DELFT UNIVERSITY OF TECHNOLOGY

TIL THESIS

TIL5060

On Track or On the Road?

UNDERSTANDING THE IMPACT OF DETAILED ATTITUDES OVER TIME AND THE EXPERIENCED VALUE OF TRAIN TRAVEL TIME ON THE TRAIN VERSUS CAR DECISION

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Preface

My thesis topic arises from my personal passion for enhancing the appeal of train travel. When NS presented this topic, I was filled with enthusiasm. During my bachelor, I developed a keen interest in travel behavior research and I wished that I could have pursued more related courses during my master's studies. Furthermore, I found it compelling that my research carried significant societal implications, motivating me to delve deeper into the reasons behind the stagnant market share of trains despite the evident environmental advantages.

I want to thank my entire graduation committee for their guidance during the last six months. Christine, I appreciated the coffee meetings where you showed a genuine interest in my project and in me as an individual. I'm grateful for your help in turning this scientific research outcomes into practical recommendations and for connecting me with the right people at NS. I also want to thank Maarten for helping me find a relevant research topic, which was a struggle for me. Additionally, I appreciate Arjan for taking the time to review my work and to give detailed feedback, even when he was busy with his own deadlines. Lastly, I'm thankful to Niels for his guidance in the official meetings and for organising the helpful Smart Public Transportation Labs, which gave me insights into other students' master thesis projects. I also want to express my gratitude to my family, boyfriend, housemates and friends for their ongoing support during my thesis. I particularly enjoyed studying together with my study friends at the Civil Engineering Department, where we all put in hard work but also had enjoyable breaks together.

Looking back on my time at NS, I had a great six months. I have not only learned a lot about doing research and the topic of Modal Shift, but I have also had the chance to see more of the company NS and the work they do. I participated in skills training sessions like Problem Solving and Powerpoint, which helped me develop in various areas during my thesis. Moreover, the projects in the Strategy & Innovation department piqued my interest and taught me more about how such projects can be effectively approached. At times, I wished I could have been more involved in those projects in addition to my thesis. The most memorable day of my time at NS was definitely when I shadowed a train conductor for a day. It provided me with a fresh perspective on railway transport and enhanced my understanding of the industry.

For me the most challenging part of my thesis was the significant amount of individual work, as I prefer working together with other people. Therefore, the highlight of my thesis was the week of my greenlight meeting, when I presented my research to multiple departments at NS. It was rewarding to see the interest among NS employees in my topic and to discuss the real-world impact of my research with them. I really hope that my work has prompted further consideration at NS and will lead to continued exploration.

As I have personally become more conscious of my own modal choices through writing this report, I hope that reading my report sparks a similar thought process for you. Enjoy the reading!

Eveline Gielisse
Delft, May 22, 2024

Summary

Reducing CO_2 emissions is crucial in mitigating climate change and meeting the targets of the Paris Climate Agreement. In 2022, private cars and vans accounted for approximately 10% of energy-related carbon dioxide (CO2) emissions worldwide, while train travel produces substantially lower or in some countries even no CO_2 emissions (IEA, 2023). The need for transitioning from car to train usage emerges as a key factor in reducing CO_2 emissions and thereby necessary in reaching the Paris Climate Agreement (European Environment Agency, 2023). Therefore gaining a better understanding of how travellers choose between the train and car is necessary to implement effective measures in order to enhance a modal shift from car towards train use.

Upon reviewing the literature on attitudes and travel time, which are two main factors in understanding individuals' mode choice, two research gaps have been identified. Firstly, while previous studies have demonstrated a reciprocal impact of attitudes towards mode use and mode use over time, a more in-depth exploration into the relationship between detailed attitudes towards mode use and mode use over time is needed. This is particularly important as detailed attitudes towards mode use can potentially explain the reasons behind having a positive or negative attitude towards mode use and how these reasons exactly relate to mode use over time. The second research gap is centered on the findings from prior literature that indicate a significant difference in the experienced travel time value between train travel time components, including access time, (hidden) waiting time, transfer time, egress time, and in-train time. However, these previous studies primarily quantified this valuation based on Stated Preference research and solely focused on the decision between train alternatives. Yet, there is currently no empirical research that has quantitatively assessed the valuation of all these train travel time components and examined their significance in explaining individuals' actual mode choice between train and car.

To address both knowledge gaps the main research question is: *What is the influence of detailed attitudes towards mode use over time and the experienced valuation of the door-to-door train travel time components on the mode choice between train and car?* To answer this main question, the research has been divided into two distinct parts. The first part centers on exploring the longitudinal relationship between detailed attitudes towards mode use and actual mode use, while the second part delves into estimating the travel time valuation for the various components of the door-to-door train trip based on Revealed Preference data to declare the modal share of the train.

Both research parts include a quantitative analysis. The first part utilises Structural Equation Modelling to assess the relationships between detailed attitudes (cost-consciousness, environmental awareness, and status-sensitivity) towards mode use and mode use over time. Furthermore, the study considers the impacts of gender, age, possession of a driver's license, and education level on detailed attitudes and mode use. This analysis is conducted using data from the Mobiliteitspanel Nederland (MPN) from 2014 and 2016, which encompassed information regarding respondents' attitudes, behavior, and socio-demographic variables for both years. In the second part, a multiple linear regression model is applied to calculate the perceived importance of access, (hidden) waiting, in-train, transfer, and egress time in influencing the mode choice between train and car, using Revealed Preference data. This analysis also takes into account car travel time and socio-economic characteristics. Additionally, the linear regression models enable the comparison of the valuation approach based on Revealed Preference data with the approach used in prior research, which is based on Stated Preference data, as well as with the approach of solely using the actual travel time without separately considering the experienced valuation of its different components. For this second part, data from the Dutch National Traffic Model (LMS) is integrated with the door-to-door train travellers Revealed Preference Survey ('Rittenonderzoek 2023') to collect information about the total number of car and train travellers, along with the travel time by train and car, as well as socio-economic characteristics.

The main findings of part 1 of the study are:

- The attitudes environmental awareness and cost-consciousness towards mode use result in an increased train usage and decreased car usage. The attitude status-sensitive does not have a significant influence on mode use.
- Train and car use do not significantly influence the detailed attitudes of environmental awareness and cost-consciousness towards mode use over time.
- The detailed attitudes and behavior demonstrate relative stability over time. Changes in behavior can be partially attributed to the attitudes cost-consciousness and environmental awareness towards mode use.
- People with higher levels of education tend to be more environmentally aware, leading to increased train usage and reduced car usage. However, individuals with higher education levels also tend to be less conscious to costs, resulting in decreased train usage and increased car usage. As a result, for individuals with higher education levels, greater emphasis could be placed on the environmental benefits of train usage when promoting a modal shift from

cars to trains. Conversely, for those with lower education levels, more focus could be placed on the cost advantages associated with train travel.

The main findings of part 2 of the study are:

- Travellers attribute varying importance to different train travel components in their mode choice. With a minute of additional transfer time having the largest negative effect, followed by access- and egress time, (hidden) waiting time, and in-train time, on the modal share of train in comparison with car.
- Travellers assign a greater value to a minute of door-to-door car travel time than door-to-door train travel time. However, when comparing the perceived value of in-train time, it is assessed at more than twice the value of car travel time. As a result, the other components of the door-to-door train journey have such a negative impact on the perceived value that ultimately, the value of the door-to-door train travel time is perceived as lower than the perceived value of the car.
- The perceived valuation of the train travel time components is a better indicator for individuals' modal choice between train and car, than the actual D2D train travel time.
- Comparing the two perceived valuation methods of train travel time, the Revealed Preference method used in this research is about as equally effective in explaining the modal share of the train as the valuation method based on previous Stated Preference studies.
- The ratio between the actual travel time by train and actual travel time by car can only partially account for the modal share of train relative to car. When analysing the specific origin-destination modal share of train relative to car, it is recommended to consider the experienced valuation of the train travel time, as well as, the experienced value for car travel time, as well as, the socio-economic characteristics of the origin and destination.
- One euro higher car parking tariff in the destination zone increases the modal share train with 6.2%.

These findings indicate that facilitating a shift from car to train transportation requires attention to three main aspects: influencing cost and environmental attitudes toward mode use, affecting the (perceived) travel time, and shaping the spatial characteristics of areas. To address the first aspect, it is important to encourage travellers to consider the actual costs and environmental impact alongside travel time when deciding between car and train. This can be accomplished through initiatives such as awareness campaigns, integrating cost and environmental impact comparisons into travel planning applications, and ensuring that companies encourage their employees to consider the environmental and cost factors related to their mode selection. For the second aspect, efforts could be directed towards optimising train timetables to reduce the amount of transfers and transfer time, as well as enhancing the perceived value of transfers and access and egress transportation options. Lastly, for the third aspect, strategies aimed at aligning the spatial environment more closely with train travel, and less with car travel, should be explored. The implementation of a car parking tariff has been identified as a highly effective measure in this regard.

Future research could investigate whether the identified relationships between detailed attitudes towards mode use over time and the valuation of train travel components on the mode choice between train and car have been altered because of COVID. In addition, considering alternative modes of transportation such as the e-bike would enable the examination of the impact of travel time valuation and attitudes on other transportation modes as well. Furthermore, broadening the scope of research to also investigate the relation between other detailed attitudes towards mode use in connection to mode use, would enhance the overall comprehension of attitudes towards mode use. Finally, specifying and exploring the quantification of experienced value could involve examining specific experienced values for different access and egress modes of transport for train, as well as the difference in experienced value between free-flow driving and driving in congestion for car. Moreover, improving the Revealed Preference approach by leveraging the strengths of the current Stated Preference approach, including the exploration of non-linear relationships and additional attributes related to the train trip components could give deeper insights into the specific valuation of the time components.

Contents

1 Introduction

1.1 Problem exploration

In 2022, private cars and vans accounted for over 25% of global oil consumption and approximately 10% of energy-related carbon dioxide (CO_2) emissions worldwide (IEA, 2023). To meet the United Nations' 2030 Sustainable Development Agenda and the Paris Agreement on climate change, proactive measures are necessary (European Environment Agency, 2023). The European Commission has addressed this need by initiating the European Green Deal, aiming to achieve climate neutrality by 2050 (European Environment Agency, 2023). The transport sector plays a crucial role in attaining this climate neutrality by 2050. Despite efforts, the transportation sector has not succeeded in achieving a substantial decrease in CO_2 emissions. Marginal improvements in efficiency have been outweighed by the growing demand for transportation services (European Environment Agency, 2023).

Achieving climate goals requires a reduction in overall travel and a greater adoption of sustainable transportation modes. Apart from walking and cycling, train travel stands out as one of the most environmentally friendly modes of transportation. Compared to using cars, train travel is significantly less harmful in CO_2 emissions (European Environment Agency, 2021). According to research by Rail Delivery Group (2024) on business routes across Britain, trains emit nearly 9 times less CO_2 than diesel-powered cars and over 2 times less than electric cars. NS, the largest train operator in the Netherlands, even runs their trains CO_2 (Nederlandse Spoorwegen, n.d.). Hence, the Climate Agreement emphasises the goal of making train travel more appealing to individuals who currently opt for cars for their regular trips, while also ensuring that this modal shift does not lead to an increase in overall transportation demand (Rijksoverheid, 2019).

Transitioning to train travel presents a promising solution for addressing not only the reduction of CO_2 emissions but also other societal concerns such as space limitations and the nitrogen crisis. Trains are more space-efficient compared to cars, offering fewer square meters per traveller (Kennisinstituut voor Mobiliteitsbeleid and Centraal Planbureau, 2009; Will et al., 2020). Additionally, train travel results in lower nitrogen emissions per traveller-kilometer compared to car usage (Mu Consults and Panteia, 2022). In spite of the numerous societal benefits of train travel in comparison to car usage, the modal split for train usage relative to car usage in passenger kilometres was only 10.5% in 2022 (Kennisinstituut voor Mobiliteitsbeleid, 2023). As a result, there is a strong need to find ways to influence travellers' behavior in order to encourage the shift from car to train travel.

As outlined by De Bruyn and Van Oort (2023), the trends observed during the COVID-19 pandemic did not result in a positive modal shift towards train usage. Instead, there was an increase in car purchases, indicating a likelihood of continued reliance on cars as an alternative to train travel even after the pandemic. Moreover, the pandemic accelerated the advancement of ICT capabilities, making remote work more feasible. Research revealed that especially public transport userswere more inclined to continue working from home as a result of these ICT changes after the pandemic (De Haas, 2023). The combination of increased car purchases and more remote working especially by train travellers has resulted in a slower rebound in train passenger numbers post-pandemic, in contrast to the usage of cars (De Haas, 2023).

To conclude, the modal shift from car towards train use is necessary to reduce CO_2 emissions, preserve public space, and mitigate nitrogen emissions. The COVID-19 pandemic has negatively impacted this modal shift, highlighting the urgent necessity for measures enhancing a modal shift towards train travel. The research objective is to pinpoint crucial factors that could facilitate a transition from car travel to train travel.

1.2 Knowledge gap

In order to promote a socially preferred modal shift, it is essential to understand the factors driving travellers' choice between train and car. A literature review is performed to find out what research in mode choice behavior has been done and how this study can contribute to the existing literature about mode choice behavior.

Exploring mode choice is complex due to the wide range of variables that can influence an individual's decision. Many of these variables are linked to the specific context in which the decision is made. This contextual situation can encompass a variety of factors, such as mode availability, travel time, cost-related attributes or the individuals socioeconomic context (Galdames et al., 2011). However, individuals in similar situations may still exhibit different behaviors (Van Acker et al., 2010). Consequently, psychological factors emerge as an alternative pathway for understanding individuals' intentions and habits (Johansson et al., 2006). The Theory of Interpersonal Behavior (TIB) states that a combination of psychological and contextual factors can ultimately explain individual's mode choice behavior (Triandis, 1977). Therefore, the following sections will delve deeper into the existing literature on psychological factors as well as on contextual factors.

1.2.1 Psychological factors

The exploration of psychological factors frequently revolves around the Theory of Interpersonal Behavior or the Theory of Planned Behavior (Ajzen, 1991; Triandis, 1977). Both the Theory of Interpersonal Behavior and the Theory of Planned Behavior introduce attitude towards mode use as a means to anticipate travel behavior, with Kroesen et al. (2017) even affirming that attitude towards mode use remains the most significant predictor of mode choice behavior. Table 1 provides an overview of various studies that incorporate attitudes towards mode use in their research. It is noteworthy that most of these studies concentrate on cross-sectional research, overlooking the repetitive nature of travel behavior. Recent studies also have raised concerns about the cross-sectional approach's implications for policy, suggesting that attitudes are partly an endogenous variable, by providing evidence that behavior could also influence attitudes over time (Chorus and Kroesen, 2014; Kroesen et al., 2017).

Psychological factors	Method	Perspective	Source
Comfort, convenience, flexibility, safety, environmental preferences	Factor Analysis, Discrete Choice Model	Cross-sectional	(Johansson et al., 2006)
Detailed attitudes towards mode use: Comfort, flexibility	Integrated Choice and Latent Variable	Cross-sectional	(Sarkar & Mallikarjuna, 2018)
Attitudes towards mode use, Health concerns, Climate morality concerns	Factor Analysis	Cross-sectional	(Andersson, 2020)
Attitude towards mode use,, Perceived Behavior Control, Subjective norm, Moral norm, Descriptive norm, Environmental concern	Structural Equation Model	Cross-sectional	(Donald et al., 2014)
Attitude towards mode use, Social factors, Affective factors, Habit	Structural Equation Model	Cross-sectional	(Osman Idris et al., 2015)
Attitude towards mode use, Social factors, Affective factors, Habit	Structural Equation Model	Cross-sectional	(Galdames et al., 2011)
Detailed attitudes towards mode use: Status Giving, Environmentally friendly, Relaxing, Comfortable, Time saving, Flexible and Pleasant	Latent Class Cluster Analysis	Cross-sectional	(Molin et al., 2016)
Detailed attitudes towards mode use: Car-minded, cost-sensitive, status-sensitive, environmental awareness, social consciousness	Latent Transition Model	Longitudinal	(Kalter et al., 2020)
Attitudes towards mode use	Structural Equation and Latent Transition Model	Longitudinal	(Kroesen et al., 2017)
Subjective norm, Attitude towards mode use, Perceived Behavior Control	Structural Equation Model	Longitudinal	(Thøgersen, 2006)

Table 1: Comparison of studies that include attitude towards mode use to declare mode use

Due to the limitations associated with cross-sectional research, some studies have shifted their focus towards investigating the longitudinal association between attitudes and behavior. For instance, Thøgersen (2006) explored the reciprocal influence of attitudes, perceived control, subjective norm, and car ownership on travel behavior, while Kroesen et al. (2017) examined the relationship between attitudes towards mode use and behavior over time. However, these approaches fail to comprehensively elucidate the underlying reasons behind individuals' positive or negative attitudes towards specific modes. Therefore, a more in-depth analysis of attitudes towards mode use is needed.

Although cross-sectional studies have included detailed factors related to attitudes towards mode use, such as research from Molin et al. (2016) or Sarkar and Mallikarjuna (2018), to the best of the authors' knowledge, only one longitudinal study has encompassed detailed attitudes towards mode use. The investigation conducted by Kalter et al. (2020) considered diverse facets of attitudes towards mode use, encompassing cost-sensitivity, status-sensitivity, environmental awareness, and social consciousness. However, the principal focus of this study was on the progression of individuals between latent classes over time, rather than delving into the causal relationships between detailed attitudes regarding mode use and mode use over time.

To conclude, this study aims to address an existing knowledge gap due to the fact that the combination of studying longitudinal effects and detailed attitudes towards mode use has never been explored in this manner before. Studying the longitudinal effect allows for the exploration of attitude changes and behavior changes over time, as well as the causal relations between the two. Studying detailed attitudes towards mode use, allows to delve into the underlying reasons behind a positive or negative attitude towards a specific mode use, such as costs and environmental considerations.

1.2.2 Contextual factors

When examining studies related to contextual factors, the pyramid of customer needs can be employed to prioritise the contextual dimensions in mode choice behavior (Van Hagen et al., 2000). As shown in Figure 2, the pyramid of customer needs highlights safety and reliability as the most critical dimension. According to Van Hagen and De Bruyn (2012), customer satisfaction regarding safety and reliability leaves limited opportunities for additional improvements to stimulate a modal shift. Consequently, the focus shifts to speed as the primary customer need to influence. This indicates that the most significant aspect that could be improved is the door-to-door travel time (Hagen, Mark van and Exel, Maarten, 2011). Therefore many studies have focused on analysing how variances in travel time between train and car impact the modal distribution (Hagen, Mark van and Exel, Maarten, 2011). To facilitate this, the concept of the travel time factor (TTF), also known as the ”verplaatsingstijd factor” (VF) in Dutch, is introduced (Van Goeverden & Heuvel, 1993). The Travel Time Factor is defined as the time taken from door-to-door when using the train as the primary mode of transport, in relation to the door-to-door travel time when using a car (Van Goeverden & Heuvel, 1993). A lower TTF value indicates that the train is a more attractive alternative to driving. According to Van Goeverden and Heuvel (1993), this tool is highly effective as public transport holds a 60% mode share when travel time is equal, but this share decreases to 20% when the car is twice as fast as public transport for the journey. The relation between Travel Time Factor and modal share as determined by Van Goeverden and Heuvel (1993), is illustrated in Figure 3.

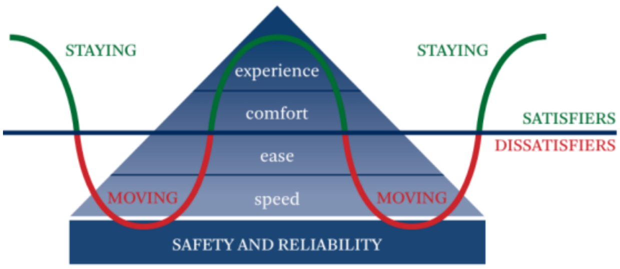


Figure 2: Pyramid of customer needs (Van Hagen et al., 2000), adapted by Van Hagen (2011)

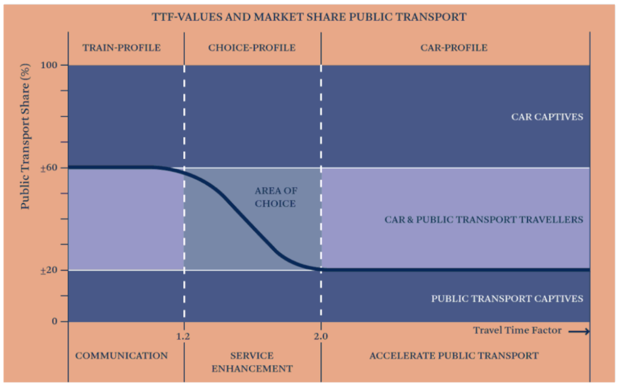


Figure 3: Travel time factor in relation to model share (Van Goeverden & Heuvel, 1993), adapted by Van Hagen (2011)

In order to determine TTF value, the door-to-door travel time by train has to be calculated by dinstinguishing the trip into several components (Van den Heuvel, 1997). In Table 2, the various components of the door-to-door train trip are listed. The station-to-station (S2S) travel time consists of the (hidden) waiting time, in-train time, and transfer time. Where the (hidden) waiting time is the difference between the time when the traveller would ideally like to depart and the time when a train actually is planned to depart (Guis & Nijënstein, 2015). Generally, the average (hidden) waiting time becomes shorter when trains operate more frequently. To eventually calculate the door-to-door (D2D) train travel time, the access and egress transport time needs to be added to the S2S travel time.

Door-to-door (D2D) travel time					
	Station-to-station (S2S) travel time				
Access time	(Hidden) waiting time	In-train time	Transfer time	In-train time	Egress time

Table 2: Components of travel time of trip by train, edited based on Van den Heuvel (1997)

The drawback of using a single D2D train travel time, is the notion that travellers assign different experienced values to the components of the D2D train trip, presented in Table 2 (Van Hagen, 2011). For instance, the time spent transferring is perceived more negatively by the train travellers due to uncertainties, inconvenience, and discomfort, compared to the in-vehicle time, and therefore has a stronger influence on the choice between car and train than the in-vehicle time (Peek & van Hagen, 2002). As a result, numerous research studies have introduced approaches to measure the assessment of different aspects of a train journey relative to the time spent in the train, resulting in multiple sets of weights and penalties differing per country and travel purpose (De Keizer et al., 2015; Guis and Nijënstein, 2015; Van Acker et al., 2010; Van der Waard, 1988; Wardman, 2004).

Consider the Dutch National Traffic Model as an example to illustrate the impact of integrating these perceived values. The Dutch National Traffic Model integrates the variation in perceived value of different components of train travel by allocating additional time for those components with a lower perceived value compared to in-train time. This adaptation is based on findings from previous studies focused on the Netherlands (De Keizer et al., 2015; Guis and Nijënstein, 2015; Van Acker et al., 2010). The cumulative travel time from station-to-station, adjusted for the additional time because of the lower perceived value of (hidden) waiting and transfer time, is known as the Generalised Travel Time. An example provided in Table 3 illustrates the difference between the Actual Travel Time (TT) and Generalised Travel Time (TT) from Den Dolder to Rotterdam Centraal, as indicated by the Dutch National Traffic Model (Rijkswaterstaat, 2018). This variance in total travel time primarily stems from the lower perceived value assigned to the (hidden) waiting time and the transfer time.

Train travel components	Actual TT (min)	Generalised TT (min)	Ratio Generalised vs. Actual
(Hidden) waiting time	7.6	15.4	2.0
Transfer time	8.4	29.8	3.5
In-train time	50.5	50.5	1.0
Total	66.5	95.7	1.4

Table 3: Actual and Generalised S2S travel time between Den Dolder and Rotterdam Centraal, according to Rijkswaterstaat (2018)

The calculation of Generalised Travel Time nowadays is based solely on Stated Preference studies. Wardman (2004) identifies this as the main limitation of his study, explaining why his estimated weights may be lower than the actual values. He reasons that Stated Preference studies do not reveal travellers' actual choices and that variations in the values presented to respondents strongly influence the weighting factors ultimately found (Wardman, 2004). Nevertheless, no research has yet estimated the valuation of train travel time components in the context of the travellers' modal choice using Revealed Preference data. The benefit of using Revealed Preference data is that it reflects real-world travellers behavior, as opposed to solely relying on their Stated Preferences. Moreover, the use of Revealed Preference data about travellers' mode choice enables the examination of the valuation of train travel time components within the context of travellers' mode choice, rather than exclusively concentrating on a single component of the train journey in the selection between various train options.

1.2.3 Conclusion

The factors under consideration in research on mode choice behavior can be broadly categorised into two groups: psychological and contextual factors. As well for the psychological and contextual factors an existing knowledge gap is identified. The first knowledge gap pertains to the longitudinal investigation of the causal relationships between detailed attitudes toward mode use and mode choice behavior. The second knowledge gap involves the Revealed Generalised estimation of the experienced value of train travel time components in mode choice. This study will address both knowledge gaps in two distinct research parts, ultimately aiming to achieve the overall research goal of gaining a better understanding of travellers' mode choice in order to implement effective measures for a modal shift.

1.3 Research questions and approach

The current state of knowledge does not include information on how detailed attitudes towards mode use over time and the experienced valuation of travel time influence the actual realised modal share. This leads to the overarching main question: *What is the influence of detailed attitudes towards mode use over time and the experienced valuation of the door-to-door train travel time components on the mode choice between train and car* As the two different knowledge gaps have a different focus, it has been decided to also conduct separate research questions and approaches. Nevertheless, the studies share common ground in investigating the fundamental motivations behind mode choice behavior.

1.3.1 Longitudinal relationship between detailed attitudes towards mode use and actual mode use

To fill the initial knowledge gap concerning the mutual influence of detailed mode-related attitudes and actual mode use over time, the main question of the first part of the research is: *1. What is the reciprocal impact of detailed attitudes related to mode use and actual mode use of car and train over time, when controlling for socio-demographic variables?*

This main question can be subdivided into 3 subquestions outlined below. Firstly, a conceptual model regarding the relationships of socio-demographic characteristics, attitudes, and behavior over time needs to be developed based on theory and previous literature research. The second subquestion specifically focuses on evaluating the strength and significance of the conceptualised relationships from attitude to behavior and from behavior to attitude. The third subquestion delves into the role of socio-demographic characteristics in the relationship between attitude and behavior over time.

1.1 *How can the relationship between attitudes and mode use over time be conceptualised based on existing theories and research, while controlling for socio-demographic variables?*

1.2 *What is the reciprocal impact of detailed attitudes and mode use over time, while controlling for socio-demographic variables?*

1.3 *What is the influence of socio-demographic characteristics in the relation between detailed attitude and mode use behavior over time?*

To investigate these questions, data from the Mobiliteits Panel Nederland (MPN) collected at two distinct time periods will be utilised (Hoogendoorn-Lanser, 2014, 2016). This Revealed Preference survey includes inquiries about the frequency of mode usage and statements concerning attitudes towards mode use (Hoogendoorn-Lanser et al., 2015). An Exploratory Factor Analysis can be applied to extract the specific attitudes towards mode use that are present in these statements.

Once the specific detailed attitudes associated with mode use have been identified, the longitudinal relationship between these attitudes and actual mode use will be explored using Structural Equation Modelling (SEM). SEM is a statistical technique used to analyse and quantify relationships among observed and latent variables within a comprehensive model (Firdausi et al., 2023). The flexibility of Structural Equation Modeling (SEM) in handling both latent and observed variables allows for the incorporation of attitudes as a latent construct and socio-demographic variables, as well as mode use, as observed variables (Hair et al., 2014). Additionally, SEM's ability to estimate direct and indirect effects enables the differentiation between the direct and total effects of attitudes and behavior over time (Hair et al., 2014). However, it is crucial to note that a theoretical basis supporting the direction of the causal relationship is necessary beforehand, as empirical testing of causality with SEM is not possible (Golob, 2003). Therefore, prior to estimating the SEM model, the conceptual relationship between socio-demographic variables, attitudes towards mode use and mode use over time should be established based on existing literature to answer research question 1.1.

1.3.2 Investigation of valuation of train travel time based on actual mode choice

To address the identified knowledge gap in subsubsection 1.2.2 regarding the assessment of train travel time value using Revealed Preference data, the computation of Revealed Generalised Travel Time will be executed. This calculation will assess how a minute of the train travel time component influences the modal share relative to the in-train time. Subsequently, this weighting factor is used to adjust the train travel time component, and then all perceived train travel time components are summed to generate the Revealed Generalised Travel Time. Subsequently, the Revealed Generalised Travel Time can be compared with both the Actual Travel Time and the Stated Generalised Travel Time, the latter being the valuation method based on previous Stated Preference studies. In addition to assessing the value of train travel time, the inclusion of car travel time enables the comparison between train and car travel. Additionally, each zone displays unique socio-economic characteristics, thus prompting consideration of variations in zonal features, referred to as zonal characteristics.The main question of research part two is therefore: *2. What is the effect of incorporating the Revealed Generalised Travel Time compared to the Actual and Stated Generalised Travel Time when assessing the modal share of train relative to car, while taking into account the D2D travel time by car and zonal characteristics?*

To address this question, the collection of Revealed Preference data is necessary. Therefore, a case study will be conducted in specific provinces in the Netherlands. The required Revealed Preference data can be gathered utilising two sources: the Dutch National Traffic Model (referred to as LMS) and a door-to-door train traveller Revealed Preference survey (referred to as "Rittenonderzoek"). The modal share of train relative to car and D2D car and train travel time can be derived using these LMS combined with the "Rittenonderzoek". The LMS divides the country into 1406 zones. The LMS output provides extensive information, including an estimation of car travellers and travel time between zones, an estimation of actual train travellers and train travel time between stations and socio-economic characteristics of the zones. The "Rittenonderzoek" provides information for the train regarding the access and egress distribution and travel time for train travellers.

Multiple regression can be utilised to estimate the impact of travel time and socio-economic characteristics on the modal share of train compared to car. The input data for this regression analysis includes the zonal origin-destination pairs along with their respective values for train and car travel time, socio-economic characteristics, and the modal share of train.

Regression analysis is a suitable approach as it enables the examination of the relationship between the modal split and the D2D travel time components, while controlling for socio-economic characteristics. Importantly, regression analysis can offer statistical insights into the significance of each variable and the strength of their relationship to the modal split, facilitating comparisons of the three approaches for incorporating D2D travel time measurement variables.

