * c7) + (b_moment * m7) + (b_crowdQ * c7*c7)
  V[["Optie8"]]  = d_optout

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(Optie1=1, Optie2=2, Optie3=3, Optie4=4, Optie5=5, Optie6=6, Optie7=7, Optie8=99),
    avail         = list(Optie1=1, Optie2=1, Optie3=1, Optie4=1, Optie5=1, Optie6=1, Optie7=1, Optie8=1),
    choiceVar     = gekozenreis,
    utilities     = V
  )

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

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

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

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

# Print output
apollo_modelOutput(model)

# Save output
apollo_saveOutput(model)
```

F.2. Latent Class Choice Model

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

```
########################################

# Clear memory
rm(list = ls())


# Load Apollo library
library(apollo)

# Initialise code
apollo_initialise()

# Set core controls
apollo_control = list(
  modelName       = "LCCM_final_thesis",
  modelDescr      = "LCCM_final",
  indivID         = "respid",
  outputDirectory = "output",
  panelData = TRUE
)

setwd("~/TU␣Delft/EPA/Master␣Thesis/Data/resultaten_survey")
# Load data
database = read.csv('data_frame_final_csv_cov_dummy_nieuw.csv',sep = ',',header = TRUE)

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

# Define parameters
apollo_beta = c(
     b_price_single_1 = 0, b_price_1 = 0, b_crowd_1 = 0, b_crowdQ_1 = 0, b_moment_1 = 0, optout_1 = 0
    ,b_price_single_2 = 0, b_price_2 = 0, b_crowd_2 = 0, b_crowdQ_2 = 0, b_moment_2 = 0, optout_2 = 0
    ,b_price_single_3 = 0, b_price_3 = 0, b_crowd_3 = 0, b_crowdQ_3 = 0, b_moment_3 = 0, optout_3 = 0
    ,b_price_single_4 = 0, b_price_4 = 0, b_crowd_4 = 0, b_crowdQ_4 = 0, b_moment_4 = 0, optout_4 = 0

    ,delta_1 = 0
    ,delta_2 = 0
    ,delta_3 = 0
    ,delta_4 = 0

    ,gamma_0615_1 = 0 ,gamma_0645_1 = 0 ,gamma_0715_1 = 0 ,gamma_0815_1 = 0 ,gamma_0845_1 = 0 ,gamma_0915_1 = 0
    ,gamma_0615_2 = 0 ,gamma_0645_2 = 0 ,gamma_0715_2 = 0 ,gamma_0815_2 = 0 ,gamma_0845_2 = 0 ,gamma_0915_2 = 0
    ,gamma_0615_3 = 0 ,gamma_0645_3 = 0 ,gamma_0715_3 = 0 ,gamma_0815_3 = 0 ,gamma_0845_3 = 0 ,gamma_0915_3 = 0
    ,gamma_0615_4 = 0 ,gamma_0645_4 = 0 ,gamma_0715_4 = 0 ,gamma_0815_4 = 0 ,gamma_0845_4 = 0 ,gamma_0915_4 = 0

    ,gamma_pay_full_1 = 0, gamma_pay_part_1 = 0, gamma_pay_else_1 = 0
    ,gamma_pay_full_2 = 0, gamma_pay_part_2 = 0, gamma_pay_else_2 = 0
    ,gamma_pay_full_3 = 0, gamma_pay_part_3 = 0, gamma_pay_else_3 = 0
    ,gamma_pay_full_4 = 0, gamma_pay_part_4 = 0, gamma_pay_else_4 = 0
    )

    apollo_fixed = c('delta_1'
                     ,'gamma_0615_1','gamma_0645_1','gamma_0715_1','gamma_0815_1','gamma_0845_1','gamma_0915_1'
                     ,'gamma_pay_full_1', 'gamma_pay_part_1', 'gamma_pay_else_1'
                    )


    # Define class membership functions
    apollo_lcPars=function(apollo_beta, apollo_inputs){
      lcpars = list()
      lcpars[["b_price_single"]] =    list(b_price_single_1, b_price_single_2, b_price_single
```

```
        _3, b_price_single_4)
    lcpars[["b_price"]] =         list(b_price_1,      b_price_2,      b_price_3,      b_price_4)
    lcpars[["b_crowd"]] =         list(b_crowd_1,      b_crowd_2,      b_crowd_3,      b_crowd_4)
    lcpars[["b_crowdQ"]] =        list(b_crowdQ_1,     b_crowdQ_2,     b_crowdQ_3,     b_crowdQ_4)
    lcpars[["b_moment"]] =        list(b_moment_1,     b_moment_2,     b_moment_3,     b_moment_4)
    lcpars[["delta_optout"]] =    list(optout_1,       optout_2,       optout_3,       optout_4)

    V=list()
    V[["class_1"]] = (delta_1
                      +gamma_0615_1  * t0615 + gamma_0645_1  * t0645 + gamma_0715_1  * t0715 + gamma_0815_1  * t0815 + gamma_0845_1  * t0845 + gamma_0915_1 * t0915
                      +gamma_pay_full_1 * pay_full +  gamma_pay_part_1 * pay_part + gamma_pay_else_1 * pay_else
                      )