In order to eventually answer the main question for the second research part, this question is subdivided into 4 subquestions in order to be addressed. Initially, the linear coefficients for all train travel time components need to be determined in relation to the modal share of the train. This enables the investigation of the relative perceived value of access time, (hidden) waiting time, transfer time, and egress time in relation to in-train time regarding to mode choice. These linear coefficients allow for the calculation of the perceived weights in relation to the in-train time, ultimately leading to the computation of the Revealed Generalised Travel Time. Therefore, the first subquestion is:

2.1 What is the relative impact of the train travel time components: access time, (hidden) waiting time, transfer time, and egress time, compared to in-train time, on the realised modal share of train relative to car, while considering D2D car travel time and zonal characteristics?

Upon completion of this, the impact of the various valuation methods of train travel time on the modal share of train can be compared through the estimation of three models. Each model considers the modal share of train relative to car for zonal origin-destination pairs as the dependent variable, with zonal characteristics and travel time by car included as independent variables. The models differ in their approach of incorporating the travel time components of the D2D train journey. The first model is based on the average Actual Travel Time from the origin zone to the destination zone by train, also called the Actual Travel Time approach. The second model integrates the valuation of train travel time components obtained from prior literature, also called the Stated Generalised Travel Time valuation approach. The third model uses the empirically determined linear coefficients for all train travel time components from research question 2.1 to calculate the D2D Revealed Generalised Travel Time, also called the Revealed Generalised Travel Time approach. In Figure 4 the conceptualisation of these three models is visualised.

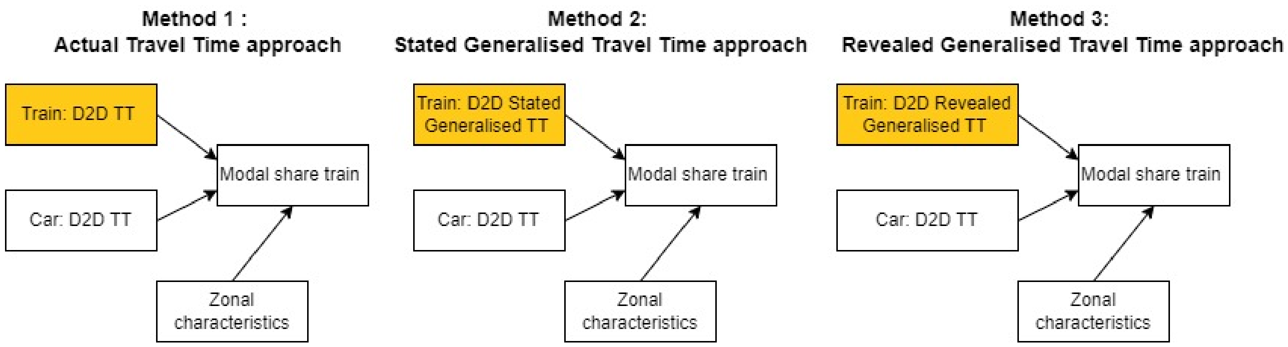


Figure 4: Conceptual models to evaluate train travel time valuation approaches

By employing these three methods, the following subquestion can be addressed:

2.2 What is the effect of using the D2D Actual, Stated Generalised and the Revealed Generalised Travel Time by train in estimating the modal share of train relative to car, while also considering zonal characteristics and the D2D travel time by car?

Considering the preference for minimising the number of variables during the evaluation of the modal share, the study aims to explore the potential outcomes of consolidating the travel time by car and train into a single variable, known as the TTF value, using three different methods of train travel time valuation. This involves assessing three different TTF values derived from the Actual, Stated Generalised, and Revealed Generalised Travel Time by train. Leading to the third subquestion being:

2.3 What is the effect of using the Actual, Stated Generalised and Revealed Generalised TTF value, in evaluating the modal share of train relative to car, while considering zonal characteristics?

As evident from the literature review, various factors can impact an individual's modal choice. Consequently, in research, there is often consideration regarding the inclusion or exclusion of specific factors from the analysis. The aim of this final subquestion is to assess the extent to which the incorporation of certain factors, such as the valuation of the train travel time components, truly enhances the comprehension of the modal share of train relative to car. This leads to the final subquestion:

2.4 What is the impact of including additional explanatory information, instead of the TTF value, about the valuation of travel time by train, travel time by car, and zonal characteristics, in assessing the modal share of train relative to car?

To conclude, in Figure 5, an overview is provided that illustrates the connection between research part 1 and 2, and the factors considered in each distinct research part.

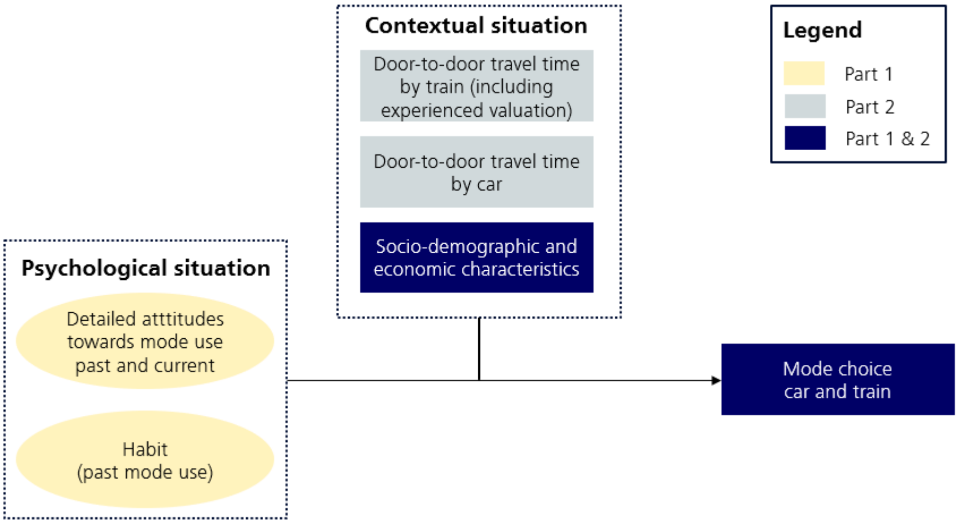


Figure 5: Conceptual link research part 1 and 2 based on Theory of Interpersonal Behavior (Triandis, 1977)

1.4 Societal relevance

The previous section introduced two research questions addressing knowledge gaps in literature. This section addresses how answering this research questions will contribute to the broader societal goal of promoting a modal shift from car to train. This section further explores how both research parts can specifically offer recommendations to the national Dutch train operator, NS, to facilitate this socially desirable modal shift. These recommendations may also hold value for other stakeholders and train operators in other countries.

1.4.1 Longitudinal relationship between detailed attitudes towards mode use and Actual mode use

Analysing the relationship over time gives valuable information into whether measures should primarily focus on influencing attitudes or behavior. Kroesen et al. (2017) emphasise the various implications of the strength of this causal relationship. If attitudes have a large impact on behavior, then it makes sense to try to shape behavior by influencing people's attitudes through promotional and information campaigns. On the other hand, if behavior has a stronger influence on attitudes, then measures should focus on directly changing people's behavior, perhaps through regulations, or by targeting the 'hard' factors that influence behavior, such as travel cost.

Should attitudes significantly influence behavior, it is possible to investigate the impact of the specific detailed attitudes studied on actual mode selection. Although the exact detailed attitudes to be examined will become apparent following the Exploratory Factor Analysis, previous research utilising the MPN data by Kalter et al. (2020) identified cost considerations, status, social consciousness and environmental awareness as detailed attitudes related to mode use. This provides a preliminary indication of the detailed attitudes that may also emerge in the exploratory factor analysis for this research. Analyzing these specific components empowers NS to effectively cater to particular traveller attitudes. For instance, if the travellers' environmental awareness regarding mode use impacts their actual mode choice, NS could customise its informational and marketing efforts to accentuate environmental awareness. Likewise, if the cost-consciousness regarding mode use significantly influences actual mode use, NS could address individuals' perspectives on the costs of a train trip in comparison to those of a car trip.

1.4.2 Impact of train travel time valuation and zonal characteristics on origin-destination model share

The practical significance of the second part lies in providing NS with insights into the added value of different approaches of train travel time valuation in predicting the model share for origin-destination pairs based on D2D travel time by train, D2D travel time by car and zonal characteristics. In the end, NS can assess the most suitable approach. A model that eventually describes the relationship between D2D travel time differences between modes and actual model share, can be used for two distinct purposes:

1. **Evaluating the impact of improvements on specific time components on the origin-destination (OD) model share**
   The research can assist in assessing the valuation of the various travel time components and thereby the rationale behind a lower model share. It provides insights into the relative value of the train travel time components to each other in travellers' mode choice. This enables NS to better analyse the potential impact of measures on the modal split. According to Van Hagen (2011), there could be three distinct strategies based on different time perceptions. The first two are acceleration and concentration, centered on reducing the actual travel time. Acceleration involves increasing train frequency, resulting in reduced (hidden) waiting and transfer times. Concentration involves focusing activities around stations to decrease access and egress time. The final strategy, as proposed by Van Hagen (2011), is enhancement, which targets the experienced value of travel time. Enhancement could involve enhancing the waiting experience, thereby increasing the experienced value of transfer and (hidden) waiting time.

2. **Evaluating the impact of other characteristics besides travel time on the origin-destination (OD) modal share**
   For origin-destination pairs with a low actual modal share, despite favorable train travel time, further research can explore potential factors that may have contributed to a lower modal share than expected based on the travel time valuation of train and car for that specific OD pair. To accurately identify if travel time is not the reason behind these lower market share, the valuation of travel time needs to be taken into account. Potential factors that could declare a low market share than expected, are the socio-economic characteristics of the origin and destination zone.

1.5 Thesis outline

Figure 6 provides an outline of the chapter structure in the report. Chapter 2 identifies the conceptual framework for research part 1 and focuses on the state-of-knowledge about the Stated Generalised Travel Time for research part 2. The methodology decisions for research parts 1 and 2 are then detailed in chapters 3 and 4. Chapter 5 interprets the results for Part 1, while Chapter 6 discusses the results for Part 2. Finally, Chapter 7 provides the synthesis of part 1 and 2, revisiting the research questions and addressing the societal implications of this study, along with discussing the limitations and opportunities for future research.

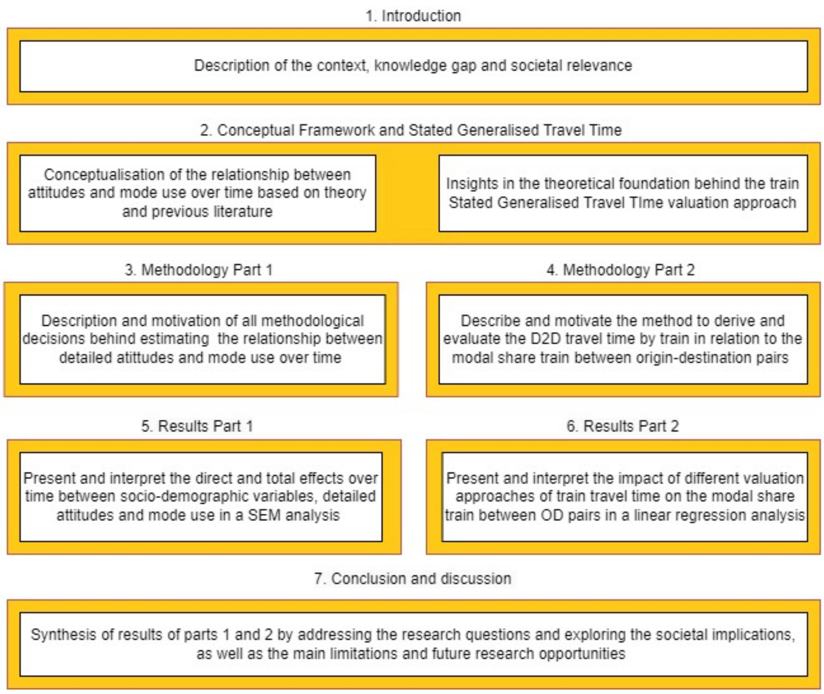


Figure 6: Thesis outline

2 Conceptual Framework and Stated Generalised Travel Time

This chapter centers on a specific question for part 1 and 2 that must be explored in the literature before conducting the SEM and regression analysis. For Part 1, it is crucial to conceptualise the association between socio-demographic characteristics, attitudes and mode use over time based on theory and prior literature, as SEM cannot examine this causal relationship. For Part 2, the Revealed Generalised TT valuation approach established in this study will be compared with the Stated Generalised TT valuation approach from previous literature. A thorough understanding of how this Stated Generalised valuation of train travel time based on previous literature is determined, is essential for the ultimate comparison of these Revealed Generalised and Stated Generalised valuation approaches.

2.1 Part 1: Conceptualisation of detailed attitudes and mode use over time

In this subsection, the goal is to address the question: How can the relationship between attitudes and mode use over time be conceptualised based on existing theories and research, while controlling for socio-demographic variables? This question will be answered by first examining how previous cross-sectional studies addressed the relationship between attitudes and behavior, followed by an exploration from the longitudinal perspective.

2.1.1 Cross-sectional studies

For cross-sectional research, almost all studies make use of one of three prominent theories:

1. Theory of Planned Behavior: Attitudes, subjective norms and perceived behavior control shape behavior (Ajzen, 1991)

2. Theory of Reasoned Action: Attitudes and subjective norms shape behavioral intention; behavioral intention shapes behavior (Hale et al., 2002)

3. Theory of Interpersonal Behavior: Attitudes, affective and social factors shape intention; intention, habit and the contextual situation shape behavior (Galdames et al., 2011; Triandis, 1977)

All these theories draw a causal relationship from attitudes towards behavior. Cross-sectional studies commonly employ one of these theories, presuming a causal sequence and arguing for a direction of causation from personal socio-demographic characteristics towards attitudes towards behavior (Molin, 2005; Paulssen et al., 2014). The rationale behind this causation direction is rooted in the differing ease of change; personal characteristics are often unalterable or difficult to change, attitudes may be more amenable to change but typically changes occur over an extended period, whereas behavior can change on a daily basis (Molin, 2005). Thus, the widely accepted cross-sectional conceptualisation of socio-demographic factors, attitudes, and mode use in previous literature is depicted in Figure 7.

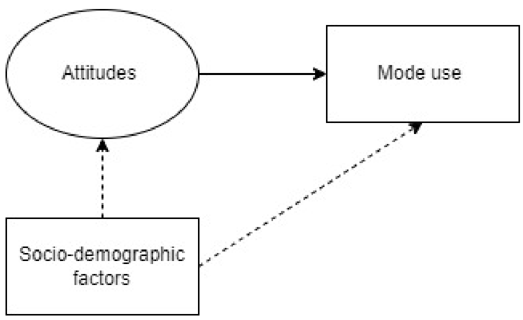


Figure 7: Conceptual framework cross-sectional research

2.1.2 Longitudinal studies

Longitudinal analysis necessitates having at least two lags, also known as waves, at different points in time from the same individual. In the conceptual longitudinal model, this is denoted as t=0 and t=1. The causal relationship in longitudinal studies must be conceptualised based on theory as well. Based on the premise that socio-demographic factors are relatively stable or challenging to alter, the theoretical causal direction indicates that these factors influence attitudes and behavior in both lags(Molin, 2005).

In a longitudinal analysis, it is important to consider autoregressive effects, which refer to the influence of a variable on itself over time. Autoregressive effects capture the impact of the variable's prior values on its current value. By examining the influence of past attitudes (t=0) on current attitudes (t=1), it is possible to investigate the stability of attitudes over time. Research suggests that individuals' attitudes tend to remain relatively stable, with the level of stability depending on the individual (Xu et al., 2020). The causal order from attitude (t = 0) to attitude (t = 1), is already predefined since these measurements are at different points in time. Similarly, studying the influence of past mode use (t=0) on current mode use (t=1), has a predefined causal order due to the different points in time. The relationship between past mode use and mode use aligns with the Theory of Interpersonal Behavior, which posits that travel behavior is influenced by habit (Triandis, 1977). According to this theory, frequent performance of an action leads to minimal contemplation when deciding on that behavior again (Wood et al., 2002).

The relationship between attitudes and behavior is challenging to conceptualise due to the varying assumptions in different studies regarding the causal order. To shed light on this relationship, insights from Thøgersen (2006) and Kroesen et al. (2017) are considered. Both studies recognise a causal relationship from behavior to attitude and vice versa. They both suggest that individuals may adjust their attitude over time to align it with their behavior. This perspective aligns with the Theory of Cognitive Dissonance proposed by Festinger and Carlsmith (1959), which posits that individuals tend to modify their attitude to correspond with their actions if these are contradictory to their private attitude.

The studies by Thøgersen (2006) and Kroesen et al. (2017) concur on estimating the sequential effect from behavior to attitude. However, they differ in their estimation of the relationship from attitude to behavior. Thøgersen (2006) employs a simultaneous estimation according to the Theories of Planned Behavior. This approach suggests that mode use is directly influenced by the favorable attitude towards that mode in the same wave. Conversely, Kroesen et al. (2017) estimates the relationship from attitude to behavior as sequential, stating that theory does not definitively resolve the debate about the direction of causality.

This study integrates the approaches of the two studies by simultaneously and sequentially estimating the relationship from attitude towards mode use. The rationale behind this is that attitude does exert a direct and a long-term influence on an individual's mode use depending on the availability of the modes. When individuals have both modes in their daily choice set, their actual mode use can be directly reflected based on their attitude. The influence of attitude on behavior is also cross-lagged, as an attitude may not immediately lead to a behavior, but rather have a more long-term influence on mode use. For instance, when an individual's attitude leans more towards car use, but this person does not yet own a car, this would necessitate an investment and ultimately lead to different behavior in the longer term. The final conceptualisation of the longitudinal research is illustrated in Figure 8.

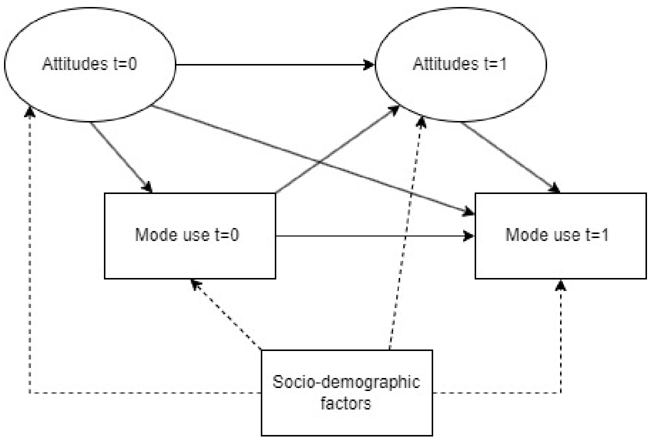


Figure 8: Conceptual framework longitudinal analysis

2.2 Part 2: Literature-based Stated Generalised Travel Time

The literature overview in subsubsection 1.2.2 introduces the concept of Stated Generalised valuation of travel time based on previous Stated Preference literature. To compare the Stated Generalised valuation approach with the Revealed Generalised valuation approach used in this study, it is essential to understand how previous literature has incorporated the valuation of travel time. Therefore, this part of literature review aims to address the question: How does previous literature studies account for the difference in valuation of the train travel time components?

To derive the value of D2D travel time by train, the question persists as to which perspective the door-to-door travel time is being considered. The conventional perspective of the value of travel time entails the duration that a traveller spends on transport from the origin to the destination (Lugano & Cornet, 2018). This is frequently perceived as ”wasted time”, merely a means to achieve a desired level of utility at the destination (Jain & Lyons, 2008). Nonetheless, some studies challenge the notion that travel time is inherently unproductive, particularly when considering the traveller’s perspective (Jain & Lyons, 2008). Arguing that travel time holds a certain value for the traveller, could explain why travellers do not always choose the fastest mode of travel. For example, a person may choose to spend more time traveling by train than they would have in a car because it allows them to work during the train ride.

As noted by Duarte et al. (2010), advancements in research about the value of travel have driven the aspiration to integrate individual reasoning into modeling tools to truly comprehend people’s behavior. National Traffic Models aim to consider travellers’ mode choice by recognising their three distinct journey budgets: time, money, and effort (De Keizer et al., 2012). The financial aspect is dealt with independently in these models. Therefore, the focus of calculating experienced value of travel time is primarily on time and effort (De Keizer et al., 2012).

To capture the significant difference in experienced value for the different components within a train journey, it is beneficial to calculate the door-to-door travel time by breaking down the trip into several components, as demonstrated in Table 2 in subsubsection 1.2.2 (Van Hagen, 2011). As train passengers encounter varying levels of inconvenience during access, egress, transfer, and (hidden) waiting times in comparison to the in-train travel time, the perceived value for these parts needs to be considered separately (De Keizer et al., 2015; Van Hagen, 2011). To accommodate the for the additional resistance, a penalty can be included in the train travel time component, or the travel time component can be modified using a weight relative to the in-train time. This process aligns the actual travel time of the component to a duration in minutes, signifying the significance of this time component in relation to the in-train time. The subsequent subsections explore how previous literature quantifies these resistance terms for the various components of a train trip relative to the in-train time. This involves first examining the internationally recognised literature on weights established by Van der Waard (1988) and Wardman (2004). However, it is important to note that the perceived value of travel time components may vary by country, and a single weight factor may not always fully represent the valuation (Wardman and Hine, 2000; Wardman et al., 2001). Therefore, a more detailed exploration is conducted for each component to understand how this has been studied in the Netherlands, ultimately aiming to gain insights on how to effectively incorporate the valuation based on Stated Preference research for the case study in the Netherlands.

2.2.1 Transfer time

For a long time, a fixed penalty was utilised on top of the transfer time to measure the transfer resistance (Wardman & Hine, 2000). The magnitude of this fixed penalty varied by country and depended on which characteristics were taken into account of the transfer (Wardman et al., 2001). For instance, for a Stated Preference research in Britain the interchange penalty was 13 minutes when the connecting service was guaranteed to be on time. This penalty increased to 20 minutes with a 10% chance of a 5-minute delay, and further rose to 39 minutes in case of a 30-minute delay (Wardman et al., 2001).

In the Netherlands, NS previously employed a fixed penalty of 10 minutes (De Keizer et al., 2015). Subsequently, research by De Keizer et al. (2012) led to a revised approach, where the penalty was proved to be much higher that these 10 minutes. Also, according De Keizer et al. (2012) the actual consumer experience depends on the amount of transfers, but also on factors like the transfer time, frequency of the connecting service, whether the connection is cross-platform or not and the number of transfers.

New research from De Keizer et al. (2015) quantified these findings, proposing a reference penalty around the 22.63 minutes when having a cross-platform transfer of 2 minutes with a next train option within 15 minutes as reference case. Figure 9 shows the connection between time and the additional penalty. Showing that a transfer time from 5 minutes is preferred, shorter or longer transfer times than 5 minutes lead to higher penalties. Besides transfer time, the variable penalty also takes cross-station interchanges, possible additional waiting time by missing an interchange into account. In this regard, De Keizer et al. (2015) estimated coefficients for these characteristics based on a Stated Preference survey, which can be seen in Table 4.

Characteristics	Coeff.
Transfer time	
2 minutes	0
For each minute between 2-5 min	-1.89
For each minute above 5 min	1.67
Number of interchanges	
0	0
1	22.63
2	38.25
Possible extra waiting time	
15 minutes	0
For each minute different from 15 min	0.72
Type of interchange	
Cross-platform	0
Cross-station	7.22

Table 4: Interchange coefficients for determining transfer resistance, adapted from De Keizer et al. (2015)

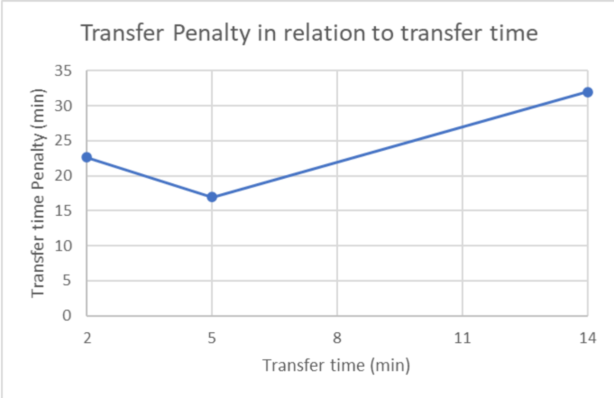


Figure 9: Transfer Penalty in relation to transfer time for 1 interchange, less than 15 minutes extra waiting time for the next train and a cross-platform interchange (De Keizer et al., 2015)

2.2.2 (Hidden) waiting time

Travellers typically have specific desired departure and arrival times and generally prefer minimal deviation from these times. Literature varies in its interpretation of this (hidden) waiting time, depending on the assumption of random versus scheduled arrivals. When assuming random arrivals, it is presupposed that individuals have a uniform distribution of desired departure times and do not check departure times in advance, being able to arrive at the station at any given time. In this scenario, the average waiting time equates to half of the service interval time. Conversely, other studies assume that travellers plan their trips in advance with scheduled arrivals and employ the concept of adjustment time rather than waiting time. The interpretation of the adjustment time can be exemplified through a simple example (Guis & Nijënstein, 2015). Let's consider a scenario where a train departs every 15 minutes (.00, .15, .30, and .45). If a traveller aims to depart precisely at .00, .15, .30, or .45, the adjustment time is zero. As the traveller prefers a later departure, the adjustment time increases until another train becomes a more viable option. In this instance, this occurs after 7.5 minutes. Therefore, for a train departing every 15 minutes, travellers' adjustment time ranges from 0 to 7.5 minutes, resulting in an average adjustment time of 3.75 minutes. More information about the calculation of adjustment time, can be found in Guis and Nijënstein (2015)

Van der Waard (1988) and Wardman (2004) use the concept of (hidden) waiting time, assigning a weight relative to in-train time to measure the aversion to (hidden) waiting time in comparison to in-train time. In this context, Wardman (2004) attributes a higher weight of approximately 1.8, while Van der Waard (1988) estimates this weight at 1.5.

The examination of the perceived value of (hidden) waiting in the Netherlands comprehensively utilises the adjustment time to encompass the impact of both frequency and the distribution of departures throughout the hour. Shorter average adjustment times result from higher frequency and a more even distribution of trains throughout the hour. These adjustment times can be transformed into adjustment resistance by considering the value of an extra minute of adjustment time. As indicated by Guis and Nijënstein (2015), the additional resistance for each extra minute of adjustment time gradually decreases as the adjustment time increases.

At present, there is a lack of literature describing the impact of each additional minute of adjustment time. However, the Dutch National Traffic Model (LMS) and NS utilise a piecewise linear function for addressing the resistance for this adjustment time, known as the Service Interval Penalty Their rationale is in accordance with Guis and Nijënstein (2015), by stating that the resistance is more pronounced during the initial few minutes of adjustment time, gradually diminishing in influence as the adjustment time lengthens. A piecewise linear function is employed to quantify the relationship between the adjustment time and the Service Interval Penalty. Further details about this piecewise linear function can be found in Table 5 and Figure 10.

Adjustment time category	Constant	Coefficient
0 - 6.25	0	4.032
6.25 - 12.5	25.2	3.488
12.5 -25	47	1.099

Table 5: Linear formula for different adjustment time categories according to NS and LMS

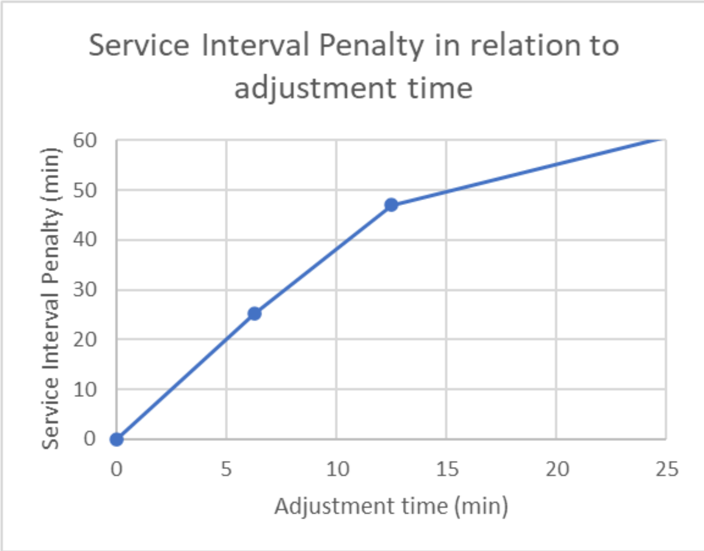


Figure 10: Piecewise linear function for Service Interval Penalty in relation to adjustment time according to NS and LMS

2.2.3 Access- and egress transport

A train traveller relies on walking, cycling, taking the bus, tram, metro (BTM), or the car to travel from their origin to the train station (access transport) and from the train station to their destination (egress transport). In order to assess the perceived resistance for the whole door-to-door journey, attention must also be given to access and egress (Guis & Nijënstein, 2015).

The valuation of access and egress transport is not uniform for everyone and depends on both personal and travel characteristics, such as mode of transport, travel purpose, and age (Wardman et al., 2001). Many studies on experienced access and egress time only provide qualitative statements about these elements (Schakenbos & Nijënstein, 2014). Only a limited number of studies have endeavored to quantify the perceived access and egress time. In the study by Wardman (2004), a comprehensive analysis of the valuation of access time for public transport usage revealed a mean weight of 1.77 compared to in-train time in Britain. However, it does not specifically address the valuation of egress time. Conversely, Van der Waard (1988) quantifies the valuation of access and egress time separately, indicating a higher resistance weight for access time (2.2 relative to in-train time) compared to egress time (1.1 relative to in-train time).

In the Netherlands, no detailed research has been employed to quantify the perceived value of access and egress time. According to Van Hagen (2011), access and egress mode time are valued at roughly half of in-train time.

2.2.4 Conclusion

Previous Stated Preference research has aimed to quantify the perceived value of train travel time, often involving a comparison of different time components within train journeys, particularly in-train time, which is typically viewed as the most valuable. Internationally recognised studies from authors such as Van der Waard (1988) and Wardman (2004, 2000) have evaluated these time components, providing weights relative to in-train time to quantify these differing perceived values. However, it is noted that the perceived value of travel time components can vary by country, and a single weight factor might not always fully capture their valuation (Wardman and Hine, 2000; Wardman et al., 2001). Recent research in the Netherlands has pursued a more detailed approach for valuing transfer and waiting time, considering additional influencing factors and employing piecewise linear functions. This refined method, derived from Stated Preference research, is utilised in models by NS and the Dutch National Traffic Model (LMS). As this study aims to perform a case study on the Netherlands that evaluates the Revealed Preference valuation method by comparing it with the Stated Preference valuation method, the more detailed research per component in the Netherlands will be used. Table 6 compares the method and weights used in various sources providing a comprehensive interpretation of each component.

	Van der Waard (1988)	**Wardman (2004, 2000)**	**Dutch detailed research per component**
Access time	2.2	1.8	2 (Van Hagen, 2011)
(Hidden) waiting time	1.5	1.8	Piecewise linear function based on adjustment time capturing frequency and distribution over the hour (see Table 5)
In-train time	1	1	1
Transfer time	-	13, 20 or 39 min penalty depending on chance and length of delay	Piecewise linear function based on possible extra waiting time, transfer time, number of transfers and type of interchanges (see Table 4) (De Keizer et al., 2015)
Egress time	1.1	-	2 (Van Hagen, 2011)

Table 6: Weights experienced travel time relative to in-train time in previous Stated Preference literature

3 Methodology Part 1

The subsequent paragraphs present a description and rationale for the methodological decisions made to analyze the longitudinal influence of attitudes on mode choice behavior and vice versa. The conceptual framework for cross-sectional and longitudinal studies established in subsection 2.1 serves as the foundation for this methodological approach. This chapter outlines and justifies the methodological steps that ultimately lead to evaluating the relationship between detailed attitudes and mode use over time based on this conceptual framework. In this chapter, the features of Structural Equation Modelling will be explored to motivate why SEM is used to evaluate the longitudinal impact of attitudes on mode choice behavior. Subsequently, the data gathering process will be examined, with detailed exposition of the key decisions taken in this context. Following this, an examination of the extent to which the sample data represents the broader population will be conducted. This will be followed by a comprehensive overview of the operationalisation process, delineating the methods used to measure and categorise the data into variables for the SEM analysis, with specific emphasis on the identification of the underlying attitudes being measured. Additionally, an overview of the mean changes and distribution of these variables within the sample will be provided. Lastly, an assessment of the model estimation procedure and an exploration of the model fit measures will be conducted. Subsection 3.2 to subsection 3.5 focus on the specific case study in the Netherlands, presenting detailed information about the data collection and operationalisation process for the utilised data source, as well as the mean values and distribution observed for this case study. The methodological steps taken can also be applicable to other case studies, provided that panel data is available regarding respondents' socio-demographic characteristics, frequency of mode use, and statements reflecting detailed attitudes towards mode use

3.1 Structural Equation Modelling

The prominence of latent variable models in modeling psychological factors has increased, following the comprehensive approach introduced by Walker (2001). This approach utilises indicator variables to measure latent psychological factors, as direct measurement of these factors is challenging. Structural Equation Modelling (SEM) is the most commonly used research method for capturing psychological factors by using latent variables. SEM is a multivariate analysis method that combines factor analysis and regression/correlation analysis to investigate the relationships between indicators and constructs, while also examining the connections among latent constructs and other variables (Firdausi et al., 2023).

In SEM, the causal relations between variables are labeled as paths. The standardised coefficient estimated for a path can be interpreted in a similar manner to a standardised regression coefficient in traditional regression analysis, indicating the strength of the causal relationship and how much an independent variable influences the dependent variable, considering other variables in the model. However, it's crucial to note that a theoretical basis supporting the direction of the causal relationship is necessary beforehand, as empirical testing of causality with SEM is not possible (Golob, 2003).

An important feature of SEM is the differentiation between direct and indirect effects (Golob, 2003). The paths in the SEM model represent the direct effects, while the indirect effects encompass the combined impact of all effects along the pathways connecting the two variables through intervening variables. This capability to model indirect effects is a important advantage compared to conventional regression analysis (Molin, 2005).

The estimation of SEM serves several purposes (Golob, 2003). Firstly, it helps in evaluating the significance (t-value) and the strength of the assumed causal paths within the model. Secondly, SEM allows for assessing how well the model as a whole fits the observed data by utilising overall fit measures. Lastly, SEM enables the examination of the extent to which the variance of the dependent variable is explained by the variables included in the model. These diverse purposes of SEM estimation collectively contribute to a comprehensive understanding and assessment of the relationships and explanatory power encapsulated within the model.

3.2 Data gathering

To conduct the longitudinal SEM analysis, two waves of panel data from the Netherlands Mobility Panel (MPN), collected in 2014 and 2016, are utilised. In the context of longitudinal research, each "wave" refers to a specific data collection period within a longer timeframe, such as data collected in 2014 and 2016, serving as distinct time points for longitudinal analyses. For these two waves of data, the respondents were asked to give their opinion on statements regarding their attitudes with respect to mode use. These statements are necessary to get a better impression of peoples attitudes, which is the reason why the data from 2014 and 2016 are used for this research. Although the data may be somewhat outdated, the specific focus of this study on analysing the connection between detailed attitudes regarding mode use and actual mode use over time is minimally impacted by the changes induced by the COVID-19 pandemic, such as the surge in remote working and increased car purchases as mentioned in subsection 1.1. It is assumed that COVID-19 and the implications of remote working do not impact the relationship between detailed attitudes and the mode choice between car and train, as well as how these mode choice in turn influences these detailed attitudes. Additionally, it is advantageous that the research was conducted entirely before the onset of COVID-19, allowing the exclusion of any potential influence of COVID-19 on the study results.

The Mobiliteits Panel Nederland (MPN) survey is a travel survey conducted for households over time. The recruitment process is carried out by a fieldwork agency that selects respondents from an established access panel using socio-demographic characteristics. The aim is for the respondents to be a reflection of the Dutch population. To mitigate selection bias, respondents are not able to volunteer themselves for participation (Faber et al., 2021). More information about the recruitment process and the questionnaire set-up can be found in the paper from Hoogendoorn-Lanser et al. (2015).

In 2014, 9489 individuals participated in the survey, while in 2016, 6786 individuals participated. Among these, 4248 respondents completed the survey in both 2014 and 2016. The decision was made to focus exclusively on respondents aged 18 and above, as they have greater autonomy in their mobility choices, particularly in the decision between car and train, given their eligibility to drive independently after obtaining their driver's license. After deleting list-wise for missing values, the final sample which will be investigated contained 3848 adults.

3.3 Data operationalisation

The data obtained from the MPN survey represents the answers given by respondents to many questions regarding their socio-demographic characteristics, opinion about statements regarding mode use and their actual frequency of mode use. To conduct the longitudinal analysis using SEM, these answers need to be operationalised to represent the socio-demographic characteristics, detailed attitudes and mode use in 2014 and 2016. The methodology and choices made to derive the measured and code variables for socio-demographic characteristics, attitudes and mode use will be specified in this section. For the socio-demographic characteristics and mode use, this is relatively directly measured in the survey. The detailed attitudes must still be specified based on the responses to the statement questions regarding mode use in the MPN.

3.3.1 Socio-demographic characteristics

The 2014 MPN questionnaire asks questions to the respondents about their personal characteristics. These answers can provide information to measure the socio-demographic characteristics. The socio-demographic variables included in this research are gender, age, possession of a driver's license and education level. These socio-demographic variables are commonly included in behavioral research, as they provide insights into personal characteristics of the traveller that may influence their attitudes and behavior (Molin, 2005). As explained in section 2, these variables are considered exogenous, implying that they are unaffected by individuals' attitudes towards mode use and mode use behavior. All socio-demographic variables are categorical. The representation of the specific categories in ascending order can be found later in the methodology section in Table 12.

3.3.2 Mode use

Mode use is evaluated based on the frequency of car and train usage. As the focus of this research is solely on assessing the choice between car and train, all other modes are excluded from the model. In the MPN survey, respondents were individually queried about how frequently they utilise the car and train, and were also requested to maintain a travel diary for a period of three days. The decision is made to use respondents' answers to the frequency question for analysis as this provides a general overview of their mode use, rather than relying on specific travel diary data for three days. However, it's important to acknowledge the potential for memory errors among respondents, as they may struggle to accurately recall the frequency of their travels, possibly leading to inaccurate data. Furthermore, there is a risk of social desirability bias, where respondents might tend to portray their travel behavior more positively based on socially desirable perceptions, rather than their actual behavior.

In the MPN survey, respondents were separately asked about their frequency of car use and train use by indicating their usage on a scale from 1 to 7. A response of 1 indicates very frequent use of the mode, whereas 7 indicates never. To ensure that in the SEM a higher value represents more frequent use of the specific mode, the responses were recoded. As a result, the values for mode use represent: 1 (never), 2 (<1 day), 3 (1-5 days), 4 (6-11 days), 5 (1-3 days/month), 6 (1-3 days/week) and 7 (> 4 days/week).

3.3.3 Detailed attitudes towards mode use

Although the frequency of mode use and the socio-demographic characteristics are directly measured and require minimal effort to operationalise, greater attention must be given to capturing detailed attitudes toward mode use. As previously discussed in subsection 3.1, attitudes cannot be directly measured. Hence, the decision has been made to derive these detailed attitudes by conducting an Explorative Factor Analysis based on 21 attitude-related statements regarding mode use. The aim of this Explorative Factor Analysis is to identify underlying attitudes within the statements. Explorative Factor Analysis was chosen because it does not require specific attitudes to be predetermined, offering the advantage of truly examining which attitudes underlie mode use in the given dataset. The following paragraphs will describe the implementation process for this Explorative Factor Analysis to derive the underlying detailed attitudes within the statements.

In the questionnaire the respondents were asked to express their views on 21 statements regarding their travel attitudes using a five-point scale (Hoogendoorn-Lanser et al., 2015). The statements can be seen in Table 7. The respondents could indicate whether they ”strongly disagreed”, ”disagreed”, ”neither agreed nor disagreed”, ”agreed”, ”strongly agreed”, or had ”no opinion”. To ensure that the scale remains ordinal, respondents who indicated that they had no opinion about a statement were recoded as ”neither agree nor disagree”.

After this recoding, an Explorative Factor Analysis is performed. This Explorative Factors Analysis shows which indicators are sufficiently related to each other to be combined into a latent variable. The method for conducting this Exploratory Factor Analysis is derived from a document by Molin (2017), which outlines step-by-step the process to derive a good factor structure. In a good factor structure, each variable is ideally associated with only one factor (cross-loadings are minimised), and the factors are distinct and interpretable with high loadings from the variables they are intended to represent. The Exploratory Factor Analysis is performed in IBM SPSS Statistics 29.0. Principal axis factoring is used to extract factors with eigenvalues greater than 1 in order to retain only the meaningful factors with significant variance. An oblique rotation is chosen as it better approximates simple structure than an orthogonal rotation in this case. In the initial factor analysis run, statements with commonalities below .25 are removed to focus on items that explain a significant portion of the variance. Subsequently, any variable that does not load on one of the factors or load on multiple factors with factor loadings between .30 and .50 are also deleted one by one. Finally, in Table 8 the resulting factor analysis of the MPN of 2014 is showed, which suppresses small factor coefficients below .30. The factor analysis is also performed for the MPN results of 2016, leading to the same factors and simple structure, with only slightly different factor loadings. In Table 31 in Appendix A, the results for the factor analysis for 2016 are presented. An overview of which of the 21 statements are kept as indicator statements or are removed based on the Explorative Factor Analysis for 2014 and 2016 can be found in Table 7.

Statements	**Indicator?**
The car gives me the freedom to go wherever I want	Yes
I only use a car if it is really necessary	No
It does not make sense to not drive a car in order to benefit the environment, because other people continue to drive their cars	Yes
I cannot manage without a car	Yes
With the environment in mind, in the past year I have consciously tried to drive a car less	No
Due to costs, I opt to travel by public transport and bicycle instead of by car	No
Due to high costs, I drive less with the car than I actually want to	Yes
My current financial situation is a reason to postpone the purchase of a (new) car	Yes
Due to costs, it is difficult for me to own a car	Yes
I would consider selling my (second) car if my financial situation worsened	No
My friends advised me to purchase a car	No
A car says a lot about someone’s personal taste / sense of style	Yes
Driving a car is fun	Yes
My friends believe that the traffic congestion problem in the Netherlands is greatly exaggerated	No
A car says a lot about a person’s status in society	Yes
Driving a car offers many advantages compared to the use of other transport modes	Yes
In order for accessibility to be improved, it is necessary to sharply reduce car use	No
My friends believe that you must only use a car when it is really necessary	No
If I have to go somewhere, I nearly always go by car	Yes
The environment will benefit if people drive cars less frequently	Yes
It is pointless to worry about the environment, because there is nothing you can do about it on your own	Yes

Table 7: Statement selection Explorative Factor Analysis

Furthermore, a reliability analysis is performed on the high loading variables (factor loadings >.50) to assess if the indicator variables form a reliable scale when forming a summated scale. The final row of Table 8 and Table 31 displays the Cronbach's alpha for all four factors. With each factor having a Cronbach's alpha greater than 0.70, which indicates that the summated scales are reliable.

Factors	**Statements**	**1**	**2**	**3**	**4**
Car-minded	Driving a car offers many advantages compared to the use of other transport modes	0.69			
	The car gives me the freedom to go wherever I want	0.65			
	I cannot manage without a car	0.56			
	Driving a car is fun	0.48			
	If I have to go somewhere, I nearly always go by car	0.56			
Cost-conscious	Due to costs, it is difficult for me to own a car		0.78		
	My current financial situation is a reason to postpone the purchase of a (new) car		0.72		
	Due to high costs, I drive less with the car than I actually want to		0.60		
Status-sensitive	A car says a lot about a person's status in society			0.69	
	A car says a lot about someone's personal taste / sense of style			0.77	
Environmental aware	It is pointless to worry about the environment, because there is nothing you can do about it on your own				-0.79
	It does not make sense to not drive a car in order to benefit the environment, because other people continue to drive their cars				-0.71
	The environment will benefit if people drive cars less frequently				0.54
Cronbach's alpha		0.73	0.74	0.70	0.72

Table 8: Factor analysis 2014 with factor loadings and Cronbach's alpha

The factors' names have been derived based on the author's own interpretation and are in line with the findings in the research by Kalter et al. (2020) that uses the same 21 statements for the factor analysis. It is important to note that almost all factors are based on statements related to car usage. Therefore, an individual with a high score for cost-consciousness is considered to be cost-consciousness in the context of car use. In the interest of readability of this report, the general terms car-minded, cost-conscious, status-sensitive, and environmental aware are utilised. However, it is essential for the reader to acknowledge that these factors are assessed mostly in the context of car use.

To obtain the value for the latent variable for each respondent, the answers for the indicator statements are summed together, also known as the summated score. The summated scores are then divided by the number of indicator variables to obtain the average summated score, scaling all latent variables between 1 and 5 for better interpretation of the latent variables. Given that two indicator variables for the environmental awareness factor have negative factor loadings, the answers for these indicator statements are recoded so that 1 indicates low environmental awareness and 5 indicates high environmental awareness. Following this recoding, the summated scale for environmental awareness can also be calculated.

Factor	1	2	3	4
1	1.00	-0.21	0.14	-0.25
2	-0.21	1.00	0.09	-0.01
3	0.14	0.09	1.00	-0.08
4	-0.25	-0.01	-0.08	1.00

Table 9: Correlations between factors in 2014

Factor	1	2	3	4
1	1.00	0.22	0.17	-0.23
2	0.22	1.00	0.07	-0.02
3	0.17	0.07	1.00	0.10
4	-0.23	-0.02	0.10	1.00

Table 10: Correlations between factors in 2016

Upon scrutinising the correlations between the four factors in Table 9 and Table 10, it becomes evident that car-minded exhibits a notably high level of correlation with the other three factors. This suggests that being cost-conscious and environmental aware corresponds with being less car-minded and that being status-sensitive corresponds with being more car-minded.

Upon examining the factors derived from the Explorative Factor Analysis, it becomes apparent that the latent construct "car-minded" does not align with the scope of the research of researching detailed attitudes towards mode. As car-minded is more a general attitude towards mode use instead of a detailed attitude that explores the reasons behind positive or negative attitudes towards mode use. Its strong association with mode use behavior makes it challenging to simultaneously investigate alongside the other three factors, which are more representative of a detailed attitude towards mode use rather than a general positive attitude for a mode of transport. This perception is further strengthened by the strong correlations of car-minded with the three other factors. Therefore, the research aims to prioritise the examination of detailed attitudes, with "car-minded" considered too closely linked to the general attitude and mode use behavior for inclusion. To summarise this subsection, the variables that are taken into account in the SEM model estimation can be found in Table 11.

Groups of variables	**Variables**	**Measured/latent**
Socio-demographic factors	Gender	Measured
	Age	Measured
	Driver's license	Measured
	Education level	Measured
Attitudes	Cost-conscious	Latent
	Status-sensitive	Latent
	Environmental aware	Latent
Mode use	Train use	Measured
	Car use	Measured

Table 11: Variable selection

3.4 Representativeness of the MPN data

As mentioned earlier, the goal of the MPN recruiting process is to obtain a representative sample of the Dutch population. This subsection verifies the extent to which the sample data of the MPN survey is representative for the Netherlands as a whole in order to conclude whether the results based on this sample can be generalised to the Dutch population. In Table 12, the comparison of the frequency of socio-demographic characteristics in the final sample of 3848 adults is made with those of the population in 2014, as indicated by CBS, to assess its representativeness.

Variable representativity	**Categories**	**Sample**	**Sample (%)**	**Population (%) ***
Gender	Men	1784	46.4	49.1
χ^2= 11.8. p = <.001	Female	2064	53.6	50.9
Age	18-24 year	455	11.8	10.8
χ^2 =173.0 p = <.001	25-29 year	314	8.2	7.7
	30-39 year	527	13.7	14.9
	40-49 year	788	20.5	18.2
	50-59 year	855	22.2	17.9
	60-69 year	511	13.3	15.3
	70-79 year	327	8.5	9.4
	>80 year	71	1.8	5.7
Driver's license	No	453	11.8	21.3
χ^2 = 208.4. p = <.001	Yes	3395	88.2	78.7
Education level	Primary education	151	3.9	10.0
χ^2 = 259.3. p = <.001	Vocational educational programs	514	13.4	13.4
	Junior years high school education	377	9.8	8.7
	MBO	1076	28.0	30.9
	University propaedeutic diploma	459	11.9	8.9
	Bachelor's degree	907	23.6	18.2
	Master's or doctoraal degree	362	9.4	9.9

* Population data is retrieved from CBS. The data of Gender (Statline, 2014a), Age (Statline, 2014a) and Driver's license (Statline, 2023b) is specifically for all Dutch people from 18 years and older in 2014. The education level data represents all Dutch individuals aged 15 and above (Statline, 2014b)

Table 12: Comparison of socio-demographic variables in sample and population

Upon comparing the sample with the population in Table 12, it is evident that the proportions in the sample slightly differ from those in the population. The chi-square values indicate that for all these socio-demographic groups the difference between the sample and population is significant. However, when examining the absolute numbers for each socio-demographic group in the sample, it becomes apparent that all groups are adequately represented. Furthermore, the MPN recruiting process, described in Hoogendoorn-Lanser et al. (2015), specifically aimed to fulfill the requirement of being representative for the Netherlands. As a result, despite not being a perfect reflection, the sample's composition is supportive of the generalisability of the study's findings to the entire population.

3.5 Distribution and changes over time of attitudes and mode use

This subsection offers an overview of the average values and distribution of attitudes and mode use based on the operationalised data for the 3848 respondents. The objective is to assess the levels of attitudes and behavior and analyse the changes in attitudes and behavior between the two years

Table 13 displays the average values and standard deviations of the attitudinal and behavioral variables. From the mean values, it can be deduced that, overall, people tend to be more aligned with statements concerning environmental awareness and less aligned with statements related to status-sensitivity and cost-consciousness. Additionally, the average usage of cars is substantially higher than train usage, suggesting that individuals, on average, utilise cars more frequently than trains. Furthermore, the standard deviation for train usage is greater than that for car usage, indicating a wider variation in the frequency of train usage between individuals.

When examining the transition from 2014 to 2016, the paired sample t-test aims to determine if there is a significant deviation in the mean between the observations in 2014 and 2016. Environmental awareness and car use demonstrate a p-value above 0.05, implying no significant difference between these variables between 2014 and 2016. Between 2014 and 2016, a trend emerges indicating a significant reduction in individuals' cost consciousness and status sensitivity. The decrease in cost-consciousness could be attributed to two factors. Firstly, this may be due to a general increase in purchasing power between 2014 and 2016 (Statline, 2023a). Secondly, the panel participants have aged by two years, which typically corresponds to an increase in income as they get older. The decrease in status sensitivity is statistically significant, although relatively minor compared to the decrease in cost-consciousness. Similarly, the decrease in train usage is statistically significant within this sample, although the extent of the decrease is minimal. As noted by Kennisinstituut voor Mobiliteitsbeleid (2020), there has been no decrease in the total travellers kilometers traveled by train between 2014 and 2016. Therefore, it is advisable to refrain from concluding that the slight decrease observed in the sample represents an overall reduction in train usage within the population.

	2014		**2016**		**Paired sample t-test**	
	Mean	**S.d.**	**Mean**	**S.d.**	**t**	**Two-sided p**
Cost-conscious *	2.73	0.96	2.57	0.96	11.48	<.001
Status-sensitive *	2.54	0.80	2.46	0.80	6.27	<.001
Environmental aware *	3.57	0.84	3.55	0.83	1.78	.076
Car use **	6.10	1.23	6.09	1.25	0.13	.901
Train use **	3.01	1.76	2.94	1.74	3.49	<.001

*Scale from 1 (totally disagree) to 5 (totally agree)
**Scale from 1 to 7 representing: 1 (never), 2 (<1 day), 3 (1-5 days), 4 (6-11 days), 5 (1-3 days/month), 6 (1-3 days/week), 7 (> 4 days/week)

Table 13: Comparison of attitude and mode use means and mean changes

3.6 Model estimation procedure

To estimate the relationship between the variables in Table 11, the operationalised data needs to be conceptualised in a Structural Equation Model, which estimates the direct and total effects of the relations between the variables. The structural equation models were estimated by using IBM SPSS AMOS Graphics 26. .

Every Structural Equation Model estimation follows a consistent procedure. The objective is to achieve a parsimonious model, capturing all relevant effects without unnecessary complexity. This approach is consistent with the methodology outlined in previous literature (Kroesen et al., 2017). Therefore, the process begins with an initial estimation of all causal relationships based on the conceptual models in subsection 2.1. Paths with insignificant p-values ($p < 0.05$) are eliminated and thereby fixed to zero. The model is then re-estimated. This iterative process continues until all remaining paths demonstrate statistical significance. Subsequently, variables lacking causal relations with mode use are systematically removed to ensure the attainment of a parsimonious model.

In accordance with the procedure used in Thøgersen (2006), first the relationships between socio-demographic variables, attitudes and mode use are analysed at the cross-sectional level. After that is done, the relationships are estimated at the longitudinal level. The main reason of first estimating at the cross-sectional level is to identify if variables can be removed when having no significant influence on mode use before starting the longitudinal analysis, in order to arrive at a parsimonious model. Additionally, the cross-sectional results offer insights into how socio-demographic variables and attitudes influence mode use within a single time period, allowing for comparison of these effects with those obtained in a longitudinal context. In the subsequent paragraphs, the estimation procedure at the cross-sectional and longitudinal level will be discussed in more detail.

The way socio-demographic variables, attitudes and behavior are included and the covariations between the (error) terms are the same from the analysis on cross-sectional and longitudinal level. The socio-demographic variables from 2014 are utilised as exogenous variables for all models, assuming minimal changes over the two-year period and being independent from attitudes and behavior. Covariances between these exogenous variables are considered. To address random measurement errors in the attitudinal factors, the average summated scales of the factors are utilised as indicators for their latent variables, with the error variance of these average summated scales being fixed. This fixed error variance is ascertained by multiplying the variance of the average summated scale by 1 minus Cronbach's alpha of the factor. Moreover, the covariation between the error terms of the latent attitude variables will also be considered. Additionally, the behavioral variables car use and train use are included independently. To address potential shared variances between car and train use, the error terms for car and train use are also correlated with each other.

For the cross-sectional analysis, the causal relationships between the variable categories outlined in the conceptual framework in Figure 7 are utilised. Therefore causal paths from the socio-demographic variables towards attitudes and behavior are drawn and causal paths from attitudes towards behavior. For the longitudinal analysis, the socio-demographic variables are only entered for 2014, while the attitudes and behavior variables are included for 2014 and 2016. Between the different categories of variables causal relationships are drawn according to Figure 8.

The assessment of the model fit is conducted to determine how well the estimated model aligns with the actual relationships within the data, indicating the reliability of the model's results. Upon assessing the model fit in Table 14, it is evident that the models do not meet the desired threshold for the chi-square test. Nevertheless, one drawback of utilising the chi-square test is that for large samples, the model tends to be nearly always rejected (Hooper et al., 2008). Therefore, due to the relatively large sample size in this model, the failure to pass the chi-square test does not necessarily result in the rejection of the model. Upon reviewing the three other goodness-of-fit measures CFI, GFI, and RMSEA, it is evident that the desired thresholds for a good model fit have been achieved for all the estimated models. This suggests that the estimated relationships in the model agree with the actual relationships within the data, signifying the reliability of the model's results.

	Threshold*	**Cross-sectional 2014**	**Cross-sectional 2016**	**Longitudinal 2014 & 2016**
Chi square p-value	>.05	.089	.000	.000
CFI	>.95	.999	.997	.998
GFI	>.95	1.000	.998	.998
RMSEA	<.08	.016	.021	.021

*Threshold values are based on the research from Hooper et al. (2008)

Table 14: Goodness-of-fit statistics for model fit assessment

4 Methodology Part 2

This chapter describes the methodological decisions made for the second part of the research. Firstly, the choice to use multiple regression analysis for this part of the research is clarified. This encompasses explaining the features and discussing the advantages and disadvantages of using multiple regression analysis for this research part. Subsequently, the data sources utilised as input, namely the LMS and 'Rittenonderzoek', are discussed. The scoping decisions are then elucidated. Following this, the representativeness of the 'Rittenonderzoek' is evaluated within the defined scope and purposes. The operationalisation process is described to specify and motivate how the variables incorporated in the linear regression models are determined. Subsequently, the outcomes of the data operationalisation, particularly the mean values and distribution of the most significant values, are examined. Lastly, the model estimation procedure applied to derive the linear regression results is further detailed.

Subsection 4.2 through subsection 4.6 concentrate on the specific case study in the Netherlands, providing insights into the data collection and operationalisation process using information from two Dutch data sources: a National Traffic Model and a Revealed Preference Survey regarding door-to-door train transportation. Depending on the available data sources and the level of aggregation for studying the modal share between zones, this approach can also be applied for other case studies. Subsection 4.7 discussed the model estimation for this case study, which could also be applicable to other case studies, provided that data on passenger numbers between zonal origin-destination pairs, train travel time components, car travel time components, and zonal characteristics are available.

4.1 Multiple linear regression

Regression analysis is 'a statistical technique for estimating the relationship among variables which have reason and result relation' (Uyanık & Güler, 2013). Given that the objective of this second part of the research is to assess the influence of various travel time components and socio-economic characteristics on the origin-destination modal share of the train, multiple regression analysis is the appropriate approach. Various methods of valuing train travel time components can be used as independent variables to ascertain the extent to which these different components contribute to explaining the origin-destination modal share of the train.

Linear regression analysis allows to evaluate the train travel time components separately, enabling the derivation of the average experienced value for travellers for these specific train travel time components based on the linear coefficient. Further details on this procedure will be provided later in subsection 4.7. Additionally, using linear regression offers the advantage of providing a goodness-of-fit indicator, which facilitates the comparison of different linear regression models with diverse sets of independent variables in terms of their ability to explain the variance in the dependent variable. Another benefit of using linear regression analysis is that the influence of the independent variables om the modal share of the train can be interpreted separately, providing a clear understanding of the role of the independent variables in influencing the modal share of the train.

A drawback of using linear regression analysis is that it requires to make assumptions about normality, linearity, absence of extreme values, and missing values (Uyanık & Güler, 2013). In this research, the linearity assumption has a significant impact, as it presupposes that the relationship between the independent variable and modal share is linear, while in reality, the relationship may not always be linear. However, despite this limitation, linear regression analysis still remains a valuable method for exploring and understanding the impact of experienced valuation of train travel time components and other independent variables on the modal share.

4.2 Data gathering

To gather information about the number of car and train passengers, travel time aspects for both modes of transportation, and socio-economic characteristics, the National Traffic Model is crucial. In this case study focusing on the Netherlands in collaboration with NS, the National Traffic Model specifically offers train data from station-to-station. However, this requires supplementing with a Revealed Preference Survey for train passengers to estimate train travel from door-to-door. In the context of the Dutch case study, two data sources will be analysed: the 'Landelijk Model Systeem' (LMS) and the 'Rittenonderzoek'. These sources will be individually examined, including a discussion on the specific data obtained from each and their respective intended use.

4.2.1 'Landelijk Model Systeem (LMS)'

The Dutch National Traffic Model, known as 'Landelijk Model Systeem (LMS)' and managed by Rijkswaterstaat, is used to obtain data on the number of car and train passengers and mode-specific travel time. (Rijkswaterstaat, 2018). The LMS is a spatial model, which divides the Netherlands into 1406 zones. The LMS estimates realised traffic and transportation numbers between these zones for the base year and utilises this as a starting point to make long-term projections (Rijkswaterstaat, n.d.)

For this research, data from the base year of the LMS is relied upon to delve deeper into the numbers of car and train passengers, in relation to their respective travel times. The choice to utilise data from the base year stems from its representation of actual travel behavior. While the LMS also generates forecasts for future years, it is crucial to scrutinise the real impact of travel time on the actual mode choice, rather than anticipated effects. The most recent data available is from the base year 2018. Using data from 2018 has some disadvantages, since travel behavior has changed since then, as discussed in subsection 1.1. In comparison to 2018, the modal share for trains has decreased relative to cars, resulting in the need to avoid directly interpreting the absolute values for modal share as being the same in 2024 (De Haas, 2023). However, the aim of this research is not to determine the absolute model share of trains versus cars; it primarily focuses on empirically establishing the relative impact of travel time components on the modal share of train. Assuming that the valuation of travel time components in relation to each other has not changed significantly since 2018, this research can still provide valuable insights.