    V[["class_2"]] = (delta_2
                      +gamma_0615_2  * t0615 + gamma_0645_2  * t0645 + gamma_0715_2  * t0715 + gamma_0815_2  * t0815 + gamma_0845_2  * t0845 + gamma_0915_2 * t0915
                      +gamma_pay_full_2 * pay_full +  gamma_pay_part_2 * pay_part + gamma_pay_else_2 * pay_else
                      )


    V[["class_3"]] = (delta_3
                      +gamma_0615_3  * t0615 + gamma_0645_3  * t0645 + gamma_0715_3  * t0715 + gamma_0815_3  * t0815 + gamma_0845_3  * t0845 + gamma_0915_3 * t0915
                      +gamma_pay_full_3 * pay_full +  gamma_pay_part_3 * pay_part + gamma_pay_else_3 * pay_else
                      )

    V[["class_4"]] = (delta_4
                      +gamma_0615_4  * t0615 + gamma_0645_4  * t0645 + gamma_0715_4  * t0715 + gamma_0815_4  * t0815 + gamma_0845_4  * t0845 + gamma_0915_4 * t0915
                      +gamma_pay_full_4 * pay_full +  gamma_pay_part_4 * pay_part + gamma_pay_else_4 * pay_else
                      )

  classAlloc_settings = list(
    classes      = c(class_1=1, class_2=2, class_3=3, class_4=4),
    utilities    = V
  )

  lcpars[["pi_values"]] = apollo_classAlloc(classAlloc_settings)

  return(lcpars)
}

# Validate inputs
apollo_inputs = apollo_validateInputs()

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

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

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

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

```

  ### Define settings for MNL model component
  mnl_settings = list(
    alternatives  = c(Optie1=1, Optie2=2, Optie3=3, Optie4=4, Optie5=5, Optie6=6, Optie7=7, Optie8=99),
    avail         = list(Optie1=1, Optie2=1, Optie3=1, Optie4=1, Optie5=1, Optie6=1, Optie7=1, Optie8=1),
    choiceVar     = gekozenreis
  )

  ### Loop over clas
  for(s in 1:4){

    ### Compute class-specific utilities
    V=list()
    V[["Optie1"]]  = (b_price_single[[s]] * p1) + (b_price[[s]] * p1 * (1/hprice)) +  (b_crowd[[s]] * c1) + (b_moment[[s]] * m1) + (b_crowdQ[[s]] * c1*c1)
    V[["Optie2"]]  = (b_price_single[[s]] * p2) + (b_price[[s]] * p2 * (1/hprice)) +  (b_crowd[[s]] * c2) + (b_moment[[s]] * m2) + (b_crowdQ[[s]] * c2*c2)
    V[["Optie3"]]  = (b_price_single[[s]] * p3) + (b_price[[s]] * p3 * (1/hprice)) +  (b_crowd[[s]] * c3) + (b_moment[[s]] * m3) + (b_crowdQ[[s]] * c3*c3)
    V[["Optie4"]]  = (b_price_single[[s]] * p4) + (b_price[[s]] * p4 * (1/hprice)) +  (b_crowd[[s]] * c4) + (b_moment[[s]] * m4) + (b_crowdQ[[s]] * c4*c4)
    V[["Optie5"]]  = (b_price_single[[s]] * p5) + (b_price[[s]] * p5 * (1/hprice)) +  (b_crowd[[s]] * c5) + (b_moment[[s]] * m5) + (b_crowdQ[[s]] * c5*c5)
    V[["Optie6"]]  = (b_price_single[[s]] * p6) + (b_price[[s]] * p6 * (1/hprice)) +  (b_crowd[[s]] * c6) + (b_moment[[s]] * m6) + (b_crowdQ[[s]] * c6*c6)
    V[["Optie7"]]  = (b_price_single[[s]] * p7) + (b_price[[s]] * p7 * (1/hprice)) +  (b_crowd[[s]] * c7) + (b_moment[[s]] * m7) + (b_crowdQ[[s]] * c7*c7)
    V[["Optie8"]]  = delta_optout[[s]]

    mnl_settings$utilities = V
    mnl_settings$componentName = paste0("Class_",s)

    ### Compute within-class choice probabilities using MNL model
    P[[paste0("Class_",s)]] = apollo_mnl(mnl_settings, functionality)

    ### Take product across observation for same individual
    P[[paste0("Class_",s)]] = apollo_panelProd(P[[paste0("Class_",s)]], apollo_inputs , functionality)
  }

  ### Compute latent class model probabilities
  lc_settings   = list(inClassProb = P, classProb=pi_values)
  P[["model"]] = apollo_lc(lc_settings, apollo_inputs, functionality)

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

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

# (Optional) starting values search
apollo_beta=apollo_searchStart(apollo_beta,
                               apollo_fixed,
                               apollo_probabilities,
                               apollo_inputs,
                               searchStart_settings = list(nCandidates = 15) # pas het aantal kandidaten aan
)

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

# Print output
apollo_modelOutput(model)

# Save output
```