The 'Landelijk Model Systeem' utilises a variety of sources in order to retrieve the volume of travellers for each mode of transportation per OD pair for the base year. Firstly, it includes counts for road and rail transport such as road section counts for cars and check-in and check-out data at train stations for train travellers. Moreover, it incorporates two extensive Revealed Preference surveys in the Netherlands: ODiN and 'Rittenonderzoek'. The ODiN survey is a Revealed Preference survey that evaluates the travel behavior of the Dutch population (Centraal Bureau voor Statistiek, 2018). The 'Rittenonderzoek', previously known as the Klimaat Survey, from NS is a comprehensive Revealed Preference survey specifically focused on train passengers, giving more information about the door-to-door train trip including access and egress transport (NS, 2023b). Additionally, the LMS comprises extensive zonal data, encompassing a wide variety of socio-economic characteristics.

Based on the counts and Revealed Preference surveys, the realised number of travellers by car and train are determined for the base year. For cars, this is done by estimating the movements per car between zones based on ODiN research and zonal data, which is then calibrated using counts at the road section level. For trains, the station-relationship matrix based on check-in and check-out data is utilised for the base year to determine the station-to-station amount of train travellers.

The travel times for car are calculated taking congestion into account, by assigning car trips to both the main road network and the underlying road network (Snelder & Vonk Noordegraaf, 2022). For the travel times by train, the model considers various components of a train journey, taking into account both (hidden) waiting and transfer times. Additionally, the model calculates the valuation of (hidden) waiting and transfer times in relation to in-train time by travellers based on earlier Stated Preference research discussed in subsection 2.2. This results in a Service Interval Penalty and Transfer Penalty reflecting the relationship with in-train time based on literature. It is important to note that the LMS calculates travel time based on schedules and does not take into account capacity, crowding, or delays for trains (Snelder & Vonk Noordegraaf, 2022). Therefore, the train travel time in this research have to be interpreted as the scheduled travel time when having no delays.

The LMS is an important tool in examining policy effects and is extensively utilised by Rijkswaterstaat, ProRail, and the Ministry of Infrastructure and Water Management's policy directorates (Hofman, 2017). The outcomes and methodology of the 'Landelijk Model Systeem' have undergone thorough examination by the research agency TNO, which affirmed that the LMS is an advanced and comprehensive tool with well-structured underlying allocations (Snelder & Vonk Noordegraaf, 2022). Rijkswaterstaat (2018) has stated that the models have proven to be remarkably reliable over the years. Therefore, it is presumed that the 'Landelijk Model Systeem' furnishes sufficiently reliable data on passenger numbers and travel times by car and train for this research purposes.

The results generated by the LMS regarding the number of car drivers are publicly available. However, the data pertaining to the volume of train travellers from the LMS is not publicly accessible due to its sensitive nature in terms of competition. As this research is carried out in partnership with the train operator NS, only data for NS train travellers is accessible for this study. In conclusion, the following data is used from the LMS for this research:

- D2D number of car drivers between OD LMS zone pairs
- S2S number of train travellers by NS (NS station-relationship matrix)
- D2D car travel time between OD LMS zone pairs, accounting for congestion
- S2S train travel time components(service interval time, Service Interval Penalty, transfer time, Transfer Penalty, in-train time)
- Zonal data: socio-economic characteristics of the zones

4.2.2 'Rittenonderzoek'

The 'Rittenonderzoek' is utilised to retrieve more information about the access and egress transport to include the D2D train trip in the model. The 'Rittenonderzoek 2023' was conducted by Blauw Research on behalf of NS. The NS manages the results of this survey, which are not publicly available. Previously known as the Klimaat Survey, the 'Rittenonderzoek' is part of a series of recurring studies carried out in the years 2000, 2001, 2005, 2008/10, 2014, and 2019. This survey is a significant benchmark Revealed Preference study aimed at mapping out the entire door-to-door train journey in a detailed manner. Data from previous 'Rittenonderzoek' surveys were also used as information source for the LMS.

The 'Rittenonderzoek 2023' had 17,781 participants, who in total recorded 88,090 train journeys throughout the year. For each journey, respondents were asked to provide their origin postal code, origin train station, destination train station and destination postal code. Respondents were able to use Google Maps to identify their origin and destination postal code. Additionally, respondents indicated the mode of transport used for their access and egress transport. Menno de Bruyn has checked the data from the respondents for outliers and incomplete information, resulting in 70,659 trips that can be used for information about access transport and 70,186 trips that can be used for information about egress transport.

The decision was made to use the latest 'Rittenonderzoek' from 2023 as input, as it has a larger number of respondents and utilised Google Maps for origin and destination postal codes. In previous versions of the 'Rittenonderzoek' respondents were asked to provide their postal code without the option to use Google Maps inside the survey. Using Google Maps is expected to provide a more accurate description of the actual origins and destinations of the trip compared to previous versions. The drawback of using data from 'Rittenonderzoek 2023' is that it differs by five years from the base year of the LMS. As a result, the assumption is made that access and egress transport has not largely changed over these years.

The 'Rittenonderzoek' is applied for three specific purposes. Firstly, it is used to determine the access and egress distribution of travellers from train stations to origin/destination zones. Secondly, it aids in determining the D2D train route, including the origin and destination train station for OD pairs. Lastly, based on the mode use information in the 'Rittenonderzoek', the straight-line distance for access and egress transport is converted to access and egress time. A more detailed explanation of this process will be provided in subsection 4.5. To conclude, the following data is utilised for this operationalisation from the 'Rittenonderzoek':

- Access transport: origin postal code, origin train station, access mode of transport
- Egress transport: destination postal code, destination train station, egress mode of transport

4.3 Scope

This subsection elaborates and motivates the scoping decisions. A crucial initial decision is that the 'Landelijk Model Systeem' contains 1406 LMS zones which are aggregated into 239 zones. In this report, these 239 zones will be referred to as 'NS zones'. Aggregating the areas from LMS zone level to NS zone level offers the advantage of reducing some of the uncertainty associated with determining the amount of car and train travellers from origin-destinations pairs since the origin and destination do not have to be determined that precisely. Furthermore, this results in investigating more relevant origin-destination pairs with a greater number of travellers determining the modal share. However, important to note is that a higher aggregation level assumes uniform characteristics for the entire zone, such as access and egress times, despite the significant variations that may exist depending on the specific location within the zone. Because of the advantages and disadvantages, it is crucial to select an appropriate aggregation level that is neither too high nor too low. Eventually this has led to the aggregation from 1406 LMS zones towards 239 NS zones.

For the aggregation from LMS zones to NS zones, multiple LMS zones are combined into NS zones based on their relevance to NS in terms of train services offered. This is done according to the following principles:

1. Most NS zones correspond to a Municipality, such as Municipality of Middelburg
2. Certain large municipalities are divided into multiple NS zones, such as Rotterdam Centrum, Rotterdam Noord, etc.
3. Some smaller municipalities with low transportation numbers are merged, such as Zeeuws Vlaanderen

Figure 11a shows the aggregation from LMS zones to NS zones. The black edges depict the LMS zones, while the aggregation into NS zones is illustrated by the various colored areas. In Figure 11b, the NS zones are represented by the same colored areas, whereas the black dots indicate the train stations. This clearly demonstrates that not every NS zone necessarily contains a train station.

(a) LMS zones (black edges) within NS zones (colors)

(b) Train stations (black dots) within NS zones (colors)

Figure 11: Aggregation to NS zones

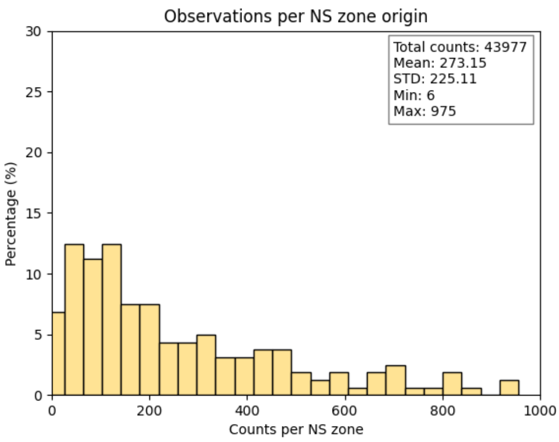
Another scoping decision has been made to focus on travel during an average working day's morning rush hour. This choice was made because it allows to make assumptions about the direction of travel. Typically, people commute from home to work during the morning rush hour. This assumption is essential for operationalising the data and incorporating zone-specific characteristics, particularly related to home-bound and activity-bound travel, into the linear regression model. However, it is important to consider that because of this assumption, the results primarily reflect the value of travel time for journeys to work.

Of the 239 NS zones, a total of 57,121 origin-destinaton (OD) pairs can be formed. However, NS only has access to the NS station-relationship matrix concerning the number of train travellers who utilised NS services, as opposed to the station-relationship matrix for all train operators. To ensure that this does not impact the modal share, only the provinces of Noord-Holland, Zuid-Holland, Zeeland, Noord-Brabant, Utrecht and Flevoland are included in the multiple linear regression analysis, as in these provinces the influence of other train operators is small. This leaves us with 25,921 OD pairs. Furthermore, the analysis focuses solely on travel distances of more than 15 kilometers, as the train and car are primarily competitive from this distance, and other modes of transportation are relatively less chosen. This leads to a total of 25,166 origin-destination pairs at the NS zone level that are being considered.

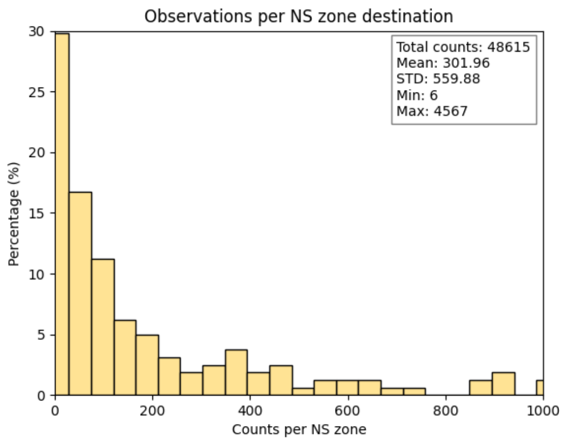
4.4 Representativeness NS and LMS zones in 'Rittenonderzoek'

As detailed in subsubsection 4.2.2, the 'Rittenonderzoek 2023' serves three specific purposes. This subsection will assess the representativeness of the LMS zones and NS zones in the 'Rittenonderzoek' and the implications for the three purposes for which the 'Rittenonderzoek' is used. The detailed explanation of the process of operationalising the data based on the 'Rittenonderzoek' for these three purposes will be provided later in subsection 4.5.

The first purpose of using the 'Rittenonderzoek', is to determine the access and egress distribution from the number of travellers towards the different NS zones. Figure 12 shows the amounts of observations per NS zone in the 'Rittenonderzoek' for access and egress transport. This shows that after filtering on specific provinces for access transport, there are still 43,977 trips with valuable information about access transport. For egress transport, 48,615 trips still have valuable information. The information of the 'Rittenonderzoek' is used to distribute the amount of station-to-station travellers over the NS zones. In Figure 12 can be seen that at least every NS zone has 6 observations as origin and 6 observations as destination and on average every NS zone has about the 273 observations as origin and 301 observations as destination. Since the 'Rittenonderzoek' only is used to distribute the check-in and check-out data of the stations to a specific origin and destination zone, the 'Rittenonderzoek' should provide enough information to perform this distribution.



(a) Origin NS zones

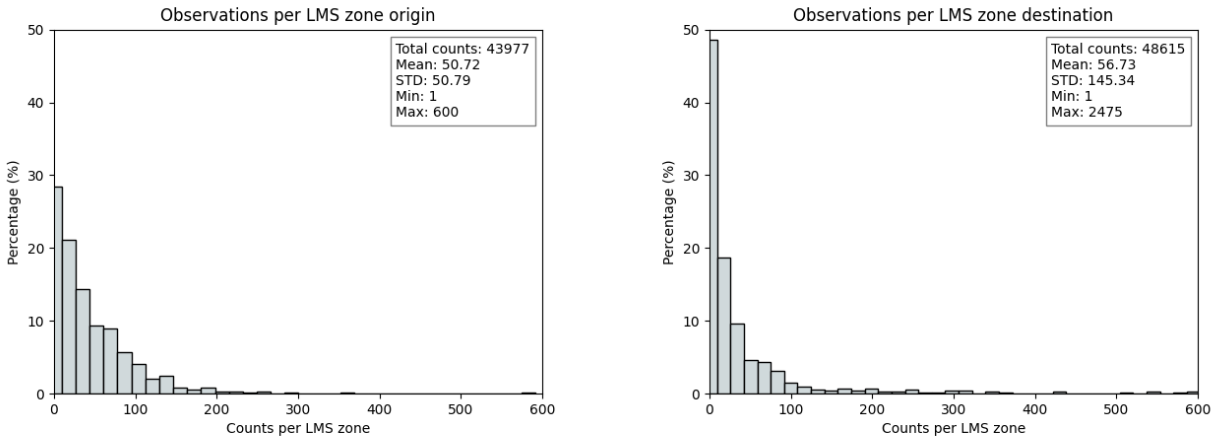


(b) Destination NS zones

Figure 12: Amount of trips observations NS zones in 'Rittenonderzoek 2023'

The second purpose for which the 'Rittenonderzoek' is used, is to determine the D2D train route, including the origin and destination train station.Instead of performing station allocation for each NS zone, station assignment takes place at the LMS zone level to ensure a more accurate representation of actual travel behavior. Each LMS zone is then assigned a specific station that is the most frequently utilised. Hence, every LMS zone must have at least one observation to ensure that a train station can be assigned. While having more observations is preferable, it is not essential, as the assignment of the train station to the LMS zones is also verified. This verification is based on ensuring that the straight-line distance between the assigned station and the LMS zones is not excessively long to be deemed unreliable. Figure 13a and Figure 13b depict the number of observations per LMS zone, indicating a lower aggregation level and consequently a lower average number of observations per LMS zone in comparison to the number of observations per NS zone. The average number of observations per LMS zone is about 50, indicating a reliable amount of observations to assign a train station to the LMS zone. Furthermore, the minimum amount of observations per LMS zone is 1, indicating that every LMS zone meets the minimum requirement of having at least one observation.

The last purpose for which the 'Rittenonderzoek' is utilised is to convert the straight-line distance between the originating LMS zone and the origin train station to access time, as well as to convert the straight-line distance between the destination train station and the ending LMS zone to egress time. Upon reviewing the number of observations in Figure 13, it is evident that the number of observations per LMS zone are not sufficient to facilitate this conversion specifically for every LMS zone. Nevertheless, a generic conversion for access and egress transport is feasible, given the high overall number of observations for access transport (43,977 trips) and egress transport (48,615 trips). More details about the actual operation of the 'Rittenonderzoek' data for these three purposes will be given in the next section.



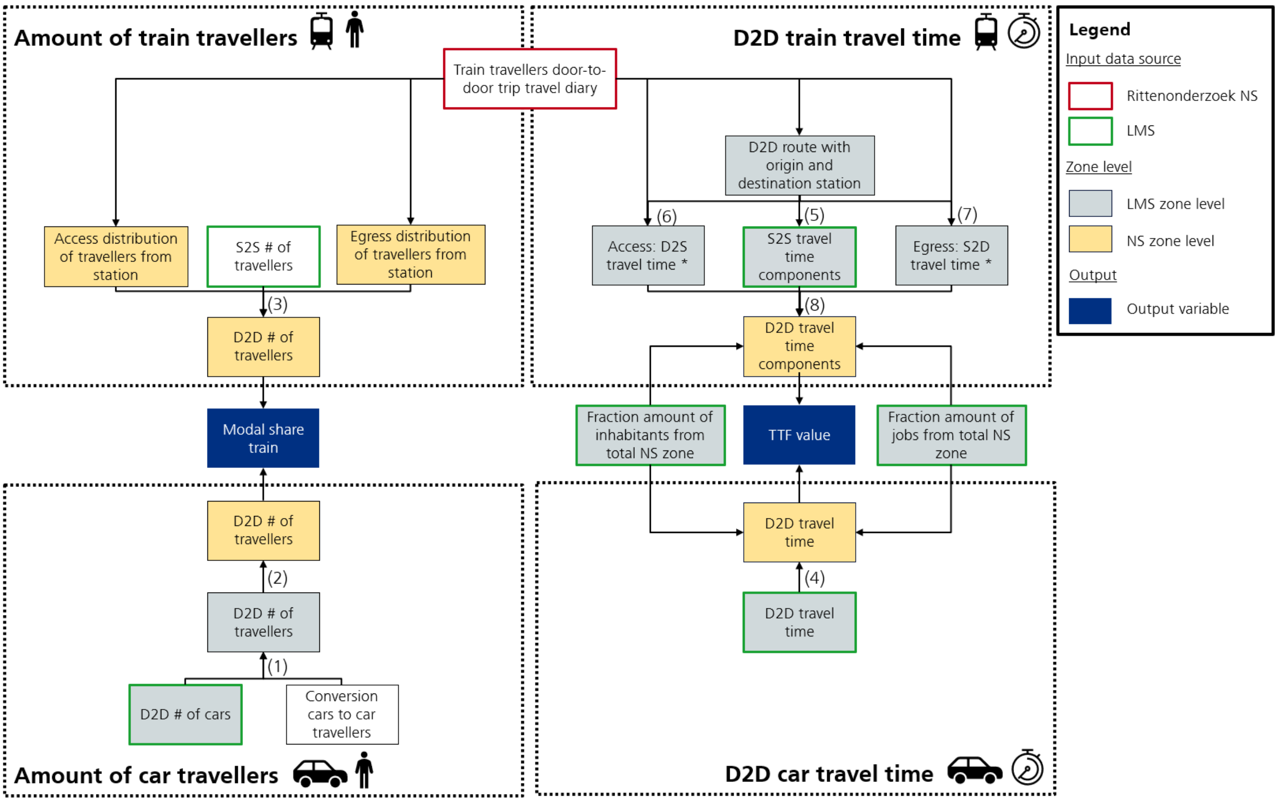
(a) Origin LMS zones

(b) Destination LMS zones

Figure 13: Amount of trips observations LMS zones in 'Rittenonderzoek 2023'

4.5 Data operationalisation

The multiple regression analysis requires having comprehensive information on traveller numbers and travel time for NS zone level OD pairs as input. However, the data obtained from the LMS regarding the car, is at LMS zone level OD pairs. This requires data operationalisation to ultimately obtain the D2D number of car travellers and the car travel time for each NS zone level OD pair. Additionally, the data obtained from the LMS regarding the train, is currently provided only from station-to-station. The goal for the data operationalisation process is to eventually obtain the D2D number of train travellers and the train travel time components for each NS zone level OD pair. The entire data operationalisation process has been executed using Python.



Note: The detailed calculation method for train access and egress travel time is described in Figure 15

Figure 14: Overview data operationalisation

An overview of the data operationalisation process can be observed in Figure 14. The dashed large blocks in Figure 14 outline the operationalisation for each of the four components: the number of car travellers, the number of train travellers, D2D train travel time, and D2D car travel time. Eventually, the number of train travellers and the number of car travellers contribute to the calculation of the train modal share, while the D2D train travel time and car travel time are essential for calculating the TTF value. The process of aggregating data from LMS zone level to NS zone level is represented by a transition from a light grew rectangle to a yellow rectangle. The red and green contours of the blocks indicate their respective data sources. A more detailed operationalisation of the four components will be discussed in the next subsections. The reference numbers for the equations used in these subsections correspond to the reference numbers in Figure 14.

4.5.1 Amount of car travellers

The model elements in Table 15 show what is needed to calculate the number of car travellers for each NS zone level OD pair. Therefore, two parameters are needed as input. First of all, the amount of car drivers from every LMS zone level OD pair in the morning rush hour on a average working has to be retrieved from the LMS data. Furthermore, the average occupancy rate per car during morning rush hour is needed. According to the Dutch Ministry of Infrastructure and Water Management (2023), this is on average 1.1 during rush hour.

Name	Description
	Sets
X	Set of LMS zones
Y	Set of NS zones
$X_y \subseteq X$	Set of LMS zones in NS zone y
	Arcs
$L = \{(i,j)\}\ \forall i,j \in X$	D2D trip from LMS zone i to LMS zone j
$N = \{(o,d)\}\ \forall o,d \in Y$	D2D trip from NS zone o to NS zone d
	Parameters
p_{ij}^{cd}	Amount of car drivers from LMS zone i to LMS zone j from LMS
w	Occupancy rate of cars in rush hour
	Variables
p_{ij}^{ct}	Amount of car travellers from LMS zone i to LMS zone j
	Output variables
q_{od}^{car}	Amount of car travellers from NS zone o to NS zone d

Table 15: Model elements amount of car travellers

In Equation 1, the average number of car drivers per LMS zone level OD pair will be multiplied by the occupancy rate to derive the number of car travellers per LMS zone level OD pair.

$$p_{ij}^{\text{ct}} = p_{ij}^{\text{cd}} \cdot w \quad \forall (i,j) \in L \tag{1}$$

In order to obtain the number of car travellers per NS zone level OD pair, all LMS zones in the origin NS zone need to be combined with all LMS zones in the destination NS zone. The number of car travellers from all these LMS zone level OD pair combinations are added together to derive the number of car travellers per NS zone level OD pair. This summation is illustrated in Equation 2.

$$q_{od}^{\text{car}} = \sum_{i \in X_o} \sum_{j \in X_d} p_{ij}^{\text{ct}} \quad \forall (o,d) \in N \tag{2}$$

4.5.2 Amount of train travellers

The amount of train travellers can be directly derived on NS zone level and therefore does not have to be aggregated from LMS zone level. In Table 16, the parameter description shows which data is derived from both the LMS and the 'Rittenonderzoek'. The number of train travellers from station a to station b is obtained from the LMS, which relies on check-in and check-out data at the stations. The distribution of access and egress transport is then determined based on the travel diary data from the 'Rittenonderzoek'. The data in 'Rittenonderzoek' displays the origin and destination postal codes for each trip. By converting the postal codes to their respective NS zones, the travel diary can be transformed to indicate the origin NS zone and destination NS zone for each trip of a respondent. After this conversion, the dataset allows for the calculation of the number of respondents using each station as an origin, as well as the number of respondents per NS zone utilising the station as destination.

Name	Description
	Sets
Y	Set of NS zones
Z	Set of stations
	Arcs
$N = \{(o,d)\}\ \forall o,d \in Y$	D2D trip from NS zone o to NS zone d
$S = \{(a,b)\}\ \forall a,b \in Z$	S2S trip from station a to station b
	Parameters
r_{ab}^{train}	Amount of train travellers from station a to station b from LMS
k_{oa}	Amount of trips starting their trip in NS zone o using origin station a from 'Rittenonderzoek'
g_a	Amount of trips using origin train station a from 'Rittenonderzoek'
l_{bd}	Amount of trips ending their trip in NS zone d using destination train station b from 'Rittenonderzoek'
h_b	Amount of trips using destination train station b from 'Rittenonderzoek'
	Output variables
q_{od}^{train}	Amount of train travellers from NS zone o to NS zone d

Table 16: Model elements amount of train travellers

The distribution of the number of travellers from station a to station b to NS zone level OD pairs involves the use of two fractions based on the trip data in 'Rittenonderzoek'. The first fraction is the amount of trips originating in NS zone o and utilising origin station a in comparison with the total number of trips using station a as origin train station. The second fraction is the amount of trips with a destination in NS zone d and utilise destination station b is compared with the total number of trips using station b as destination station. Multiplying the number of travellers from origin station a to destination station b by these two fractions yields the number of travellers that use that specific station-to-station combination for the NS zone level OD pair. A summation over all station-to-station combinations leads to deriving the total amount of train travellers for a NS zone level OD pair, as described in Equation 3.

$$q_{od}^{\text{train}} = \sum_{(a,b)\in S} \frac{k_{oa}}{g_a} \cdot r_{ab}^{\text{train}} \cdot \frac{l_{bd}}{h_b} \quad \forall (o,d) \in N \tag{3}$$

4.5.3 D2D travel time by car

The model components utilised to calculate the D2D travel time by car for each NS zone level OD pair are illustrated in Table 17. The average travel time by car during the morning rush hour for each LMS zone level OD pair can be directly obtained from the LMS. In order to assess the significance of these LMS zone level OD pairs in determining the average car travel time per NS zone level OD pair, two weighting factors are employed. The first factor is the fraction of inhabitants in a LMS zone compared to the total number of inhabitants in the corresponding NS zone. The second factor is the fraction of jobs in a LMS zone compared to the total number of jobs in the corresponding NS zone.

Name	Description
	Sets
X	Set of LMS zones
Y	Set of NS zones
$X_y \subseteq X$	Subset of LMS zones in NS zone y
	Arcs
$L = \{(i,j)\} \; \forall i,j \in X$	D2D trip from LMS zone i to LMS zone j
$N = \{(o,d)\} \; \forall o,d \in Y$	D2D trip from NS zone o to NS zone d
	Parameters
m_{ij}^{car}	D2D car travel time from LMS zone i to LMS zone j from LMS
u_x	Fraction of inhabitants in LMS zone x from total inhabitants in corresponding NS zone from LMS
v_x	Fraction of jobs in LMS zone x from total jobs in corresponding NS zone from LMS
	Output variables
t_{od}^{car}	D2D car travel time from NS zone o to NS zone d

Table 17: Model elements amount D2D car travel time

In order to calculate the D2D car travel time from NS zone o to NS zone d, the car travel time of each LMS zone level is weighted by an average factor based on the fraction of inhabitants for the origin LMS zone and the fraction of jobs for the destination LMS zone, as depicted in Equation 4.

$$t_{od}^{\text{car}} = \sum_{i \in X_o} \sum_{j \in X_d} m_{ij}^{\text{car}} \cdot ((u_i + v_j)/2) \quad \forall (o,d) \in N \tag{4}$$

4.5.4 D2D travel time by train

To calculate the travel time for individuals travelling from a specific NS zone to another NS zone by train, it is important to determine the specific route they would likely take, including the origin and destination stations. Because of the large size of the NS zones, creating a single route for every origin-destination combination for the entire NS zone is not realistic. This is due to the fact that the selection of the train station and the travel time significantly rely on both the specific origin and destination within the NS zone. Therefore, the route is initially determined at the LMS zone level, calculating the corresponding average times for all travel time components. In the end, similar to the process for car travel time in Equation 4, this data is aggregated from LMS zone level to NS zone level.

To determine which origin station is likely to be chosen when travelling from a particular LMS zone, the 'Rittenonderzoek' is utilised. In this process, the origin and destination postal codes for each trip in the 'Rittenonderzoek' are first translated to their respective LMS zones. Subsequently, the origin train station that was most frequently used by respondents commencing their trip in the respective origin LMS zone was identified. This approach results in assigning a specific origin station a to each origin LMS zone i, based on the train station most commonly used by travellers in that particular LMS zone. In cases, where two stations were used equally often, one of the two stations was chosen. The same process was repeated to assign a specific destination train station b to each destination LMS zone j. Since every LMS zone has a origin and destination zone assigned, the route for every LMS zone level OD pair including origin and destination train station could be determined, this information is described with the arc $(i,a,b,j) \in R$ in Table 18.

The LMS data provides all the travel time information needed between station-to-station pairs. For every station-to-station pair, the service interval, transfer time, and in-train time between two stations are given. The average (hidden) waiting time can be derived by dividing the service interval by 2, assuming random arrivals and homogeneous distribution of desired departure times. Additionally, the LMS data contains the Service Interval Penalty and Transfer Penalty between all stations, which is calculated based on previous Stated Preference research outlined in subsection 2.2.

Name	Description
	Sets
X	Set of LMS zones
Y	Set of NS zones
Z	Set of stations
$X_y \subseteq X$	Set of LMS zones in NS zone y
	Arcs
$L = \{(i,j)\}\ \forall i,j \in X$	D2D trip from LMS zone i to LMS zone j
$N = \{(o,d)\}\ \forall o,d \in Y$	D2D trip from NS zone o to NS zone d
$S = \{(a,b)\}\ \forall a,b \in Z$	S2S trip from station a to station b
$R = \{(i,a,b,j)\}\ \forall a,b \in Z\ i,j \in X$	D2D train route from LMS zone i via origin station a and destination station b to LMS zone j
	Parameters
d_{xz}	Average straight line distance between midpoint LMS zone x and train station z from LMS
p_{ab}^{wait}	(Hidden) waiting time from station a to station b from LMS
p_{ab}^{intrain}	In-train time from station a to station b from LMS
p_{ab}^{transfer}	Transfer time from station a to station b from LMS
p_{ab}^{SIP}	Service Interval Penalty from station a to station b from LMS
p_{ab}^{TP}	Transfer Penalty from station a to station b from LMS
u_x	Fraction of inhabitants in lms zone x from total inhabitants NS zone from LMS
v_x	Fraction of jobs in lms zone x from total jobs NS zone from LMS
	Variables
m_{ij}^{access}	Access time from LMS zone i to LMS zone j
m_{ij}^{wait}	(Hidden) waiting time from LMS zone i to LMS zone j
m_{ij}^{intrain}	In-train time from LMS zone i to LMS zone j
m_{ij}^{transfer}	Transfer time from LMS zone i to LMS zone j
m_{ij}^{egress}	Egress time from from LMS zone i to LMS zone j
m_{ij}^{SIP}	Service Interval Penalty from LMS zone i to LMS zone j
m_{ij}^{TP}	Transfer Penalty from LMS zone i to LMS zone j
	Output variables
t_{od}^{access}	Access time from NS zone o to NS zone d
t_{od}^{wait}	(Hidden) waiting time from NS zone o to NS zone d
t_{od}^{intrain}	In-train time from NS zone o to NS zone d
t_{od}^{transfer}	Transfer time from NS zone o to NS zone d
t_{od}^{egress}	Egress time from NS zone o to NS zone d
t_{od}^{SIP}	Service Interval Penalty from NS zone o to NS zone d
t_{od}^{TP}	Transfer Penalty from NS zone o to NS zone d

Table 18: Model elements amount of train travellers

The arc $(i,a,b,j) \in R$ contains specific information about the origin and destination train stations used to travel from LMS zone i to LMS zone j. The station-to-station train travel time components can therefore be established for each LMS zone level OD pair. This process is detailed in Equation 5.

$$\begin{aligned}
m_{ij}^{\text{wait}} &= p_{ab}^{\text{wait}} && \forall (i,a,b,j) \in R \\
m_{ij}^{\text{intrain}} &= p_{ab}^{\text{intrain}} && \forall (i,a,b,j) \in R \\
m_{ij}^{\text{transfer}} &= p_{ab}^{\text{transfer}} && \forall (i,a,b,j) \in R \\
m_{ij}^{\text{SIP}} &= p_{ab}^{\text{SIP}} && \forall (i,a,b,j) \in R \\
m_{ij}^{\text{TP}} &= p_{ab}^{\text{TP}} && \forall (i,a,b,j) \in R
\end{aligned} \tag{5}$$

While the travel time components from station-to-station are given in the LMS. The access and egress time between the LMS zone and the train station, have to be derived based on the 'Rittenonderzoek'. Figure 15 provides a detailed overview of this approach to estimate the average access time from these LMS zones to the most frequently used origin stations. The same process is used to estimate the average egress time for the LMS zones and the most used station combinations.

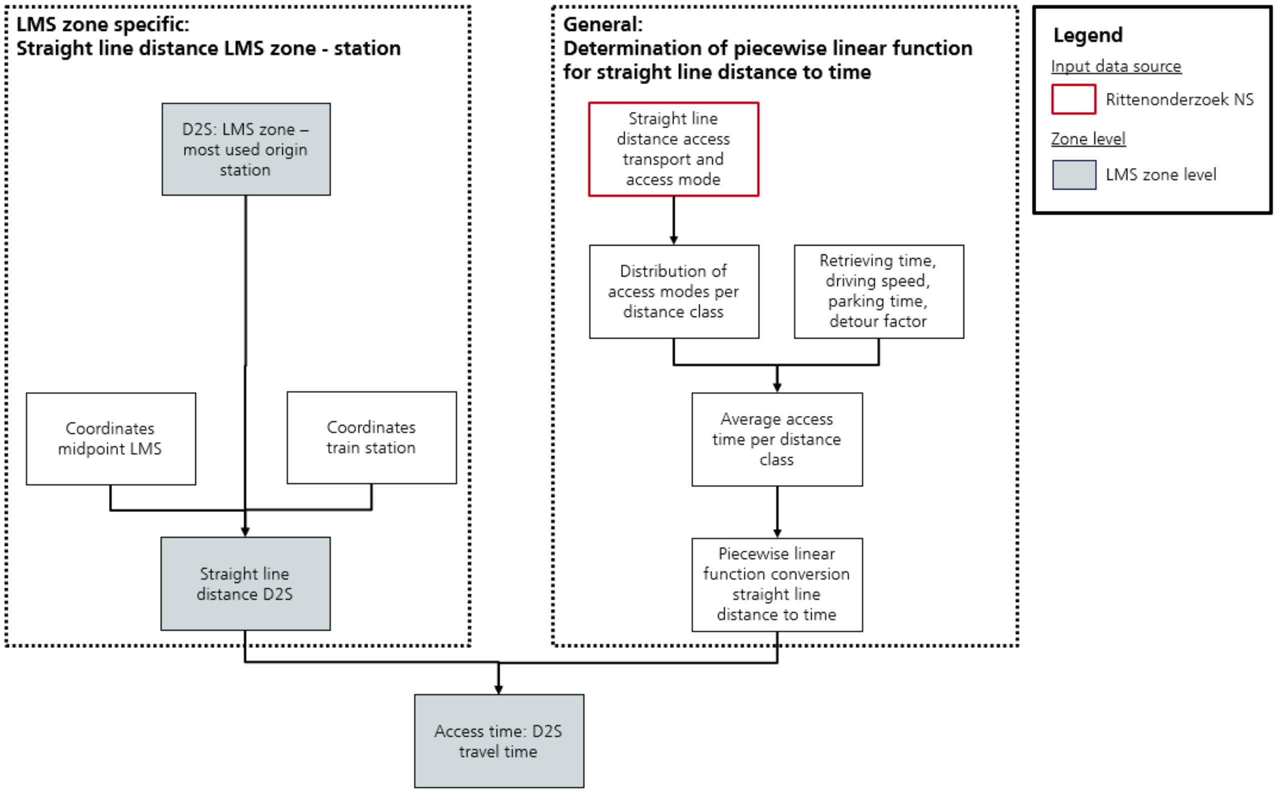


Figure 15: Methodology determining access time, the same procedure is performed for egress time

The process of determining the access and egress time, involves calculating the straight-line distance between the LMS zone and the most frequently used train station based on the coordinates of the most used train station and the midpoint of the LMS zone. This is done specifically for every LMS zone for access and egress transport separately. This process is displayed on the left side of Figure 15.

After that is done, the straight-line distance must be converted to time. This is challenging due to various factors that could influence the actual time, such as the transportation mode available to the individual, the road and public transport options in the LMS zone, and the ease of parking a bike or car at the station. Due to the insufficient number of respondents per LMS zone in the 'Rittenonderzoek', mentioned in subsection 4.4 it is not possible to determine the conversion of straight-line distance per LMS zone specifically. As a result, a generic conversion function for access transport and egress transport has been derived based on the 'Rittenonderzoek' Separate estimation of the conversion function for access and egress transport allows for the consideration that individuals may have access to different modes of transport for each. This is confirmed by the comparison of Figure 25 and Figure 26 in Appendix C, which clearly demonstrates that for egress transport, walking is used more often compared to access transport. Since the approach to derive the conversion from straight-line distance to time is limited by the inability to consider the specific access and egress transport networks and parking options within each LMS zone, this limitation should be taken into consideration when zooming in on the access and egress time for specific LMS zone level origin-destination pairs. Given that the regression analysis is conducted at a higher aggregated level (NS zone level instead of LMS zone level), the generic conversion function should provide a reasonable estimation of the average access and egress travel times on this level.

In Appendix C, the subprocess steps for establishing the generic conversion from straight-line distance to time for access and egress transport, as outlined on the right side of Figure 15, are elaborated further. Ultimately, the piecewise linear function enables the conversion of the straight-line distance between the midpoint of the LMS zone and the train station into time. A piecewise linear function is selected for the conversion from straight-line distance to time because the access and egress travel time does not increase linearly with distance. Ultimately, the piecewise linear functions to derive the access and egress travel time are described in Equation 6 and Equation 7.

$$m_{ij}^{\text{access}} = \begin{cases} (d_{ia}/3.66)\cdot 60 & \text{if } d_{ia} \leq 0.5 \\ 8.19+(d_{ia}/7.61)\cdot 60 & \text{if } 0.5 \leq d_{ia} < 2 \\ 20.02+(d_{ia}/13.21)\cdot 60 & \text{if } 2 \leq d_{ia} < 4 \\ 29.10+(d_{ia}/24.04)\cdot 60 & \text{if } 4 \leq d_{ia} < 7.5 \\ 37.83+(d_{ia}/21.90)\cdot 60 & \text{if } 7.5 \leq d_{ia} < 17.5 \\ 65.23+(d_{ia}/27.59)\cdot 60 & \text{if } d_{ia} > 17.5 \end{cases} \qquad \forall(i,a,b,j) \in R \tag{6}$$

$$m_{ij}^{\text{egress}} = \begin{cases} (d_{jb}/3.66)\cdot 60 & \text{if } d_{jb} \leq 0.5 \\ 9.03+(d_{jb}/5.64)\cdot 60 & \text{if } 0.5 \leq d_{jb} < 2 \\ 24.99+(d_{jb}/13.25)\cdot 60 & \text{if } 2 \leq d_{jb} < 4 \\ 34.05+(d_{jb}/53.56)\cdot 60 & \text{if } 4 \leq d_{jb} < 7.5 \\ 37.97+(d_{jb}/20.46)\cdot 60 & \text{if } 7.5 \leq d_{jb} < 17.5 \\ 67.30+(d_{jb}/27.70)\cdot 60 & \text{if } d_{jb} > 17.5 \end{cases} \qquad \forall(i,a,b,j) \in R \tag{7}$$

To compute the train travel time components from NS zone o to NS zone d, each LMS zone level's train travel time component is weighted by an average factor determined by the fraction of inhabitants in the origin LMS zone and the fraction of jobs in the destination LMS zone compared to the total corresponding NS zones, using the same methodology as described in Equation 4 for aggregating the travel time by car from OD LMS zone level to OD NS zone level. The process for all train travel time components is outlined in Equation 8.

$$\begin{aligned} t_{od}^{\text{access}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{access}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \\ t_{od}^{\text{wait}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{wait}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \\ t_{od}^{\text{intrain}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{intrain}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \\ t_{od}^{\text{transfer}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{transfer}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \\ t_{od}^{\text{SIP}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{SIP}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \\ t_{od}^{\text{TP}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{TP}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \\ t_{od}^{\text{egress}} &= \sum_{i\in X_o}\sum_{j\in X_d} m_{ij}^{\text{egress}}\cdot((u_i+v_j)/2) && \forall(o,d)\in N \end{aligned} \tag{8}$$

4.5.5 Zonal data

In order to account for zonal characteristics that could impact the train modal share for origin-destination pairs, three characteristics for the origin and three for the destination will be incorporated. These specific characteristics are outlined as output variables in Table 19. As explained in subsection 4.3, the analysis is restricted to trips during morning rush hour, assuming the predominant direction of travel is from home to work or education. Therefore, when evaluating the origin, emphasis is placed on attributes associated with the home environment. This includes examining the impact of income on the modal share, as well as population density, serving as an indicator of the level of urbanisation in the origin NS zone. Additionally, the car ownership rate is considered, as car ownership could potentially make car travel a more appealing option, thereby reducing the modal share for train travel. For the destination, considerations encompass attributes related to the number of jobs and education in an area, which are typical morning rush hour destinations for individuals. Furthermore, attention is given to the car parking tariff, as this could be the reason to use the train instead of the car.

Name	Label	Measuring unit	Description
			Parameters
il_i	Income LMS	10^3€	Average income per household per year in lms zone i
ih_i	Inhabitants LMS		Inhabitants in LMS zone i
al_i	Area LMS	ha	Area of LMS zone i
cl_i	Cars LMS		Number of passenger cars in LMS zone i
jl_j	Jobs LMS		Number of jobs in LMS zone j
el_j	Education LMS		Number of education spots (MBO, HBO, WO) in LMS zone j
cl_j	Car parking tariff LMS	0.01 €	Average car parking tariff in LMS zone j
u_x	Fraction inhabitants LMS		Fraction of inhabitants in LMS zone x from total inhabitants NS zone
v_x	Fraction jobs LMS		Fraction of jobs in LMS zone x from total jobs NS zone
			Output variables
ic_o	Income O	10^3€	Average income per household per year in euros
pd_o	Population density O	/ha	Number of people living per hectare
co_o	Car ownership rate O		Average amount of passenger cars per inhabitant
jd_d	Job density D	/ha	Number of jobs per hectare
ed_d	Education density D	/ha	Number of education spots (MBO, HBO, WO) per hectare
ct_d	Car parking tariff D	0.01€	Average car parking tariff in eurocents

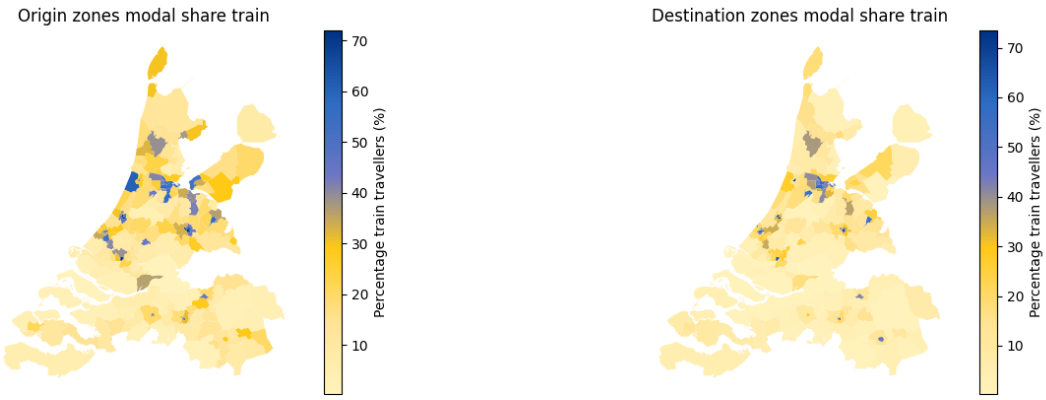
Table 19: Description of zonal characteristics based on origin and destination

The LMS provides the parameter information outlined in Table 19 for all LMS zones. By operationalising this data to the NS zone level, the required zonal characteristics can be derived. The details of this operationalisation are described in Equation 9. The same sets and arcs mentioned in Table 18 are used for this operationalisation.

$$
\begin{aligned}
ic_o &= \sum_{i\in X_o} il_i \cdot u_i \quad \forall o \in X \\
pd_o &= \sum_{i\in X_o} ih_i / \sum_{i\in X_o} al_i \quad \forall o \in X \\
co_o &= \sum_{i\in X_o} cl_i / \sum_{i\in X_o} ih_i \quad \forall o \in X \\
jd_d &= \sum_{j\in X_d} jl_j / \sum_{j\in X_j} al_j \quad \forall d \in X \\
ed_d &= \sum_{j\in X_d} el_d / \sum_{j\in X_j} al_j \quad \forall d \in X \\
ct_d &= \sum_{j\in X_d} cl_j \cdot v_j \quad \forall d \in X
\end{aligned} \tag{9}
$$

4.6 Distribution of travel time, zonal characteristics and modal share

This section provides additional information regarding the mean and distribution of the variables used in the linear regression analysis. Firstly, Figure 16 visually presents the average modal share train for both origin and destination zones. Additionally, in Appendix B, the zonal characteristics included in this research are displayed per zone. An immediate observation from Figure 16 is that the modal share of train usage appears to be higher in urban areas overall. This is consistent with the findings of Centraal Bureau voor Statistiek (2024), which concluded that significantly more train travel occurs in urban areas compared to less urban areas. Furthermore, in Figure 16a, more origin zones indicate a high train model share compared to destination zones showing a high train model share in Figure 16b. This disparity may be attributed to the emphasis on morning rush hour commutes from home to work. Workplaces with strong train connectivity are concentrated in specific zones, while individuals who commute by train may live somewhat more scattered. This suggestion seems to be confirmed by the maps showing population density and job density in Appendix B.



(a) Modal share origin

(b) Modal share destination

Figure 16: Modal share comparison

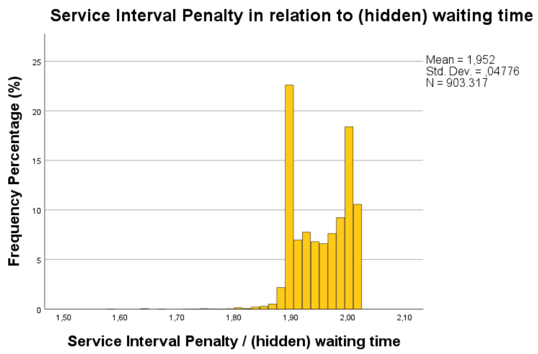
Based on the operationalised data regarding the number of trips by car and train, it is estimated that 903,317 trips occur between zones spanning a distance greater than 15 kilometers in the specific provinces under consideration in this research in the morning rush hour. The mean, standard deviation, minimum, and maximum of the variables involved in the linear regression analysis are presented in Table 20. These descriptive statistics are based on the values of the origin-destination pairs, with the variables being weighted by the volume of trips between the origin-destination pairs. This ensures that each trips can equally contribute to determining the mean value and standard deviation.

Based on these descriptive findings, it can be inferred that, on average, a train trip is approximately 1.5 times longer than a car trip. In addition, the access time, in-train time and egress time are longer than the (hidden) waiting time and transfer time. According to Kennisinstituut voor Mobiliteitsbeleid (2020), the overall modal share of train travel relative to car travel in the Netherlands in passenger kilometers was around 12% in 2018. The higher modal share in this study could be attributed to the specific scope focusing on predominantly urban provinces and trips covering distances longer than 15 kilometers.

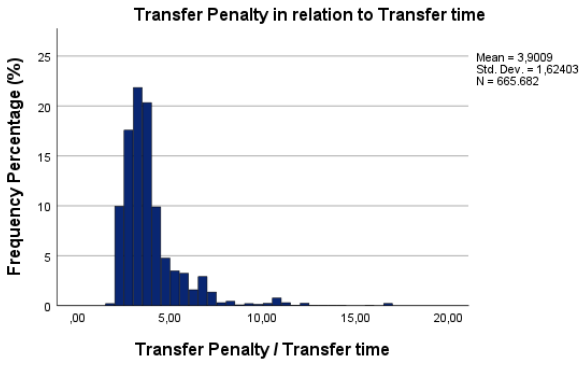
Category	**Variable**	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
D2D TT	Car: Travel Time (min)	62.4	30.7	25.2	425.5
	Train: D2D Travel Time (min)	96.5	28.1	37.0	383.4
	Train: Access time (min)	26.7	13.6	3.3	90.3
	Train: (Hidden) waiting time (min)	9.9	3.4	3.6	20.4
	Train: In-train time (min)	28.7	17.7	3.9	245.8
	Train: Transfer Time (min)	3.8	4.5	0.0	39.0
	Train: Egress time (min)	27.4	12.9	2.0	91.7
Zonal data	Income O (10^3€)	44.1	5.6	28.6	62.0
	Population density O (/ha)	21.3	26.2	0.0	174.7
	Car ownership rate O	0.5	0.1	0.2	0.9
	Job density D (/ha)	24.1	39.6	0.5	188.7
	Education density D (/ha)	6.3	13.5	0.0	77.3
	Car parking tarif D (0.01€)	80.2	115.0	0.0	444.6
Modal share train	Modal share train (%)	20.3	27.9	0.0	100.0

Table 20: Descriptive statistics based on 903317 travel movements in the morning rush hour

Figure 17 provides additional insights into the distribution of the Service Interval Penalty and Transfer Penalty, as established based on previous literature studies, in relation to the (hidden) waiting time and transfer time. In Figure 17a, the Service Interval Penalty is compared with the (hidden) waiting time for each OD pair. On average, the Service Interval Penalty is 1.96 times higher than the (hidden) waiting time, which can be interpreted as the average resistance weight for (hidden) waiting time compared to in-train time. The distribution and standard deviation indicate that the ratio between the Service Interval Penalty and (hidden) waiting time is reasonably consistent, ranging between 1.80 and 2.05. In Figure 17b, the same comparison is made between the Transfer Penalty and the transfer time. The mean value of 3.90 leads to the conclusion that the average resistance factor for transfer time is higher than for (hidden) waiting time based on literature. This conclusion is logically explainable, considering that the (hidden) waiting time can still be partially spent at home, whereas a transfer during a train journey is relatively negatively perceived due to the inconvenience. It is also notable that the ratio between Transfer Penalty and transfer time shows a relatively wide spread. For some transfers, this ratio is around 2.5, while outliers with ratios above 10 also occur. The wider spread in this ratio is logically explainable, as the Transfer Penalty depends on multiple factors beyond travel time, leading to significant differences between OD pairs in this ratio.



(a) Service Interval Penalty



(b) Transfer Penalty

Figure 17: Distribution of Service Interval Penalty and Transfer Penalty used in the Stated Generalised approach for the OD pairs in this case study

4.7 Model estimation procedure

In the data operationalisation in subsection 4.5, the process of operationalising the data from the LMS and 'Rittenonderzoek' to obtain the number of car travellers, number of train travellers, D2D car travel time, and the D2D train travel time components is explained. This section now details how this information is used to estimate the linear regression models.

The linear regression analysis is conducted using IBM SPSS Statistics version 29.0, with the unit of analysis being the 25,166 NS zone level origin-destination pairs. To ensure that all trips equally contribute to the linear coefficient estimation, the OD pairs are weighted based on the total number of travellers. As a result, OD pairs with a larger number of travellers carry more weight in the linear analysis than OD pairs with fewer travellers.

The dependent variable in all estimated regression models is the modal share train since the goal is to analyse the mode choice of individuals between train and car. The modal share is calculated by dividing the number of train passengers by the total number of travellers (see Equation 10) and is expressed in traveller numbers, rather than passengers kilometers, which is another commonly used measure for the model share of train. The focus solely on the number of travellers stems from the specific emphasis on identifying the mode choice for each individual traveller. Additionally, the modal share train is calculated for each NS zone level origin-destination pair, where the distances traveled by train and car are approximately equal.

$$Modal\ share\ train_{od} = \frac{q_{od}^{\text{train}}}{q_{od}^{\text{train}} + q_{od}^{\text{car}}} \cdot 100 \quad \forall (o,d) \in N \tag{10}$$

Several linear regression model are estimated in SPSS, differing in the included independent variables. The first estimated linear regression model is for the empirical assessment of all train travel time components. This involves separately incorporating the access time, (hidden) waiting time, in-train time, transfer time and egress time, along with the travel time by car and the zonal characteristics, into the linear regression model. The coefficients of these travel time components are then compared with the coefficient of in-train time to estimate the relative impact. This comparison is based on the ratio by dividing linear regression coefficient of the train travel time component by the linear regression coefficient of the in-train time. This ratio provides, to some extent, an indication of the additional resistance generated by an extra minute of travel time for the specific travel time component, compared to an extra minute of in-train time. The specific travel time components ratio (α) can be utilised to calculate the D2D Revealed Generalised Travel Time for all origin-destination pairs using the equation presented in Equation 11.

$$Train : D2D\ Revealed\ Generalised\ TT_{od} = \alpha_1 \cdot t_{od}^{\text{access}} + \alpha_2 \cdot t_{od}^{\text{wait}} + t_{od}^{\text{intrain}} + \alpha_3 \cdot t_{od}^{\text{transfer}} + \alpha_4 \cdot t_{od}^{\text{egress}} \quad \forall (o,d) \in N \quad (11)$$

To compare the impact of determining the modal share train based on the Actual, Stated Generalised, and Revealed Generalised Travel Time by train, it is essential to compute the Actual Travel Time and Stated Generalised Travel Time for each origin and destination pair. Equation 12 describes the approach for determining the Actual Travel Time, where each travel time component is assigned the same weight of 1. For the literature-based D2D Stated Generalised Travel Time, the Service Interval Penalty and Transfer Penalty are utilised instead of the (hidden) waiting time and transfer time, as these are the valuation values in comparison to in-train time established in literature research, as explained in subsection 2.2. Specific information regarding the valuation of the access and egress time is less available in the literature. According to Van Hagen (2011), the access and egress time is roughly valued at half of the in-train time. Therefore, when calculating the Stated Generalised Travel Time, the access and egress time are multiplied by 2. The final equation to calculate the Stated Generalised Travel Time can be observed in Equation 13.

$$Train : D2D\ TT_{od} = t_{od}^{\text{access}} + t_{od}^{\text{wait}} + t_{od}^{\text{intrain}} + t_{od}^{\text{transfer}} + t_{od}^{\text{egress}} \quad \forall (o,d) \in N \quad (12)$$

$$Train : D2D\ Stated\ Generalised\ TT_{od} = 2 \cdot t_{od}^{\text{access}} + t_{od}^{\text{SIP}} + t_{od}^{\text{intrain}} + t_{od}^{\text{TP}} + 2 \cdot t_{od}^{\text{egress}} \quad \forall (o,d) \in N \quad (13)$$

Following the calculation of the D2D Actual TT, D2D Stated Generalised TT, and D2D Revealed Generalised TT for every origin-destination pair, the TTF value, Stated Generalised TTF value, and the Revealed Generalised TTF value can be obtained by dividing the Actual, StatedGgeneralised, and Revealed Generalised train travel time by the travel time by car. Equation 14, Equation 15, and Equation 15 present the equations for the three TTF values, each incorporating its respective approach for train travel time valuation.

$$TTF_{od} = \frac{Train : D2D\ TT_{od}}{Car : D2D\ TT_{od}} \quad \forall (o,d) \in N \quad (14)$$

$$Stated\ Generalised\ TTF_{od} = \frac{Train : D2D\ Stated\ Generalised\ TT_{od}}{Car : D2D\ TT_{od}} \quad \forall (o,d) \in N \quad (15)$$

$$Revealed\ Generalised\ TTF_{od} = \frac{Train : D2D\ Revealed\ Generalised\ TT_{od}}{Car : D2D\ TT_{od}} \quad \forall (o,d) \in N \quad (16)$$

Subsequently, three linear regression models can be estimated, each varying in the inclusion of the Actual TT, Stated Generalised TT, and the Revealed Generalised TT by train, alongside the travel time by car and zonal characteristics. Subsequently, another set of three linear regression models can be estimated, focusing solely on the ratio between train and car travel time. These three linear regression models would vary in the inclusion of the Actual TTF, Stated Generalised TTF, and the Revealed Generalised TTF, while also accounting for zonal characteristics.

Ultimately, to demonstrate the relative explanatory power of integrating additional information to explain the modal split, four linear regression models are compared. This comparative analysis of the relative explanatory power facilitates the understanding of whether the additional information significantly contributes to improved predictions in modal share train. Therefore, each new estimated model will incorporate additional information to account for the modal share. The conceptualisation of these four linear regression models can be seen in Figure 18. The yellow block indicates the variables that have changed compared to the previously estimated model. Initially, Model A only declares the modal share Train based on the TTF value. Subsequently, the TTF value is dissected into the D2D travel time by train and the D2D travel time by car, acommodating for the difference in experienced value between the D2D travel time by train and car. Next, the Train D2D TT is replaced by the Train D2D Revealed Generalised TT to also accommodate for the difference in valuation for the train travel time components. Finally, to ascertain the additional explanatory value of including zonal characteristics beyond the modal share based on travel time, Model D is also estimated.

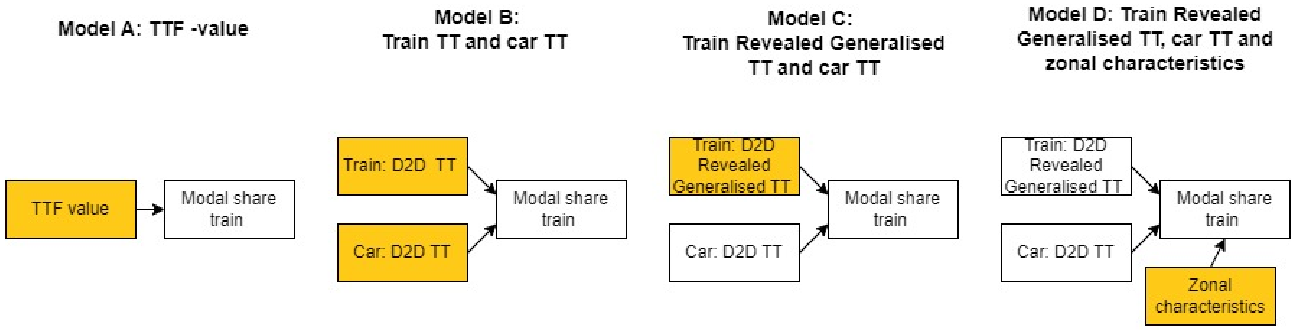


Figure 18: Models for estimating the influence of adding more additional information

5 Results Part 1

As discussed in subsection 3.6, first the results of the cross-sectional model will be discussed and afterwards the results of the longitudinal model. As also motivated in subsection 3.6, all insignificant paths are removed from the SEM model. Therefore all effects shown in the results section of this chapter are significant. Furthermore, all coefficients are displayed in standardised form, as this enables the comparison of coefficient measured on different scales.

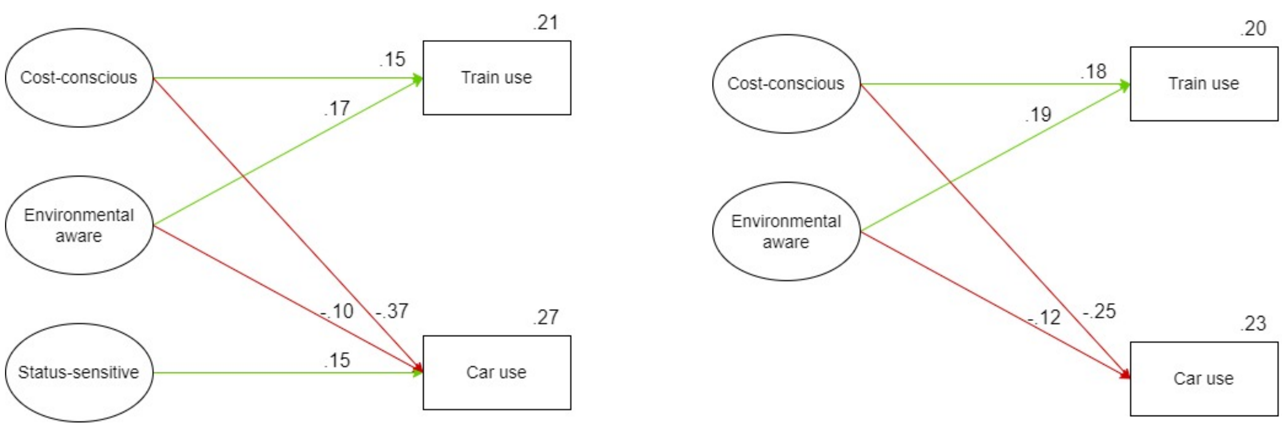
5.1 Cross-sectional results

Initially, the analysis focuses on examining the influence of attitudes on travel behavior. Subsequently, the direct and total effects of socio-demographic variables on mode use behavior mediated by attitude are interpreted.

5.1.1 Influence of attitudes on travel behavior

Figure 19 displays the standardised linear coefficients of attitudes on mode choice behavior separately for 2014 and 2016, depicting only significant paths. These linear coefficients are presented in standardised form to facilitate comparisons between coefficients measured on different scales. Therefore, the coefficients in Figure 19 and subsequent figures, which refer to standardised coefficients, can be interpreted as linear weights. For instance, a standardised coefficient of .17 for the path from environmental awareness towards train use indicates that train use increases by .17 standard deviations for every 1 standard deviation increase in the attitude environmental awareness.

Comparing the cross-sectional SEM results, it becomes apparent that the attitude status-sensitive is only depicted in Figure 19a and not in Figure 19b. This suggests that in 2014, being status-sensitive had a significantly positive impact on the extent of car use. However, this effect was no longer statistically significant in 2016, suggesting that being status-sensitive no longer significantly influenced car use.



(a) Standardised coefficients attitudes on behavior 2014

(b) Standardised coefficients attitudes on behavior 2016

Figure 19: Standardised coefficients cross-sectional analysis

Analyzing the influence of cost-consciousness and environmental awareness attitudes on both train and car use in 2014 and 2016 reveals a consistent pattern. Each attitude consistently exerts a positive influence on the use of one mode of transportation and a negative influence on the use of the other, confirming that these modes of transport are to some extent substitutes for each other. Cost-conscious individuals tend to favor train use and are less inclined towards car use. Similar effects are observed for environmental awareness, with individuals displaying higher environmental awareness using the car less and the train more.

The impact of being cost-conscious has a greater effect on car use compared to train use, and the effect of environmental awareness on train use is relatively stronger than its effect on car use. The unequal relative effect on both variables indicates that car and train are only partially interchangeable. Increased car usage does not necessarily result in a proportional decrease in train usage. This can be attributed to the fact that for certain trips, alternative modes of transportation besides the car and the train can be chosen, and the notion that cost-consciousness and environmental awareness might possibly influence also absolute numbers of train or car usage, rather than always representing a modal choice between train and car.

When comparing the coefficients of the relationship in 2014 with those in 2016, it becomes evident that the directions of the relationships correspond. However, some variations in the strength of the influence of attitudes on behavior are observed. The largest difference can be seen for the relationship between cost-consciousness and car use which is stronger in 2014 than in 2016. This can be attributed to the absence of control for status-sensitivity in 2016 due to its lack of significant relationship. As there is a positive correlation between status-sensitivity and cost-consciousness, as indicated in Table 9 and Table 10, cost-consciousness now exerts a reduced negative impact on car use, since status-sensitivity had a positive influence on car use.

According to subsection 3.6, one of the objectives of the cross-sectional analysis was to investigate if certain variables could be excluded from the analysis before estimating the longitudinal analysis. Based on the results, none of the variables can be excluded. While the influence of status-sensitivity on mode use is insignificant for most of the estimated relationships, there is still a significant relationship with car use in 2014. Hence, the decision is made to retain the influence of status-sensitivity in the longitudinal analysis.

Right above the dependent variables, the proportion of explained variance of the train and car use based on socio-demographic variables and the detailed attitudes can be observed. The higher proportion of explained variance for car use than train use suggests that the prediction of train use is less accurate than the prediction of car use, based on environmental awareness, cost-consciousness, and socio-demographic variables. Additionally, the proportion of explained variance, ranging from .20 to .27, indicates that other influential factors not accounted for in this cross-sectional analysis impact mode use for both train and car travel.

5.1.2 Influence of socio-demographic variables on attitudes and travel behavior

Table 21 and Table 22 show the standardised direct and total effects for the cross-sectional model in 2014 and 2016. This gives more insights in the direct and indirect impact of socio-demographic variables on mode choice behavior. The empty cells in the tables indicate that no association was estimated between those two variables, or that the association was not statistically significant, and therefore is fixed to zero in the final model.

The impact of gender on mode use is relatively minor, as indicated by the standardised total effect of -.05 on car use and .04 on train use. This is because gender only has an indirect effect through attitudes on mode use but no direct significant effect from gender towards mode use is found. Women, in general, tend to be more cost-conscious and environmentally aware which could explain a decrease in car use and an increase in their train use. Moreover, the older the individual, the less they travel by train and the less they travel by car. However, when travelling with one of these modes, the older the individual the more inclined to choose the car over the train, as indicated by the stronger negative correlation between age and train use compared to age and car use. Although age also influences attitudes, the total indirect effect on mode use is small due to the negative effect of age on cost-consciousness which results in more car use and less train use while age is also a indicator of being more environmentally aware which results in less car use and more train use. Possessing a driver's license leads to a higher likelihood of car use and less frequent use of the train. This suggests that individuals who have the ability to drive are more inclined to choose the car and less likely to opt for the train. The influence of education level is particularly noteworthy. While education level seems to have little impact on car use, it has a large positive influence on train use. Moreover, there is also an indirect effect of education level via cost-consciousness and environmental awareness on train use. Individuals with higher education levels are less cost-conscious, leading them to choose the train less frequently. On the other hand, there is a contrary effect as highly educated individuals tend to be more environmentally aware, resulting in increased train use. The overall effect of these two indirect effects are that a higher education level leads to a slight increase in train usage through attitudes, but not necessarily to a decrease in car usage

Independent variables	Dependent Variables Attitudes			Mode use			
	Cost-conscious	Status-sensitive	Environmental aware	Car use		Train use	
				Direct	Total	Direct	Total
Socio-demographic							
Gender	.12		.11		-.05		.04
Age	-.13	-.08	.08	-.04	-.01	-.20	-.21
Driver's license	-.12	-.08	-.06	.40	.43	-.19	-.21
Education level	-.21	-.15	.33	-.04	-.02	.25	.27
Attitudes							
Cost-conscious				-.37	-.37	.16	.16
Status-sensitive				.15	.15		
Environmental aware				-.10	-.10	.17	.17

Table 21: Standardised direct and total effects of cross-sectional analysis 2014

Independent variables	Dependent Variables Attitudes		Mode use			
	Cost-conscious	Environmental aware	Car use		Train use	
			Direct	Total	Direct	Total
Socio-demographic						
Gender	.10	.06		-.03		.03
Age	-.09	.06	-.09	-.08	-.16	-.17
Driver's license	-.15	-.06	.36	.41	-.16	-.20
Education level	-.24	.34	-.04	-.03	.27	.30
Attitudes						
Cost-conscious			-.25	-.25	.18	.18
Environmental aware			-.12	-.12	.19	.19

Table 22: Standardised direct and total effects of cross-sectional analysis 2016

5.2 Longitudinal results

In the longitudinal analysis, the same structure of interpreting the results will be used as in the cross-sectional analysis. Initially, the focus will be on the relationship between attitudes and behavior over time. After interpreting these relationships, the direct and total role of socio-demographic variables on attitudes and behavior over time will be discussed.

5.2.1 Influence of attitudes on travel behavior

Figure 20 shows the significant causal relationships for the longitudinal analysis between attitudes and behavior. Since the impact of attitudes and mode use in 2014 are in line with those observed in the cross-sectional model, no further emphasis is placed on these effects. The primary focus is on assessing the implications of integrating past attitudes and past behavior on the outcomes recorded in 2016. When interpreting, the attitudes and behavior in 2016 are regarded as current attitudes and current behavior, while the attitudes and behavior in 2014 are considered as past attitudes and past behavior.

The study findings demonstrate that past behavior serves as the most accurate predictor of current behavior. Incorporating past behavior as a variable results in a substantially higher proportion of explained variance compared to solely explaining car and train use based on attitudes and socio-demographic variables. The subsequent sections will delve into the primary conclusions extracted from the autoregressive effects, cross-sectional effects, cross-lagged effects, and indirect effects.

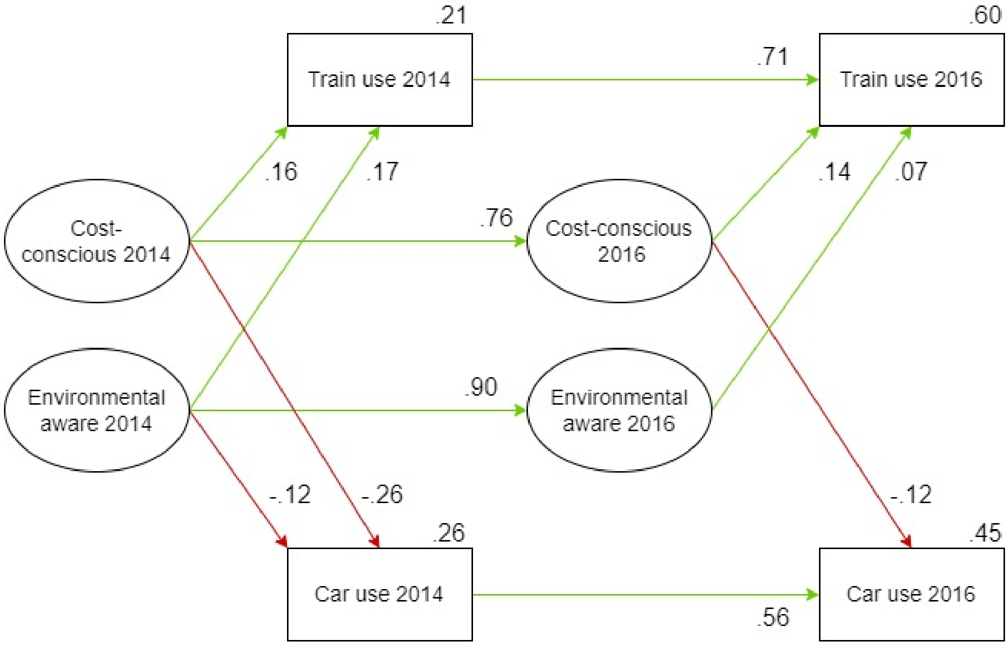


Figure 20: Standardised significant coefficients panel analysis

Autoregressive effects
The autoregressive effects observed for behavior, reflecting the extent to which behavior predicts itself over time, are substantial for both car use and train use. This aligns with the theoretical understanding that habit profoundly shapes individuals' mode use behavior. Furthermore, the analysis affirms that the autoregressive impact of attitudes is even more pronounced. Past attitudes exert a substantial influence on current attitudes, underscoring the stability of attitudes over time.

Cross-sectional effect attitude towards behavior
When considering autoregressive it means that the influence of a variable on itself across different time points has been accounted for in the analysis. From the residual significant relations between attitudes and behavior in 2016 two important conclusions can be drawn.

Firstly, there is a noticeable reduction in the path coefficients from attitudes towards behavior compared to 2014. This implies that the measure of past behavior encompasses these attitudes to a certain extent. The absence of a significant association between environmental awareness and car use in 2016 implies that the influence of current environmental awareness on current car use is likely captured by previous behavioral patterns, leading to a non-significant relationship in 2016.

Secondly, when controlling for the autoregressive effect, a path from another variable towards behavior is still significant, suggests that this "other variable" plays a role in accounting for changes in the explained variable behavior (Schnabel, 1996; Thøgersen, 2006). Considering the autoregressive effects of train and car use over time, the enduring significant relationships between cost-consciousness and environmental awareness in 2016 with train and car use in 2016 demonstrate the degree to which these attitudes influence changes in train and car use. This suggests that being more cost-conscious and environmentally aware in 2016 partly explains the increased use of trains from 2014 to 2016, with cost-consciousness exerting a greater influence. Furthermore, being cost-conscious also results in significant reduced car usage from 2014 to 2016. As cost-consciousness has a positive effect on changes in train use and a negative effect on changes in car use, an increase in individuals's cost-consciousness regarding their mode of transportation could lead to a modal shift towards the train.

Cross-lagged effects
Figure 20 shows no significant cross-lagged relationships. This is noteworthy given that prior research had found these associations to be significant (Kroesen et al., 2017; Thøgersen, 2006). The specificity of examining detailed attitudes towards mode use in this study instead of general attitudes towards mode use may explain why the cross-lagged effects are not significant, while in previous studies these relationship were found to be significant. Therefore, the following two conclusions can be drawn:

1. Examining the cross-lagged relationship from past behavior to current attitude leads to the conclusion that train and car use do not significantly influence changes in individuals' cost-consciousness and environmental awareness.
2. Examining the cross-lagged relationship from past attitude to current behavior indicates that past attitudes do not significantly contribute to explaining current train and car use. Consequently, it can be deduced that when controlling for the connection from current attitudes towards current behavior, past attitudes do not offer significant additional insights into current behavior.

Indirect effects

Table 23 illustrates the direct and total effects of all variables including socio-demographic variables. For clarity, only significant coefficients are depicted, and the total effect is presented only when it differs from the direct effect. This table will be used first for the interpretation of the indirect effect of past attitudes on current mode use in this subsection. In the next subsection, the direct and total effects of the socio-demographic variables will be interpreted.

Independent variables	Dependent Variables Attitudes 2014		Mode use 2014				Attitudes 2016				Mode use 2016			
	Cost-conscious	Envir. aware	Car use		Train use		Cost-conscious		Envir. aware		Car use		Train use	
	Direct	Direct	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total	Direct	Total
Socio-demographic														
Gender	.11	.11		-.04		.04		.09	-.03	.06		-.03		.03
Age	-.13	.07	-.04	-.01	-.20	-.21		-.10		.07	-.08	-.08	-.02	-.17
Driver's license	-.12	-.06	.40	.43	-.19	-.21	-.07	-.15		-.06	.15	.41	-.03	-.20
Education level	-.21	.33	-.03	-.02	.25	.27	-.08	-.24	.05	.35	-.04	-.03	.10	.30
Attitudes 2014														
Cost-conscious			-.26		.16		.76					-.23		.15
Envir. aware			-.12		.17				.90			-.07		.18
Mode use 2014														
Car use													.71	
Train use											.56			
Attitudes 2016														
Cost-conscious											-.12		.14	
Envir. aware													.07	

Table 23: Standardised significant coefficients panel analysis

Although the direct impact of past attitudes on current behavior is not statistically significant, previous attitudes continue to act as indicators of current train and car usage. Cost-consciousness in 2014 ultimately leads to increased train usage and decreased car usage in 2016. Similarly, environmental awareness in 2014 also correlates with increased train usage and decreased car usage in 2016. This is due to two indirect relations. The first indirect relation is the impact of attitudes in 2014 on behavior in 2014, which directly affects behavior in 2016. The second indirect relation is the influence that attitudes in 2014 have on attitudes in 2016, which subsequently affects behavior in 2016.

5.2.2 Influence of socio-demographic variables on attitudes and travel behavior

In the panel analysis, the results reveal insights that extend beyond the cross-sectional analysis. By controlling for autoregressive effects of attitudes and behavior, the direct effects of socio-demographic variables on attitudes and mode use in 2016 can be analysed. This enables the observation of whether socio-demographic variables also impact changes in behavior and attitudes. This subsection specifically concentrates on interpreting the education level and possession of a driver's license, as these socio-demographic variables have more prominent significant direct relations with attitudes and mode use in 2016.

The most significant impact on this change in attitude as well as behavior is observed for the education level. A higher education level is positively associated with an increasing awareness of the environment over time. Simultaneously, a higher education level is linked to a decreasing cost-consciousness over time. Furthermore, a higher education level leads to an increase in train use over time and a decrease in car use over time.

Additionally, possessing a driver's license can account for a portion of the changes in car usage. Logically, individuals who did not frequently use a car in the past find that having a driver's license facilitates the possibility of more easily adjusting their behavior and therefore specifically people with a driver's license change their behavior to use the car more often over time.

The results in Table 23 suggests that an increase in train usage does not always result in an equivalent relative decrease in car usage, and vice versa. While a higher level of education leads to increased train usage compared to the past, the impact of education level on reduced car usage is comparatively small. The same principle applies to individuals who possess a driver's license, which leads to increased car usage compared to the past, albeit with a notably smaller negative impact on train usage.

5.3 Conclusion

The results of part 1 indicate that cost consciousness and environmental awareness regarding mode use indeed lead to increased train usage and decreased car usage. This study reveals that mode use itself does not significantly influence the attitudes of cost consciousness and environmental awareness regarding mode use. By observing attitudes and behavior over time, it can be inferred that cost consciousness, environmental awareness, and mode use exhibit relative stability over time. Nevertheless, cost consciousness continues to explain some of the changes in car and train usage compared to the previous situation, indicating a modal shift towards train use among cost-conscious individuals. On the other hand, environmental awareness accounts for the increased use of the train compared to the past, but it does not exert a significant influence on car usage.

This research part reveals attitudes individuals can hold regarding mode use and confirms its significant impact on their behavior. With an understanding of the influence of environmentally aware and cost-conscious attitudes on mode choice, the second part of the study shifts its focus to how the contextual situation in which the choice is made affects the decision. While the initial part of the research predominantly centered on cost and environmental differences between train and car, the subsequent part delves into the role that travel time differences plays in the decision-making process.

6 Results Part 2

This chapter will shift focus from cost and environmental attitudes that influence mode use, towards the influence of the perception of travel time for the train and car on mode use alongside with socio-economic characteristics of the zones. In order to do this, this section will present and interpret the results of the linear regression analyses. The dependent variable explained in each regression model is the train modal share in relation to car. The independent variables considered vary for each model. Initially, in subsection 6.1, the train travel time components will be individually incorporated to evaluate the assessment of the door-to-door train travel components in contrast to the in-train time for computing the Revealed Generalised Travel Time. After that is done, in subsection 6.2 the valuation methods: Actual, Stated Generalised and Revealed Generalised are compared to each other in terms of their explanatory power of the modal share. Finally, in subsection 6.3, additional information is incrementally added to the regression model to investigate whether this information also results in a significantly improved predictive model of the train modal share.

6.1 Perceived value train travel time for Revealed Generalised Travel Time

The initial step is to empirically establish the linear weights of the perceived value for the train trip time components, while taking into account travel time by car and zonal characteristics. The focus in this paragraph will be on the interpretation of the train trip components. The interpretation of linear coefficients for the travel time by car and the zonal characteristics, will be discussed later in subsection 6.3.

In Table 24, the unstandardised (β) linear coefficients are presented. The unstandardised coefficient can be interpreted as the percentage increase or decrease in modal share when the independent variable increases or decreases by 1 unit. For instance, if the access time increases by one minute, the average modal share of the train decreases by 0.407 percent, assuming that all other independent variables remain constant.

The unstandardised coefficients reveal the extent to which the access time, (hidden) waiting time, in-train time, transfer time, and egress time contribute to explaining the modal share relative to each other. The highest coefficient is given to the transfer time, suggesting that one minute of extra transfer time has the largest negative effect on the train modal share. Demonstrating that travellers assign a lower value to transfer time than to the other train travel time components. Next, the influence of access time and egress time on the train's modal share is nearly the same, more than 3 times higher than the in-train time. The (hidden) waiting time continues to exert a greater influence on the train modal share than the in-train time. However, due to travellers' ability to schedule their trips and wait at home, heading to the train station only when a new train is departing, the effect of this (hidden) waiting time on the modal share is smaller than that for the access, egress, and transfer time.

The standardised coefficients (β') assist in comparing variables that are measured on different scales to assess their relative impact. The standardised coefficients can also be interpreted as weights, indicating that the influence of the car parking tariff on modal share is greater than that of other zonal data. If the car parking tariff increases by 1 standard deviation, the modal share increases by 0.254 standard deviations. In this subsection, the exclusive focus is on the coefficients of the train travel time components, all measured in minutes. Therefore, the standardised coefficient results are not explicitly addressed. For a more detailed interpretation of these standardised coefficients for the zonal characteristics, please see subsection 6.3.

The goodness-of-fit indicator (R^2) is the proportion of explained variance, this is the proportion of total variance of the dependent variable which can be explained by the linear regression relation with the independent variables. The higher the value, the better the model predicts the actual modal share train. The R^2 value of 0.533, indicates that 53.3% of the variability in the dependent variable can be explained by the linear regression coefficients of the independent variables in the model.

Category	Variable	β	β'	Sig.
Constant	Constant	39.522		<.001
D2D TT	Train: Access time (min)	-0.407	-0.199	<.001
	Train: (Hidden) waiting time (min)	-0.241	-0.029	<.001
	Train: In-train time (min)	-0.132	-0.084	<.001
	Train: Transfer time (min)	-1.027	-0.164	<.001
	Train: Egress time (min)	-0.400	-0.185	<.001
	Car: D2D TT (min)	0.253	0.278	<.001
Zonal data	Income O (10^3€)	0.027	0.006	<.001
	Population density O ($/ha$)	0.122	0.114	<.001
	Car ownership rate O	-29.415	-0.095	<.001
	Job density D ($/ha$)	0.052	0.073	<.001
	Education density D ($/ha$)	0.201	0.097	<.001
	Car parking tariff D (0.01€)	0.062	0.254	<.001
Goodnes-of-fit	R^2	**0.533**		

Table 24: Linear regression model for modal share train to determine experienced value train travel time components

For the empirical evaluation of the train travel time components, the unstandardised coefficients are considered, given that all train travel time components are presented in the same unit of measurement. To calculate the Revealed Generalised Travel Time based on these linear coefficients, the linear coefficient of each specific train travel time component is divided by the linear coefficient of the in-train time component. The resulting weights in Table 25 for method 3 enables the interpretation of the extent to which an additional minute of travel time from these travel time components carries weight in comparison to an additional minute of in-train time component in the decision-making between car and train. The Revealed Generalised Travel Time can be calculated by using these weigths:

$$Train: D2D\ Revealed\ Generalised\ TT_{od} = 3.08 \cdot t_{od}^{\text{access}} + 1.83 \cdot {}_{od}^{\text{wait}} + t_{od}^{\text{intrain}} + 7.78 \cdot t_{od}^{\text{transfer}} + 3.03 \cdot t_{od}^{\text{egress}} \quad \forall (o,d) \in N \tag{17}$$

Table 25 also illustrates the weights of the train travel time components utilised for calculating the Train D2D TT (method 1) and the Train D2D Stated Generalised TT (method 2). The first method computes the travel time by equally weighing all train travel time components, thus assigning all components the same weight of 1. The second method calculates the Stated Generalised Travel Time as described in Equation 13. The determination of the Service Interval Penalty and Transfer Penalty takes into account additional factors beyond just time such as whether the transfer is cross platform or not. Moreover, the relationship between time and penalty has been estimated in more detail than just using a single linear coefficient. The detailed calculation method is explained in subsection 2.2. As a result of this approach of penalty determination, one specific value cannot be established for the ratio between (hidden) waiting and in-train time, as well as for transfer time and in-train time. Therefore, only the mean ratio is presented in Table 25. The actual distributions for these ratios can be found in Figure 17a and Figure 17b.

Since both the Stated Generalised method as well as the Revealed Generalised method account in their own way for the valuation of the travel time components, it is interesting the compare the (average) weights. This evaluation allows for an assessment of the extent to which the (average) weighting factors established in the literature based on Stated Preferences align with the values that have been established based on travellers actual mode choice. The initial conclusion drawn from this is that the Revealed Generalised method estimates the same order of importance for the travel time components as the Stated Generalised method. An additional minute of transfer time has the most significant impact on the modal share, followed by an extra minute of access or egress time, then an extra minute of (hidden) waiting time, with the least influential being an extra minute of in-train time. Upon closer examination of the specific weights, it becomes evident that the average weight for (hidden) waiting time is relatively similar between the methods. In the Revealed Generalised method, both access and egress time are assigned a higher weight compared to the Stated Generalised Travel Time. The most notable difference is found in the weight assigned to transfer time, with the Revealed Generalised method assigning a larger weight than the average weight in the Stated Generalised method. This demonstrates that for the actual mode choice transfer, access and egress times have a greater impact relative to in-train time than expected based on previous Stated Preference research.

Variable	Method 1: Actual	Method 2: Stated Generalised	Method 3: Revealed Generalised
Train: Access time (min)	1	2	3.08
Train: (Hidden) waiting time (min)	1	1.95*	1.83
Train: In-train time (min)	1	1	1
Train: Transfer time (min)	1	3.90*	7.78
Train: Egress time (min)	1	2	3.03

*Note: The indicated values represent only the average relationship between time and the penalty. The literature-based value for the Service Interval Penalty and Transfer Penalty encompasses more factors than just the time duration, and the relationships between time and Penalty are not solely linear, see subsection 2.2

Table 25: (Average) weights between train travel components and in-train time for the three valuation methods

6.2 Comparison of Actual, Stated Generalised and Revealed Generalised TT and TTF

In Table 26, the three methods of valuing train travel time will be evaluated to assess their impact on the proportion of explained variance in train modal share. This enables to explore the extent to which integrating perceived value of travel time can contribute to explaining modal choice and how the Revealed Preference approach aligns with the approach of earlier Stated Preference research. This is achieved by estimating three regression models, each with its own method of incorporating the travel time valuation. Upon closer examination of the goodness-of-fit indicator (R^2), it becomes apparent that the Stated Generalised Travel Time and Revealed Generalised can better explain the train model share compared to the Actual Travel Time for train travel. From this can be concluded that the difference in perceived value of train travel time components influences the actual mode choice of travellers.

Category	Variable	Method 1: Actual		Method 2: Stated Generalised		Method 3: Revealed Generalised	
		β	β'	β	β'	β	β'
Constant	Constant	40.365		41.571		39.532	
D2D TT	Train: D2D TT (min)	-0.370	-0.373				
	Train: D2D Stated Generalised TT (min)			-0.216	-0.370		
	Train: D2D Revealed Generalised TT (min)					-0.132	-0.348
	Car: D2D TT (min)	0.338	0.372	0.286	0.315	0.253	0.279
Zonal data	Income O (10^3€)	-0.026	-0.005	-0.022	-0.004	0.027	0.006
	Population density O ($/ha$)	0.125	0.117	0.127	0.119	0.122	0.114
	Car ownership rate O	-30.169	-0.097	-23.899	-0.077	-29.438	-0.095
	Job density D ($/ha$)	0.047	0.066	0.051	0.071	0.052	0.073
	Education density D ($/ha$)	0.204	0.099	0.201	0.097	0.201	0.097
	Car parking tariff D (0.01€)	0.067	0.277	0.061	0.251	0.062	0.254
Goodness-of-fit	R^2	**0.524**		**0.534**		**0.533**	

Table 26: Regression results for modal share train when evaluating TT values for the three valuation methods (all coefficient have significance of $< .001$

The slight variation in the goodness-of-fit indicator (R^2) between the Stated Generalised and Revealed Generalised methods hinders a clear determination of which valuation method more accurately represents individuals' modal choice behavior. The reason why the Revealed Generalised method does not outperform the Stated Generalised method may lie in the fact that the Stated Generalised method offers a more detailed estimation of the valuation for transfer and (hidden) waiting components. This is achieved by considering a piecewise linear relation and multiple influencing factors for every OD pair. In contrast, the Revealed Generalised method estimates the value of travel time components based on actual revealed modal choice instead of Stated Preference, but it only accounts for a single linear relationship for each train travel time component and solely considers time as an influencing factor. Table 27 provides an overview of the strengths and weaknesses of both methods in relation to each other, explaining why neither method stands out as superior in terms of the proportion of explained variance of the train modal share.

	Stated Generalised approach	Revealed Generalised approach
Strengths	- When assessing perceived value of transfers, the number of transfers, interchange type and potential extra waiting time are considered besides transfer time	- Based on modal choice train and car
	- When assessing the perceived value of of (hidden) waiting time, the distribution of departures over the hour is considered besides service interval	- Analysing actual choices based on Revealed Preference research
	- When assessing transfer time and (hidden) waiting time, a piecewise linear function is considered	
Weaknesses	- Based on evaluating train alternatives	- Only the element of time is being considered, without taking into account any other features that contribute to the experienced value of train travel components
	-Analysing hypothetical choices based on Stated Preference research (hypothetical bias)	- Only a single linear coefficient is calculated for each travel time component, even though the actual relationship may be different in reality.

Table 27: Relative advantages and disadvantages when comparing the Stated and Revealed Generalised approach for the purpose of evaluating impact of travel time on mode choice

In Table 28, the comparison of the three methods of valuing train travel time using the TTF value instead of the car and train travel times separately reveals a common trend. This TTF value account for the ratio between the D2D travel time by train and the D2D travel time by car. It is evident that, for all three methods, combining the car and train travel time into a single factor leads to a decrease in the R^2 value. This decrease can be attributed to that combining the travel time into a single ratio results in information loss. The distinction in the valuation for an additional minute of D2D travel time by car compared to an extra minute of D2D travel time by train can no longer be considered.

Comparing the R^2 value for the TTF, Stated Generalised TTF, and Revealed Generalised TTF indicates that the Stated Generalised and Revealed Generalised values continue to result in a higher proportion of explained variance than the Actual Travel Time. However, the difference in R^2 has been decreased in comparison with the R^2 differences in Table 26. Highlighting the importance of taking into account the perceived value of train travel compared to car, while also considering the differences in perceived value among various train travel time components. Furthermore, the Stated Generalised and Revealed Generalised method once again demonstrate only a marginal difference in the proportion of explained variance. In conclusion, when evaluating the modal share based on the ratio between train and car travel time (TTF value), there is no distinct preference for either the use of the Stated Generalised valuation method or the Revealed Generalised valuation method.

Category	Variable	Method 1 Actual			Method 2 Stated Generalised			Method 3 Revealed Generalised		
		β	β'	Sig.	β	β'	Sig.	β	β'	Sig.
Constant	Constant	51.720		<.001	49.905		<.001	48.470		<.001
D2D TT	Actual TTF	-11.924	-0.260	<.001						
	Stated Generalised TTF				-6.296	-0.272	<.001			
	Revealed Generalised TTF							-4.174	-0.276	<.001
Zonal data	Income O (10^3€)	-0.060	-0.012	<.001	-0.058	-0.012	<.001	-0.031	-0.006	<.001
	Population density O ($/ha$)	0.137	0.129	<.001	0.138	0.129	<.001	0.135	0.127	<.001
	Car ownership rate O	-40.044	-0.129	<.001	-38.800	-0.125	<.001	-40.073	-0.129	<.001
	Job density D ($/ha$)	0.048	0.068	<.001	0.050	0.071	<.001	0.051	0.072	<.001
	Education density D ($/ha$)	0.230	0.111	<.001	0.231	0.112	<.001	0.228	0.110	<.001
	Car parking tariff D (0.01€)	0.075	0.309	<.001	0.073	0.299	<.001	0.072	0.296	<.001
Goodness-of-fit	R^2	**0.506**			**0.511**			**0.512**		

Table 28: Regression results for modal share train when evaluating the TTF values for the three valuation methods

6.3 Impact of adding additional information

Finally, to shed light on the relative explanatory power of integrating additional information to explain the modal split, four linear regression models are compared. In each new estimated model, additional information will be included to account for the modal share. In this model comparison, the emphasis is on the Adjusted R^2 value rather than the R^2 value. The Adjusted R^2 not only shows how well the independent variables can explain the modal share, but also adjusts for the number of independent variables considered in the model. A clear increase in the Adjusted R^2 will indicate that the incorporation of this extra information indeed contributes in explaining the variance in train modal share. The independent variables estimated in the models in Table 29 are:

- Model A: TTF
- Model B: Car D2D TT & Train D2D TT
- Model C: Car D2D TT & Train D2D Revealed Generalised TT
- Model D: Car D2D TT & Train D2D Revealed Generalised TT & Zonal characteristics

The linear regression results for model A , indicate that the TTF value alone can already account for 26.4% of the variance in the train modal share. As anticipated, a high TTF indicates that the travel time by train is relatively much longer than the travel time by car, thereby making it logical for the train modal share to decrease if this TTF becomes larger.

Upon separately including the travel time by train and car in Model B, the Adjusted R^2 value markedly increased. Focusing on the unstandardised regression coefficients in Model B reveals that when comparing the travel time by train to that of the car, an additional minute of travel time by train has 1.1 times as pronounced negative impact on the modal share for trains than an extra minute of travel time by car has a positive impact. This indicates that, overall, travellers attribute a higher experienced value to D2D car travel time than to D2D train travel time. The difference in experienced value between travel time with the car and train could also be the reason behind the significant influence of individually adding the D2D car and train travel time on the additional explained variance of the train modal share compared to including only the TTF value.

Model C shows a higher proportion of explained variance of the modal share when evaluating the Revealed Generalised door-to-door train travel time instead of the actual door-to-door train travel time. In essence, the higher proportion of explained variance highlights that it is not just about the overall travel time by train and car, but that the distribution in time over these specific components of the train trip also plays a role.

Upon comparing the increase in Adjusted R^2 from model B to C with the increase in Adjusted R^2 from model A to B, it is evident that separately including the travel time by car and travel time by train resulted in a larger additional increase in Adjusted R^2 . This indicates that it is more crucial to consider the difference in experienced value between train and car rather than the difference in experienced value between the train travel components. However, considering that the valuation of the train travel components still clearly contributes to an increase in proportion of explained variance, it remains preferable to take the difference in perceived value into account.

In model D, the inclusion of zonal characteristics results again in a large increase in the Adjusted R^2 compared to model C. This demonstrates that the socio-economic characteristics of the origin and destination zone significantly influence the modal share of the train. The impact of average income in the origin zone on the origin-destination modal share of the train is relatively very small according to the standardised regression coefficient. The influence of population density on the modal share is more pronounced, indicating that an increase of 10 persons per hectare in the origin zone leads to an increase in modal share train of 1.2%. This reinforces the notion that the level of urbanisation in an area significantly influences the number of people opting for train travel. This is a reasonable consideration, given the better public transport facilities in cities, as well as the challenges of car parking and driving, which make the car a less attractive alternative. Additionally, an increase in average car ownership per inhabitant in the origin zone of 0.1 appears to result in a decrease in model share train of 2.9%. This is coherent with the thought that car ownership leads to the possibility of using the car as alternative mode of transportation for the train. Moreover, both job and education density in the destination zone contribute to a higher modal share of the train. The impact of education density on train travel is greater than the impact of job density. For instance, an increase of 10 study spots per hectare results in a 2.0% rise, whereas 10 additional jobs per hectare lead to a 0.5% increase. This trend may be attributed to the fact that most students possess free public transportation cards, which they utilise for commuting to their educational institutions. Lastly, the zonal characteristic with the most significant impact on the modal share of the train is the car parking tariff in the destination zone. An increase of one euro in car parking tariff in the destination zone leads to a 6.2% increase in the modal share by train for a origin-destination pair. This demonstrate the importance of car parking tariff as a tool to promote a modal shift towards train usage.

Category	Variable	Model A		Model B		Model C		Model D	
		β	β'	β	β'	β	β'	β	β'
Constant	Constant	61.243		53.891		54.522		39.532	
D2D TT	TTF	-23.561	-0.514						
	Train: D2D TT (min)			-0.726	-0.731				
	Train: D2D Revealed Generalised TT (min)					-0.245	-0.646	-0.132	-0.348
	Car: D2D TT (min)			0.585	0.644	0.401	0.442	0.253	0.279
Zonal data	Income O (10^3€)							0.027	0.006
	Population density O ($/ha$)							0.122	0.114
	Car ownership rate O							-29.438	-0.095
	Job density D ($/ha$)							0.052	0.073
	Education density D ($/ha$)							0.201	0.097
	Car parking tariff D (0.01€)							0.062	0.254
Goodness-of-fit	Adjusted R^2	**0.264**		**0.366**		**0.392**		**0.533**	

Table 29: Regression results for modal share train, when adding additional information, all coefficients have significance of <0.001

6.4 Conclusion

Travellers perceive the door-to-door train travel time components differently in their mode choice, with extra transfer time having the most pronounced negative impact on train modal share compared to car. Furthermore, when comparing the perceived value of train and car, travellers place a higher value on a minute of door-to-door car travel time than on door-to-door train travel time. The Revealed Preference method used in this research proves to be equally effective as the valuation method based on previous Stated Preference studies in explaining the train modal share. When analyzing the specific origin-destination modal share of train relative to car, it is recommended to take into account the perceived valuation of both car travel time and train travel time components, along with the socio-economic characteristics of the origin and destination. From these socio-economic characteristics, car parking tariff is the most important for mode choice, an one euro increase in car parking tariff in the destination zone results in a 6.2% rise in the train modal share.

The combination of findings of research part 1 and 2 together provides a comprehensive understanding of the impact of both psychological and contextual influences on the modal share. The findings in part 2 highlight the discrepancy in perceived value between car and train, the fluctuation in perceived value of train travel time components, and the impact of socio-economic characteristics of the trip origin and destination. These complement the findings discussed in part 1, which demonstrate that cost-conscious and environmentally aware attitudes positively influence the train modal share. This provides valuable insights into the key factors to prioritise when devising strategies to increase the train modal share. For further details on potential measures, refer to subsection 7.3.

7 Conclusion and discussion

In order to reduce CO2 emissions, preserve public space, and mitigate nitrogen emissions, it is essential to encourage a shift from car usage to train usage. Despite efforts, the share of train usage compared to car usage has even decreased in recent years due to COVID. To promote the modal shift towards train usage, effective measures need to be identified to influence individuals' mode choice. Firstly, current literature recognises that attitudes towards mode use and behavior have a mutual influence over time. However, there is a lack of studies investigating how specific attitudes, offering more detailed insights into the reasons behind positive or negative attitudes, impact mode use, and vice versa. Understanding this interplay is crucial for developing effective measures based on individuals' detailed attitudes. Secondly, it is known that the perceived value of door-to-door train travel time components, such as access, (hidden) waiting time, in-train time, transfer time, and egress time, differs. However, there has been no prior research on how this perceived value influences the actual mode choice made by individuals. Therefore the overarching main question is: *What is the influence of detailed attitudes towards mode use over time and the experienced valuation of the door-to-door train travel time components on the mode choice between train and car* As these two specific types of influencing factors have distinct focuses, where attitudes provide more insight into the psychological reasons behind mode choice and the appreciation of travel time delves more into how the contextual situation in which a choice is made influences mode choice, the research is divided into two distinct parts.

The first part focuses on how detailed attitudes towards mode usage and actual mode usage influence each other. Assessing the impact of detailed attitudes on behavior and the impact of behavior on detailed attitudes provides insight into the extent to which attitudes and behavior directly influence each other. This understanding is crucial for achieving a modal shift, as it provides insight into whether it would be more effective to attempt to influence attitudes or behavior directly. Therefore the main question for part 1 is: *What is the reciprocal impact of detailed attitudes related to mode use and actual mode use of car and train over time, when controlling for socio-demographic variables?*

The second part of the research focuses on the traveller's valuation of travel time. It aims to empirically determine the valuation of different elements of the door-to-door (D2D) train journey; access time, (hidden) waiting time, in-train time, transfer time, and egress time, based on the train realised modal share for origin-destination pairs.The approach for determining the valuation of travel time based on Revealed Preference, known as Revealed Generalised Travel Time, is then contrasted with the Stated Generalised valuation method. The latter estimates the valuation of travel time components based on earlier Stated Preference research and is named Stated Generalised Travel Time. Additionally, it is compared with the Actual Travel Time method, where the valuation of all components of travel time is equal. The comparison of these three methods is based on the extent to which these three methods can explain the origin-destination modal share. Therefore the main question for part 2 is: *What is the effect of incorporating the Revealed Generalised Travel Time compared to the Actual and Stated Generalised Travel Time when assessing the modal share of train relative to car, while taking into account the D2D travel time by car and zonal characteristics?*

This concluding chapter reconciles the two research components by presenting the conclusion. It emphasises the report's contribution in relation to existing literature and provides recommendations to NS and other actors. These recommendations highlight how these two research parts together can effectively facilitate the modal shift. Additionally, the chapter addresses the limitations and potential directions for future research.

7.1 Conclusion

To ultimately address the main questions, the subquestions are addressed sequentially. Only after this, in subsection 7.2, this conclusion will be compared with earlier research, emphasising the research's contribution.

1.1 How can the relationship between attitudes and mode use over time be conceptualised based on existing theories and research, while controlling for socio-demographic variables?

Numerous studies adopt the Theory of Planned Behavior as their theoretical foundation. This theory resolves the debate surrounding the direction of causality by suggesting that attitudes typically shape behavior, given the tendency for behavior to undergo more frequent changes. Consequently, cross-sectional studies routinely estimate the impact of attitude on behavior. In longitudinal studies, it is posited that behavior could also influence attitudes in return. This concept is based on the Theory of Cognitive Dissonance, which proposes that individuals may adjust their attitude over time to align it with their behavior. Longitudinal studies vary in their conceptualisation of the influence of attitudes on behavior, with some exploring simultaneous relationships and others examining sequential connections. In the conceptualisation of this research, both simultaneous and sequential influences of attitudes on behavior are estimated. This decision is made based on the understanding that attitudes immediately and on the long term influence behavior, contingent upon the individual's ease of changing their behavior to align with their attitude. For example, this could be elucidated by considering car ownership; individuals with access to a car may find it easier to adjust their behavior to be in line with their attitude compared to those without access to one.

1.2 What is the reciprocal impact of detailed attitudes and mode use over time, while controlling for socio-demographic variables?

The survey statements in the MPN concerning attitudes towards mode use revealed three specific underlying attitudes: cost-consciousness, environmental awareness, and status sensitivity. Research into the longitudinal relationship between these attitudes and car and train usage revealed a lack of significant association between being status-sensitive and mode use. However, some estimates were found to be significant for the link between the other two detailed attitudes cost-consciousness and environmental awareness, and mode use. These relationships will be further elaborated in the following paragraphs.

Attitude and behavior exhibit a high degree of stability over time. Past attitudes better predicts current attitudes than past behavior predicts current behavior, supporting the hypothesis that behavior undergoes more frequent changes than attitudes.

Furthermore, a higher degree of cost consciousness and environmental awareness leads to increased train usage and decreased car usage. However, when past behavior is taken into account, cost-consciousness and environmental awareness have a smaller additional explanatory power of mode use, suggesting that the measure of past behavior already encompasses these attitudes to some extent. Including past behavior, enables to research if the change in behavior is influenced by cost-consciousness and environmental awareness. For train usage, both attitudes cost consciousness and environmental awareness have a significant effect on the change in behavior. In the case of car usage, only cost consciousness has a significant impact on the change in behavior.

Moreover, the analysis indicates that only partial substitution effect exists between car and train usage. An increase in train usage due to environmental awareness may not result in an equivalent decrease in car use. Conversely, being cost-conscious has a greater negative impact on car usage than a positive impact on train usage. This implies that there could be additional modes besides train and car that act as an alternative, and that cost-consciousness and environmental awareness not only impact the shift between car and train, but also influence the overall usage numbers for car and train.

In addition, it becomes evident that train and car usage do not significantly impact cost consciousness and environmental awareness in return. This leads to the conclusion that the Theory of Cognitive Dissonance does not apply to the attitudes cost-consciousness and environmental awareness. Additionally, the past attitudes cost-consciousness and environmental awareness do not significantly contribute to explaining current train and car use when also considering current attitudes, which reveals that current attitudes are a better predictor of one's behavior than attitudes in the past.

1.3 What is the influence of socio-demographic characteristics in the relation between detailed attitude and mode use behavior over time?

The influence of the socio-demographic characteristics gender, age, possession of a driver's license, and education level is assessed. Gender only has an indirect effect on mode use via attitude. Age, possession of a driver's license, and education level have both a direct effect on mode use and an indirect effect via attitude on mode use. Education level has the largest indirect effect on mode use via attitude as well as direct effect. In the following paragraphs, the socio-demographic characteristics are discussed one by one.

In general, women tend to be more cost-conscious and environmentally aware in their mode use compared to men. This also leads to slightly higher train usage and lower car usage among women. However, these effects are small.

While older individuals generally travel less, age has a much stronger negative impact on train usage than on car usage. Furthermore, older individuals are generally less cost-conscious but more environmentally aware. While being more environmental aware leads to increased train usage and decreased car usage, being less cost-conscious has a contradictory effect leading to a increased car usage en decreased train usage.

Possession of a driver's license significantly increases car usage and results in a less pronounced decrease in train usage. Individuals with a driver's license also tend to be less cost conscious and environmental aware, also indirectly leading to an increase in car usage. Furthermore, holding a driver's license influences changes in car use over time, resulting in higher usage of cars. As possessing a driver's license enables the option to use a car, it is reasonable to expect that having a driver's license impacts increased car use to some degree.

The influence of education level on attitudes is most prominent among the four demographic characteristics, with individuals of higher education levels being less cost-conscious but more environmentally aware. This results in a conflicting impact on train usage, where highly educated individuals show a greater inclination to use trains due to their environmental awareness, but at the same time, their reduced cost-consciousness makes them less inclined to use trains. When translated into the actual effect in standard deviations, the direct impact of education level leads to a 0.27 standard deviation increase in train usage. Furthermore, this effect is heightened to a 0.34 standard deviation increase through the influence of education level on environmental awareness regarding train use. However, the impact is somewhat reduced to 0.30 standard deviations due to the negative influence of education level on cost-consciousness, which decreases train use. Additionally, education level contributes to changes in travel behavior over time, with highly educated individuals tending to change their behavior more in favour of the train.

2.1 What is the relative impact of the train travel time components: access time, (hidden) waiting time, transfer time, and egress time, compared to in-train time, on the realised modal share of train relative to car, while considering D2D car travel time and zonal characteristics?

Based on empirical estimates derived from actual choices made by travellers, the impact of different elements of train travel time on the decision between car and train as the mode of transport shows significant variation. Typically, an increased travel time by train results in a reduced train modal share, although the strength of this negative effect varies across different train time components. Transfer time carries the most weight, nearly 7.8 times as much as the in-train time. Similarly, the access and egress times contribute roughly 3.1 times as much as the in-train time to the ultimate modal choice for car instead of train. The (hidden) waiting time has an influence nearly 1.8 times greater than the in-train time. Upon comparing these Revealed Generalised findings with the average Stated Generalised coefficients previously established in Stated Preference research, it becomes apparent that these Revealed Generalised results align with the order of importance of the train travel time components determined in earlier research. Notably, the Revealed Generalised results indicate a higher significance placed on transfer time and access and egress time compared to what was determined in earlier research. This indicates that access, egress and transfer time are more important in the actual modal choice than expected based on previous Stated Preference weights that were based on choices between train alternatives.

2.2 What is the effect of using the D2D Actual, Stated Generalised and the Revealed Generalised Travel Time by train in estimating the modal share of train relative to car, while also considering zonal characteristics and the D2D travel time by car?

The Stated Generalised and the Revealed Generalised Travel Time by train are better predictors of the actual modal share of train than the train Actual Travel Time. This confirms the hypothesis that the difference in experienced value by the travellers of the various components of the D2D train trip impacts the choice between train and car.

The difference between the proportion of explained variance of Stated Generalised Travel Time valuation approach and the Revealed Generalised Travel Time valuation approach is marginal, which can be explained by that both approaches have there own strengths and weaknesses. The Stated Generalised Travel Time employs a more sophisticated method for assessing the value of transfers and (hidden) waiting, taking into account a broader range of factors beyond time and also estimating other relationships beyond a linear regression coefficient. The Revealed Generalised Travel Time approach utilises only linear coefficients and considers travel time as the sole influencing factor, making it easier to interpret. Furthermore, these coefficients are determined based on Revealed Preference instead of based on Stated Preference research, providing a more concrete direct reflection of the actual realised modal choice.

2.3 What is the effect of using the Actual, Stated Generalised and Revealed Generalised TTF value, in evaluating the modal share of train relative to car, while considering zonal characteristics?

The TTF value describes the ratio between D2D travel time by train and D2D travel time by car. The benefit of using the TTF value is that it simplifies the consideration about travel time differences to a single variable. However, regardless of whether the Actual, Stated Generalised or Revealed Generalised valuation approach is used to determine the train travel time, consolidating the D2D car travel and D2D train travel into a single TTF value leads to a decrease in the explained variability of modal share. This can be ascribed to the loss of information, as only the ratio of D2D travel time by train to D2D travel time by car is used, and not the individual D2D travel times for each mode. An important explanation for this is that the experienced value of the car also differs from the experienced value of the train. By combining them into a TTF value, the difference in travel time valuation between the car and the train is overlooked. When considering the TTF value, the Stated Generalised and Revealed Generalised TTF value outperform the Actual TTF value in the explanation of the modal share, confirming that incorporating this valuation of the train travel time components contributes to predicting the modal share.

2.4 What is the impact of including additional explanatory information, instead of the TTF value, about the valuation of travel time by train, travel time by car and zonal characteristics, in assessing the modal share of train relative to car?

To assess the extent to which the inclusion of certain factors, such as the valuation of the train travel time components, truly enhances the comprehension of the modal share of train relative to car, four different models have been estimated. The first model includes only the TTF value to explain the modal share of train relative to car. The second model includes the D2D travel time by train and car separately. In the third model, the D2D travel time by train is replaced by the Revealed Generalised D2D travel time. In the final model, the zonal characteristics of income, population density, and car ownership rate are incorporated for the origin zone of the journey, and the characteristics of job density, education density, and car parking tariff are considered for the destination zone of the journey.

Evaluating the goodness-of-fit measure for all four models indicates that separately including travel time for car and train, incorporation of the valuation of the train travel time component, as well as including details about zonal characteristics, substantially results in a higher level of explained variance in the modal share train. In a model where both the travel time valuation of the train travel time components, the travel time valuation of the car travel time, and the zonal characteristics are included, it can explain 53% of the variability in the modal share for train, whereas the TTF value alone can only account for 26%.

The TTF value demonstrates that the ratio between the D2D travel time by train and the D2D travel time by car has a significant impact on the actual modal share. A higher TTF value corresponds to a lower model share of the train. By separately assessing the travel time for car and train, it is concluded that an additional minute of travel time for the D2D train journey generally has a greater negative impact on the modal share of the train, whereas an extra minute of travel time for the D2D car journey has a positive impact on the modal share of the train relative to the car. The higher proportion of explained variance of the modal share when assessing the Revealed Generalised D2D travel time confirms that in the actual decision-making process between car and train, not only the absolute travel time by train plays a role, but also the relative distribution across the different components of the D2D train travel time. A relatively longer transfer time, access and egress time, or waiting time results in a decreased model share for the train relative to the car.

The zonal characteristics of both the origin and destination zones also significantly contribute to explaining the modal share. The key variables in this regard are the car parking tariff in the destination zone and the population density of the origin zone. An increase of 10 inhabitants per hectare in population density in the origin zone is associated with a 1.2% greater modal share of train usage, confirming that higher urbanisation levels result in a relatively higher train usage. In addition, the higher the parking fees for cars, the more likely people are to choose the train. A destination where parking is one euro more expensive can lead to a potential 6.2% increase in the modal share.

In summary, by evaluating the answers on these subquestions, the main question can be addressed: *What is the influence of detailed attitudes towards mode use over time and the experienced valuation of the D2D train travel time components on the mode choice between train and car?*

Both attitudes as well as behavior show a high degree of stability over time. The detailed attitudes cost-consciousness and environmental awareness towards mode use do impact mode use, but mode use does not significantly impact the detailed attitudes cost-consciousness and environmental awareness towards mode use. Cost-consciousness can also account for the changes in train use and car use over time, while environmental awareness can only account for the changes in train use over time.

Travellers attribute varying levels of experienced value to different components of the door-to-door train travel time. The highest experienced value is placed on in-train time, followed by (hidden) waiting time. Access and egress time are experienced as less valuable, while transfer time is considered the least valuable to travellers. The assessment of these D2D train travel time components affects the actual mode choice, with a longer travel time for the low-experienced components having a greater influence on travellers opting for the car instead of the train than the high-experienced travel time components.

7.2 Comparison to the literature

When comparing the findings with earlier literature study, the added value of this research can be underpinned. The discussion will focus on confirming which insights from previous studies are validated based on this research, pointing out which insights differ from previous studies, and identifying new insights gained.

The first knowledge address in this research is about exploring longitudinal effects and detailed attitudes towards mode use in a novel manner, since this combination is never examined before. The comparison will be based on previous literature that analysed the general attitude - behavior relationships and cross-sectional analysis that focused on studying the impact of detailed attitudes towards behavior in relation to behavior.

The first important point to note is that, in this study, the detailed attitudes towards mode use extracted from the factor analysis included only cost-consciousness, environmental awareness, and status-sensitivity. Other studies have identified additional detailed attitudes towards mode use, such as health concerns, safety, flexibility, comfort, and convenience (Andersson, 2020; Johansson et al., 2006; Molin et al., 2016; Sarkar and Mallikarjuna, 2018). While this study specifically investigates the impact of attitudes associated with cost-consciousness, environmental awareness and status-sensitivity, it is important to refrain from assuming that the combination of these influences necessarily represents the general attitude towards mode use in total.

The conclusion that both attitudes and behavior exhibit a significant degree of stability over time aligns with previous research conclusions. In a latent transition cluster analysis, Kalter et al. (2020) concluded that the majority of participants remained in the same class, indicating a high stability of attitudes towards mode use over time. Likewise, Thøgersen (2006) found that past behavior is a good predictor of current behavior. However, this research found a higher stability for cost-consciousness and environmental awareness compared to the stability for behavior while research from Thøgersen (2006) as well as from Kroesen et al. (2017) observed a higher stability for behavior compared to attitude. This difference could be attributed to the focus on general attitude towards mode use in literature rather than specific detailed attitudes. The logic is that the attitudes cost-consciousness and environmental awareness towards mode use remain highly stable over time, while other attitude components towards mode use may exhibit less stability over time.

Upon examining the cross-sectional relationship from environmental awareness towards behavior, the findings align with prior research, indicating that environmental awareness contributes to increased usage of environmentally friendly modes of transport, particularly trains, as documented in Johansson et al. (2006). A novel insight of this research is that environmental awareness has a more significant positive impact on train usage than a negative effect on car usage. Furthermore, regarding the link between cost-consciousness and behavior, Kalter et al. (2020) found that individuals with a cost-conscious attitude towards car use tend to have a more unfavorable attitude towards using the car. This study confirms that being cost-conscious indeed leads to reduced car usage. The impact of cost-consciousness on train use was previously unknown. It was also plausible that cost-conscious individuals might have traveled less overall. Nevertheless, the positive influence of cost-consciousness on train use confirms its substantial effect on the modal shift, indicating that cost-consciousness impacts not only the absolute number of travel movements but also the modal choice between train and car.

The cross-lagged relationships between behavior and attitude in this research were insignificant, contrary to earlier research that found them to be significant (Kroesen et al., 2017; Thøgersen, 2006). When examining the relation from past attitudes on current behavior, it is important to keep in mind that this study controlled for the influence of current attitude on current behavior. This indicates that current attitudes are a better predictor of current behavior than past attitude, and that past attitude do not significantly contribute to explaining current behavior when current attitudes are accounted for. In addition, indirectly past attitudes still have impact on current mode use via past mode use and current attitudes. This suggests that the measurement of past behavior and current attitudes to some extent encompasses these past attitudes and thus indirectly continues to influence current behavior. Furthermore, it is notable that the relationship from past behavior to current attitude is also not significant. In research from Kroesen et al. (2017), the impact of behavior on attitude was even stronger than the influence of attitude on behavior. The reason why this study does not find the same effect may be attributed to that only specific detailed attitudes were studied. While the overall attitude towards mode use may be influenced by behavior, the impact of behavior on specific attitudes cost-consciousness, environmental awareness and status-sensitive might be too minimal to be considered significant. As a result, it can be concluded that the direction of the causal relationship is from cost-consciousness and environmental awareness towards behavior, implying a need to focus on influencing cost-consciousness and environmental awareness in order to influence mode choice behavior. Further discussion on this is provided in subsection 7.3.

The second knowledge gap addressed in this research concerns that no previous research has estimated the experienced value of train travel time components in the modal choice between car and train based on Revealed Preference. Whereas previous research often focused solely on the train journey and Stated Preference surveys when determining the experienced value of the train time components, this study examines the valuation of train journey components based on travellers' actual modal choice between the train and car. The first contribution of this study, is that this is the initial effort to test insights from prior research regarding the valuation of specific train travel components by assessing the influence of incorporating these valuation on the predictive power of the actual modal choice between train and car. Secondly, this research is the first attempt to empirically determine the experienced value of access time, (hidden) waiting time, transfer time, and egress time in relation to in-train time based on the modal choice between train and car.

This research reveals that the previously established valuation of train travel time components in literature, indeed to some extent, influence the modal choice between train and car. Furthermore, it reveals that the Revealed Generalised findings established in this study, can declare the modal choice between train and car to approximately the same extent. Given that the explanatory power of both the Stated Generalised and the Revealed Generalised method is higher than for the Actual method, it can be concluded that incorporating the valuation improves the modal share. The findings substantiate the conclusion from previous research that the experienced value of the train components varies significantly and confirms the hypothesis that these valuation indeed has an impact on the modal share (Van Hagen, 2011). Additionally, consistent with previous research, the highest experienced value is attributed to the in-train time, as travellers can utilise this time for various tasks, thereby granting it a higher level of utility (Van der Waard, 1988; Wardman et al., 2001).

This study's significant contribution lies in being the first to examine the perceived valuation of travel time in relation to actual modal choice. New findings have been revealed, indicating that the importance in determining the modal share of transfer time, access, and egress time in relation to in-train time is greater than originally anticipated based on Stated Preference studies. This emphasises the need to focus on these aspects of the door-to-door train travel in order to facilitate the modal shift towards train. Additionally, it has shed light on the perceived value of train travel time components relative to the perceived value of door-to-door travel time by car, which has not been done in previous studies. An important insight is that passengers actually experience in-train time as more favorable than in-car time. The negative impact of a minute in-train time on the train's modal share is thus half the magnitude of the positive impact of a minute of additional in-car time. Nevertheless, the transfer, access and egress time of train travel are rated much more negatively by travellers than in-car time, resulting in the overall experienced value of the door-to-door train journey being lower than the experienced value of the car journey.

7.3 Societal recommendations

Based on the findings of this study, this section will provide recommendations and implications to act upon this research. Given the significant relationships established between detailed attitudes and mode use, as well as between travel time components, zonal characteristics and mode use, a comprehensive approach is proposed. It includes recommendations for addressing traveller attitudes, the valuation of travel time, and influencing spatial characteristics. First, the focus is on how the train operator, specifically NS, can respond to these aspects. Subsequently, the recommendations are broadened, as this report can yield recommendations not only for NS but also for other stakeholders that could contribute in reaching a modal shift from car towards train usage.

7.3.1 Influencing the attitudes cost-consciousness and environmental awareness towards mode use for train operators

Analysing the relationship between attitude and behavior over time reveals whether interventions should target attitudes or behavior. If attitudes strongly shape behavior, influencing attitudes through campaigns is effective; if behavior has a stronger impact on attitudes, "hard" interventions should directly modify behavior (Kroesen et al., 2017). From this research can be concluded that being cost-conscious and environmental aware towards mode use does influence mode use, but mode use does not significantly influences the attitudes cost-consciousness and environmental awareness in return. Therefore, if NS want to promote a modal shift towards more train use through environmental awareness and cost-consciousness, it should focus on influencing the attitudes through informational campaigns.

The campaign targeting cost-conscious individuals should aim to highlight the cost comparison between using a car and taking the train. According to Nibud (2023), when traveling alone, the cost of using a car is often much higher than using public transport. However, the costs of using a car are consistently underestimated because car travellers only consider the fuel price and tend to overlook other variable costs such as car depreciation costs (Witte et al., 2022). Hence, the campaign should emphasise the importance of making an equal comparison between the variable costs of a train trip and a car trip. Additionally, a campaign targeting environmental awareness should emphasise that train travel is CO_2 neutral and compare this with the CO_2 emissions from traveling by car. NS has already developed a travel comparison tool to compare the price and CO_2 emissions per trip. This tool could be integrated into the NS app and other travel choice apps, which currently only consider travel time, to enhance travellers' awareness about both cost and the environment when selecting their mode of transportation.

Based on socio-demographic variables that are taken into account in this research, it is also possible to identify which socio-demographic characteristics influence the level of cost-consciousness and environmentally awareness. This makes it possible to direct cost-consciousness and environmental awareness campaigns to travellers who are responsive to them. In general, women, younger individuals, individuals without a driver's license, and those with a lower level of education tend to exhibit higher levels of cost-consciousness. Conversely, for environmental awareness, the situation is different, as women, older individuals, individuals without a driver's license, and those with a higher level of education are more likely to demonstrate a higher level of environmental awareness. Therefore, informational campaigns concerning environmental awareness and cost-consciousness would be more effective for women and individuals without a driver's license. Meanwhile, older individuals and people with higher education levels are more likely to respond to environmental awareness campaigns, whereas younger individuals and those with lower levels of education should be targeted more effectively with cost-consciousness campaigns. Education level, in particular, has a large impact. If NS aims to promote a modal shift towards train usage, they would be best advised to launch an informational campaign targeting cost benefits of train travel for those with a lower level of education, and to focus on promoting the environmental advantages of train travel for those with a higher level of education.

7.3.2 Influencing the (valuation of) travel time and other contextual factors for train operators

This research gives insight in the relative importance of travel time components and zonal characteristics in influencing the modal share for origin-destination pairs. Showing which components of the door-to-door train trip and which zonal characteristics, do significantly account for differences in modal share. By evaluating the origin-destination pairs with a train modal share lower than the capacity permits, attention can be directed toward enhancing the modal share for these specific origin-destination pairs by focusing on the factors that could make a substantial contribution in increasing the modal share. In Appendix D, an example is elaborated for an origin-destination pair with a lower modal share than expected based on the TTF value. In the appendix, the focus is on leveraging this research to identify potential reasons for the lower model share and to provide specific measures for the OD pair under consideration to enhance the modal share.

This subsection further explores potential recommendations for NS that can be broadly applied. First, it is crucial to remember that travel time by car is perceived to have a greater value than travel time by train. Consequently, a minute of additional D2D travel time by train has a 1.1 times more negative impact on the modal share compared to a minute of extra D2D travel time by car. Figure 21 shows the relative impact of train versus car for a minute additional door-to-door travel time on the model share of the train. Hence, NS should strive to improve the perceived value of door-to-door train travel time in order to make the train more appealing than the car.

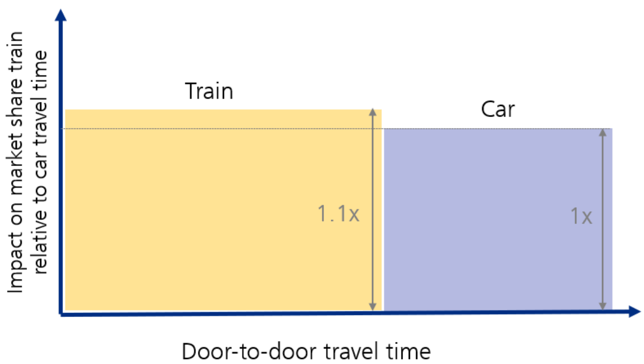


Figure 21: Relative negative impact of a minute additional D2D train travel time in comparison with the positive impact of a minute additional D2D car travel time on the model share train

Moreover, the D2D train travel time components also differ in experienced value. Taking this valuation of train travel time components into account, also contributes in better understanding the reasoning behind lower experienced value of train door-to-door travel time. In addition, including zonal characteristics significantly contributes in declaring the modal share of the train.

As outlined in subsubsection 1.4.2, the NS strategy to improve the modal share can center on enhancing (the valuation) of train travel time or on improving other influencing factors of modal share unrelated to travel time. The strategic recommendations for NS pertaining to these two distinct focuses are discussed separately.

1. **Evaluating the impact of improvements on specific train travel time components on the origin-destination (OD) model share**
This research provides insights into the experienced value of specific trip components during train travel. A higher total experienced train travel time value leads to more frequent choice of train over the car. In Figure 22, the relative impact of an additional minute of travel time on the modal share is depicted. For NS, it is crucial to consider this relative impact if they intend to influence the modal shift towards train usage. With an 8 times greater impact for a minute less transfer time and a 3 times greater impact for a minute less access and egress time on travellers' mode choice compared to a minute less in-train travel time, would it be much more effective for NS to focus on these transfer, access, egress rather than making the train itself one minute faster

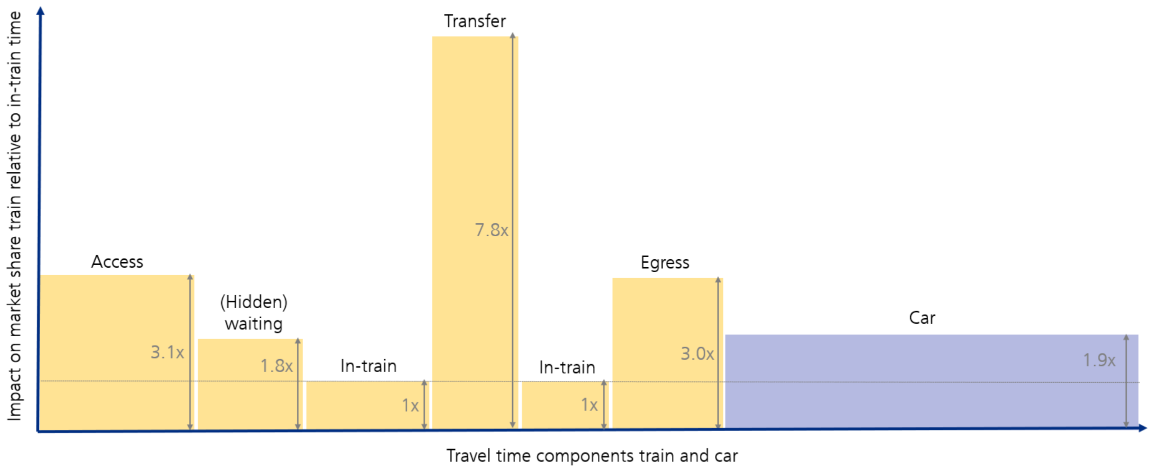


Figure 22: Relative negative impact of a minute additional train travel time component and positive impact of a minute additional car D2D travel time compared to the in train time on the model share train

With the detailed insights about the experienced value of the train travel time components from this study, these three strategies can serve as guidance for NS to influence the modal shift:

- Reducing transfer time: This research suggests that efforts should be targeted towards specifically reducing transfer time, as this factor will have the most significant impact on the modal shift, given the low experienced value of transfer time. The NS should schedule its services to minimise the number of transfers and transfer times. It is important that the new market ordering system does not involve splitting lines, as this would increase the number of transfers. It is crucial for NS to actively support this approach.
- Decreasing access and egress time: By focusing on activities and housing close to the station, it is possible to reduce access and egress time which has a relative low experienced value compared to in-train time. This efforts could involve promoting residential development near stations or encouraging economic activity around stations where the modal share is relatively low. Furthermore, the parking facilities for cars and bikes could be enhanced with a focus on reducing the parking time for the access and egress modes.
- Increasing valuation of transfer, access and egress time: Improving the valuation of travel time for the various components involves examining ways to higher the experienced value. For transfer time this could be for instance maximising the number of cross-platform transfers to enhance the transfer experience. Additionally, enhancing the waiting experience at the station can contribute to improvements in the experienced value of both waiting time and transfer time. In the case of access time and egress time, NS has a limited influence on increasing the experienced value. Efforts could be directed towards enhancing OV-bike facilities and improving bicycle and car parking facilities at stations.

2. **Evaluating the impact of other characteristics besides travel time on the origin-destination modal share**
The explanation for the low modal shares for the train is not solely attributed to the valuation of train travel time components and travel time by car. Other factors could be explored as well to potentially impact the modal shares beyond travel time measures. Based on the current analysis of the zonal data, it is apparent that population density,

job density, education density and car parking tariffs positively influence the modal share for the train, while the car ownership rate negatively affect the modal share for the train. Therefore, high levels of car ownership rate in an area could potentially account for the lower modal share for the train. If there is a desire to increase the origin-destination (OD) for specific zonal pairs, the most effective measure would be to raise the car parking tariff in the zone. In order to achieve this, efforts could be directed towards advocating for higher car parking tariff to municipalities, highlighting the positive societal impact of car parking tariffs on encouraging a modal shift from car towards train usage.

7.3.3 Recommendations for actors

This analysis provides NS (and other train operators) with insights to contribute to the modal shift strategy. However, in principle, the influence that NS can exert is limited because they primarily impact train transport, while other actors have more opportunities to influence spatial development, regulation and behavior regarding work-related trips. Key actors because of their power and interest are the bus, tram, metro, shared bikes and car providers, the Ministry of Infrastructure and Water Management, municipalities and companies. In Figure 23, the recommendations given to NS in the last two subsections are linked to recommendations that could be given to other actors based on this study.

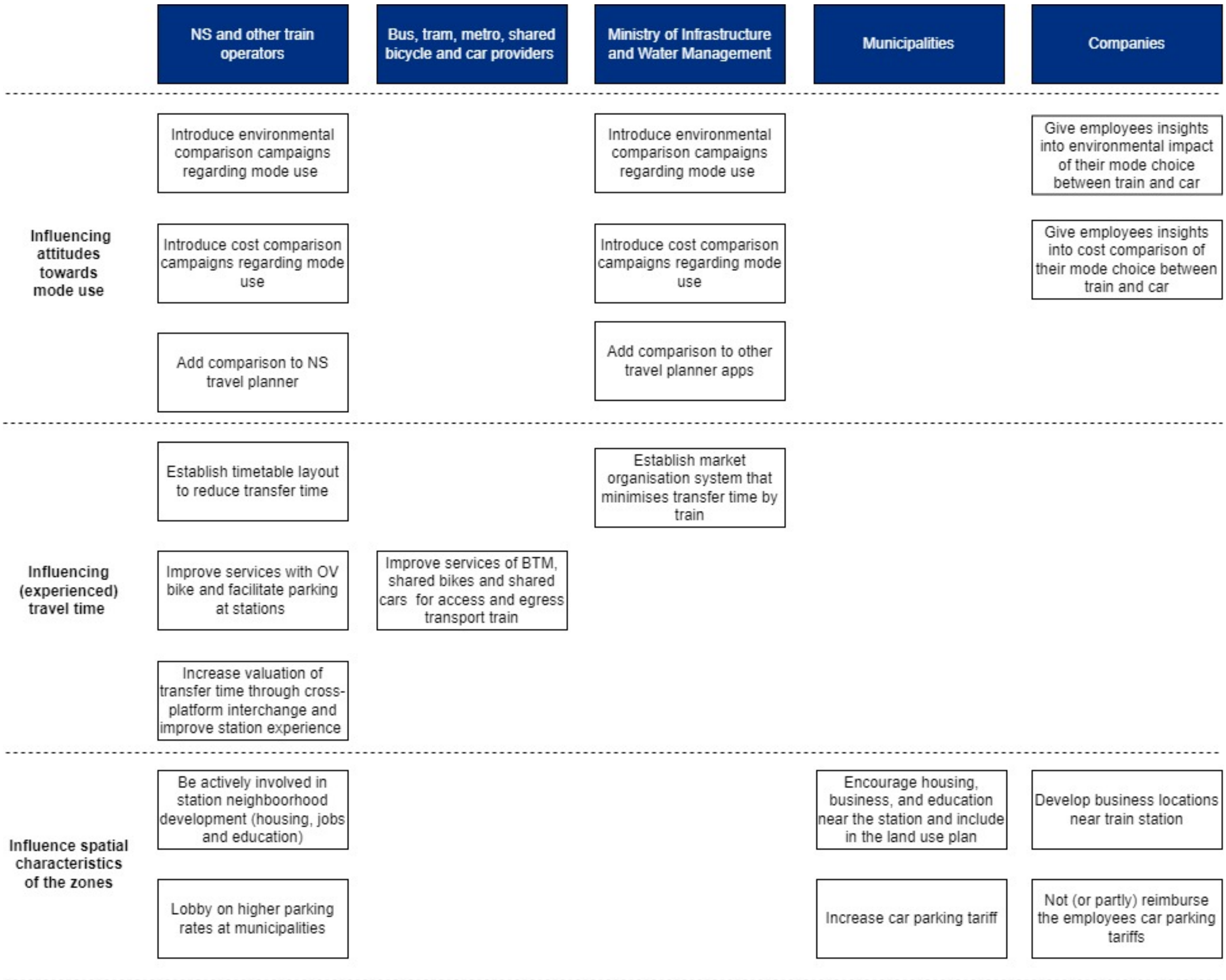


Figure 23: Measurements per actor in order to improve model share train compared to car

The parties involved in the access and egress transport of D2D train trips encompass bus, tram, metro, shared bicycle, and shared car providers. These access and egress transport service providers impact the modal share of train travel by influencing travellers' perceptions of these travel time components and potentially improving their services to reduce the access and egress time associated with train travel. Since the impact of access- and egress time on the modal share of train is 3 times as large as the in-train time it is important to focus on this part of the door-to-door train trip. The access- and egress transport can be improved, for example, by ensuring the availability of shared bikes and cars at train stations, as well as coordinating the schedules of bus, tram, and metro providers with train departure and arrival times at the stations.

The Ministry of Infrastructure and Water Management could play a role in nationwide awareness campaigns, given their commitment to sustainable transportation and the resources available to establish such campaigns. They could also develop policies that shift the consumer's consideration from solely choosing the fastest mode of transport to considering time, cost, and environmental impact when weighing the choice between car and train. Regulations focused on including cost and emission estimates per trip in travel planner apps could support this endeavor. Additionally, the Ministry is currently focused on establishing a new market organisation system that determines which train operator can operate on specific train routes. It is crucial that they consider the influence of transfer times on the modal share in their decision-making, as this research has revealed that increasing transfer times has a disproportionately negative effect, approximately eight times, on the modal share of train travel compared to in-train travel time. Therefore, to achieve the socially desirable modal shift, it is essential to minimise route fragmentation, which would otherwise increase the number of transfers.

Municipalities often seek ways to reduce car usage and promote the use of public transport. This research provides them with insights into potentially effective measures, such as prioritizing the development of housing, businesses, and educational facilities near train stations to minimise access and egress time. Additionally, the study highlights that increasing the car parking tariff is the most effective measure, as demonstrated by a 6.2% increase in the train's modal share for destinations with a one euro higher car parking tariff.

In addition to governmental organisations and public transport providers, companies also play a crucial role in enhancing the modal shift towards trains. They should encourage their employees to commute to work by train instead of by car. Firstly, this can be achieved by highlighting the cost and environmental benefits of train travel to employees in addition to time differences when showing the mobility packages. They can consider incorporating these cost and environmental benefits into a more attractive mobility package for employees who choose to travel by train. For instance, by providing them with a public transport card that allows free travel outside of working hours. Furthermore, when choosing the business location, companies should consider choosing business locations with good train connections. Ideal locations would be close to a train station on the outskirts of cities, as there is often more potential to increase the train's market share in these areas. Another highly impactful measure that companies can adopt is the non-reimbursement or partial reimbursement of employees for car parking fees, as research indicates this can notably influence modal choice.

7.4 Limitations and recommendations for future research

This subsection addresses the limitations that apply to both research parts, serving as the foundation for recommendations for future research. One shared limitation is the exclusive focus of both research parts on the relationship between car use and train use, neglecting that other modes of transport could also be an alternative in the travellers' choice set. For some connections, the car is not the only alternative to train usage, especially with the growing emergence of alternatives such as e-bikes, which also compete for longer distances trips (De Haas, 2019). Therefore, it would be advantageous to broaden the discussion in future research to encompass the influence of attitudes and the experienced value of travel time for other transportation modes as well. In the following subsections, other limitations and recommendations for future research specific to exploring detailed attitudes or perceived value of train travel time based on actual mode choice will be discussed.

7.4.1 Detailed attitudes-behavior relationship over time

In this subsection, the primary limitations associated with the methodology used to analyse the relationship between detailed attitudes and behavior over time will be addressed, along with an exploration of potential approaches for addressing these limitations in future research.

Years of data gathering

The first part of the research utilises data from the MPN from 2014 and 2016, as these were the only two years in which detailed statements regarding attitudes were gathered from respondents. It is important to note that this data is somewhat dated. Since then, two significant developments have transpired, primarily due to COVID-19: a modal shift towards car use and an increase in remote work (De Bruyn and Van Oort, 2023; De Haas, 2023). The advantage of using pre-COVID data is that it allows for an actual examination of the influence of changes over time between attitude and behavior without the observed effects being confounded by the impact of COVID on modal choice. However, a limitation of using pre-COVID data is the inability to investigate whether COVID also affected the relationship between cost-consciousness, environmental awareness and mode use. Additionally, according to Market Response (2023), the proportion of individuals considering sustainability in their purchasing decisions increased from 22% in 2012 to 52% in 2022. However, no growth in the level of environmental awareness towards mode use was observed between 2014 and 2016. Therefore, this study cannot provide direct insights into the impact of increased environmental awareness on transport behavior. In conclusion, based on the described developments, it is anticipated that the strength of the relationships may have changed somewhat since 2016, especially with the expectation that the impact of environmental awareness on mode use has increased. However, in general, it is presumed that the direction of the influence (whether it is positive or negative) has remained unchanged.

Future research should delve into the post-COVID relationship and make comparisons with pre-COVID data. This investigation can explore whether heightened environmental awareness reinforces the influence on increased train use and decreased car use, and assess potential alterations in these relationships due to the pandemic's effects.

Detailed attitudes under consideration

Another constraint is that the statements employed to depict the latent attitudes are primarily centered on car use and ownership, emphasising cost-consciousness and environmental awareness within the context of car use predominantly. Despite this focus, the significant association of these attitudes with train use implies that cost-consciousness and environmental awareness related to car use also impact train usage. This indicates that these attitudes associated with car use also partially delineate cost-consciousness and environmental awareness across mode usage in general. In addition, when comparing this research with previous literature, the constrained coverage of detailed attitudes related to cost-consciousness, environmental awareness, and status-sensitivity creates uncertainty about the longitudinal impact of all detailed attitudes on behavior and vice versa.

Future research should contemplate re-evaluating the list of statements used to explore the latent attitude constructs. Primarily, the statements should not exclusively focus on car use, but instead encompass various modes of transport. Moreover, considering previous cross-sectional research that has identified relationships from attitudes to behavior for other detailed attitudes like safety, flexibility, comfort, and convenience, it is advisable for future research to incorporate statements to measure latent constructs based on these specific variables.

Causal structure

A methodological limitation of using Structural Equation Modelling (SEM) is that SEM cannot provide support about the causal structure. SEM can only indicate how variables are related to each other, but not which variable influences the other (Golob, 2003). The decision whether or not the relationship from attitude towards behavior can be estimated simultaneously is the subject of debate in previous literature. The selected conceptualisation aligns with Thøgersen (2006), but Kroesen et al. (2017) challenges this approach. As SEM cannot verify if this causal structure is accurate, the possibility that behavior also has an immediate effect on attitude cannot be ruled out. Nonetheless, the lack of a significant relationship between past behavior and current attitude suggests that the impact of behavior on the attitudes cost-conscious and environmental aware is not substantial.

In future research, only cross-lagged relationships between attitudes and mode use could be considered, thus avoiding the need to assume the direction of detailed attitudes towards behavior in the lag. By exclusively estimating cross-lagged relationships and broadening the amount of detailed attitudes under consideration, it would then be possible to indicate which detailed attitudes exert more influence on behavior, and for which behavior may potentially have a greater impact on the detailed attitudes.

Duration of impact to evolve

Another limitation of longitudinal analysis is the necessity to determine the duration required for a cross-lagged relationship to develop, as it should align with the time needed for such a causal relationship to evolve (Lorenz et al., 1995). While existing longitudinal research suggests that a two-year timeframe is suitable (Kroesen et al., 2017; Thøgersen, 2006), it is important to consider that observing the impact of behavior on detailed attitudes towards mode use may require a longer duration than two years to become significant. Furthermore, this research only examines two waves of data, so it cannot definitively state whether these relationships will remain consistent in future waves. Future studies could consider more than two waves of data and therefore ascertain whether an observable effect from behavior towards environmental awareness and cost-consciousness emerges over a longer timeframe of more than 2 years.

Impact of measures to enhance cost-consciousness and environmental awareness

Lastly, this research indicates that both cost-consciousness and environmental awareness influence modal choice, thereby advising an increase in investment in informational campaigns to enhance cost-consciousness and environmental awareness in relation to mode use. However, this research does not definitively establish how cost-consciousness and environmental awareness surrounding modal choice can be precisely influenced. Suggestions for this are provided in subsection 7.3, but the actual impact these measures will have on people's cost-consciousness and environmental awareness remains uncertain.

By employing the longitudinal approach from this research, this methodology could be utilised to examine the relationship both before and after implementing initiatives aimed at enhancing the modal share through attitudes. For instance, it could assess the effect of an informational campaign on cost-consciousness and environmental awareness and determine whether the association between attitudes and behavior strengthens after the informational campaign. This allows for an investigation into the extent to which the information campaign fosters increased awareness and influences a shift in mode use.

7.4.2 Role of perceived value of travel time in actual mode choice

In this subsection, the primary limitations related to the research methodology for assessing the perceived value of travel time in actual mode choice will be considered, along with an exploration of potential approaches for addressing these limitations in future research.

Reliability of the train and car data per OD pair

The main limitation of the research in part 2 is that the linear regression analysis relies on estimated data from a model. While this model strives to accurately represent actual behavior and is grounded in Revealed Preference data, it was unavoidable to rely on certain assumptions. Regarding the reliability of the train data, the most uncertainty lies in translating station-to-station data into NS zone-to-NS zone data. The 'Rittenonderzoek 2023' was a crucial source for this, but it did not contain sufficient data for every OD pair to make it fully specific. As for the reliability of the car data, the primary uncertainty lies in the reliability of the data from the LMS itself. The following paragraphs will further elaborate on the implications of this uncertainty in train and car data.

Since the station-to-station information about the numbers of travellers and travel time components was already accessible from the LMS and is based on check-in and check-out data, the most challenging part of operationalising the door-to-door trip by train lay in the access and egress transport. The access and egress distribution from the number of travellers towards the different NS zones was based on the 'Rittenonderzoek 2023' which is a Revealed Preference survey. On average, the Revealed Preference survey contained 300 observations per NS zone; however, some NS zones only had 6 observations as origin or destination zones in the Revealed Preference survey. The lower the number of observations per NS zone, the more difficult to generalise that the found distribution in the sample is also representative for the population. Since the 'Rittenonderzoek' is only used for the distribution of the number of travellers rather than for absolute numbers of travellers across different stations, the influence of the lack of observations on the actual modal share remains limited.

The average access and egress time between the origin/destination NS zone to a station was measured based on a general conversion factor from straight-line distance to access/egress time. This provides an idea of the possible distribution, but it is only an approximation. If this conversion factor generally underestimates the access and egress time, the impact of access- and egress time on the modal share is higher than in reality. The general conversion factor also does not consider specific zone information such as the presence of buses, trams, and metros, and the average driving speed that can be achieved by car, resulting in greater uncertainty in the specific value for that specific zone. Moreover, it is important to note that the linear regression model takes into account the impact of the average access and egress time for the NS zone on mode choice. For individual travellers, the actual access and egress time that they experience for their specific trip is important. Therefore, ideally, it would be preferable to not only consider the average access and egress travel time but also to assess the distribution of the access and egress travel time from the station.

Furthermore, it is challenging to determine which train route the traveller would actually choose from the origin to the origin station, from the origin station to the destination station, and from the destination station to the final destination. However, it is necessary to determine a value for the various travel time components. To take into account that travellers in a NS zone may make a different choice depending on where they live in the origin NS zone or where they work in the destination NS zone, a more precise look was taken per LMS zone at what the route would be. Even here, there are still assumptions, as not everyone in the LMS zone necessarily has to choose the same departure station and arrival station. Even for an individual traveller, the selection of the origin station may also be influenced by the specific trip destination, and likewise, the choice of the destination station could also be affected by the specific origin. This introduces some uncertainty as to whether the travel time calculated for the train travel time components at the LMS zone level accurately represents the train travel time as perceived by the traveller.

The OD matrix for the number of car drivers provided in the National Traffic Model is derived from road counts at the road segment level. The challenge lies in accurately determining the origins and destinations of these road counts. The distribution is mainly based on zonal characteristics, which introduces a degree of endogeneity in the research, as these same zonal characteristics are also included in the linear model to explain the modal split. If this impacts the results, it would lead to an overestimation of the linear coefficient of the zonal characteristics, rather than affecting the evaluation of the train travel time components. Nevertheless, given the widespread acceptance of the LMS as providing an accurate representation of reality, it is assumed that the car data is reliable and that this has a limited effect on the final results in the linear regression model (Rijkswaterstaat, 2018; Snelder and Vonk Noordegraaf, 2022). Moreover, by aggregating the LMS zoning to NS zoning, the specific origin and destination do not need to be determined as precisely, which contributes to the reliability of the origin-destination modal share.

For future research about the experienced value of train travel in mode choice, it would be relevant to conduct a Revealed Preference Survey that encompasses both car and train travellers where at least about 30 respondents for each zone are incorporated. Respondents would maintain a travel diary where they not only define the mode of transport used, but also specify the duration of their journeys. For train travels, the respondents should also indicate the stations they have traveled through and, ideally, the duration of the specific components of the D2D train journey. Conducting a more extensive Revealed Preference Survey, which offers detailed information beyond just the origin, destination, and mode of transport, could reduce the need for making assumptions about these door-to-door trips and could lead to a more directly estimation the linear regression model based on the gathered data

Years of data gathering

The second part of the research predominantly relies on data from the LMS from the base year 2018. Similar to research part 1, using the LMS from 2018 has the drawback of being pre-COVID-19 outbreak data. Hence, for this research the assumption is made that the pandemic has not significantly affected the evaluation of the travel time components in relation to each other and in relation to the zonal characteristics, yet still providing information about their relative importance. Consequently, it is essential to take into account that the actual modal share of train has decreased compared to the car since COVID (De Haas, 2023). Hence, it is important to consider that the linear coefficients of the effect of the independent variables on the modal share could be somewhat smaller nowadays.

Additionally, to obtain supplementary information for modeling the distribution of travellers' access and egress transport, as well as the average access and egress travel time for each origin-destination pair, the 'Rittenonderzoek 2023' was used. The use of data from 2023, which is five years beyond the base year data from the LMS, was crucial to get more information about access and egress transport. Ideally, data from the same year as the LMS model was used to ensure consistency. Consequently, it is necessary to assume that the access and egress distribution did not undergo significant changes between 2018 and 2023.

For future research, it would be advantageous to update the data for the new LMS using a post-COVID base year. Preferably, for the same year, the "Rittenonderzoek" providing data on access and egress transport would also be available. In a ideal situation, one would avoid processing data from different data sources, as previously argued, and instead create a Revealed Preference survey that encompasses all the necessary data.

Generalisability of the results

This study relies on a specific case study that examines the modal split of origin-destination pairs in specific provinces in the Netherlands during the morning rush hour, with the expectation that similar relationships could be found to a large extent in other provinces, countries, and at different times of the day. When generalising the results to other locations and different times of the day, it is essential to take into account the potential impact of conducting the case study in the Netherlands, specifically in densely populated provinces and during the morning rush hour.

Firstly, it is plausible that the perception of train travel time components varies between countries, as the experience of train travel and stations differs across various nations. For instance, a comparison of the Dutch railway network with that of other countries reveals that NS generally operates newer trains, which could lead to a greater appreciation for in-train travel time (NS, 2017). Moreover, significant investments in stations have been undertaken in the Netherlands, potentially resulting in a higher valuation of (hidden) waiting time and transfer time compared to other countries (NS, 2023a).

Secondly, the Netherlands but also specifically the provinces where the analysis has been applied are generally more densely populated areas with a more intricate and better accessible public transportation network. This could have the effect that in other countries and provinces, access and egress time are being more important in their modal choice than in these highly densed areas.

Thirdly, another decision in scoping the model is to focus on trips during the morning rush hour of an average working day, assuming that in most cases these trips will be from home to work. This assumption was necessary to operationalise the data but has two consequences for the results. This assumption implies that all trips during the morning rush hour have the direction from home to work, while this may not necessarily be the case. Furthermore, it means that the modal share is primarily based on the choices travellers make between the car and the train for work-related trips. Perhaps the assessment of travel time components varies when the trips have a different purpose. For leisure trips, the transfer time might have an even more negative effect on the train's model share, as these travellers tend to use the train less frequently, resulting in a heightened level of inconvenience during transfers

As a result, it would be beneficial for future research to investigate the variations in the perceived value of train travel components among travellers across different countries. This investigation could offer a partial evaluation of the perceived quality of train services and the access and egress networks in these nations. By comparing these perceived values, significant factors contributing to a high perceived value for train travel components could be pinpointed, enabling the identification of "best practices" from various countries for the implementation of suitable measures to encourage a shift towards train usage. Another avenue for future research might involve assessing the value of travel time for different travel purposes at different moments in time, in order to ascertain the extent to which the valuation of travel time differs for each purpose.

Inclusion of variables

Previous literature has identified several factors that can help explain mode choice between train and car. The R^2 value indicates that the current incorporated factors already account for a significant portion of the variance in modal share. However, the inclusion of additional information can further improve the comprehension of the modal share of origin-destination pairs. This may involve incorporating data on train punctuality, train crowding, and the quality of public transportation for access and egress. This enhanced information allows for a more accurate incorporation of the pure effects of the explanatory variables. It is possible that population density and job density act as indicators of the quality of access and egress transportation, potentially elucidating the reasons for the positive influence that population and job density have on the model share in the linear regression model.

Furthermore, in addition to the differences in perceived value between access, waiting, in-train, transfer, and egress time, there are other aspects of the door-to-door train and car journey that can impact the perceived travel time value for passengers. This encompasses the variation in travel time value depending on the chosen access and egress mode of transportation, as well as the disparity in travel time value between traveling by car during the morning rush hour with smooth traffic flow compared to being stuck in heavy traffic congestion.

Subsequent research could concentrate on quantifying the perceived value of driving on uncongested routes compared to congested routes and/or on quantifying the specific perceived value for the various modes of transport for access and egress travel. The perceived value of the access and egress part remains a relatively unexplored area in research. An initial attempt was made by Schakenbos and Nijënstein (2014) to quantify the perceived value of a transfer between bus, tram, or metro and train. However, a comprehensive overview of the perceived value of all individual modes of transport is still lacking. Yet, this information could offer the Ministry and NS valuable insights into which modes of transport for access and egress they should prioritise to make the train a more appealing alternative to the car. More information about the impact of congestion on modal choice could aid in evaluating the effect of congestion on modal choice and whether it is desirable to build additional roads to reduce congestion, potentially leading to more people choosing the car over the train.

Revealed Generalised method

Lastly, it is important to note that the Revealed Generalised method's drawbacks include the estimation of only a single linear coefficient per travel time component and the exclusion of other characteristics besides time for the transfer component. These disadvantages resulted in that eventually the proportion of explained variance of the Revealed Generalised approach is about the same as for the Stated Generalised approach.

Assuming a linear association between the predictor variables and the outcome variable may not fully capture the complexity of mode choice. This limitation was evident in literature studies when attempting to address the service interval penalty and the transfer penalty. More intricate relationships were often utilised to better approximate reality, such as a piecewise linear function. For instance, in the study by De Keizer et al. (2015), it was indicated that the optimal transfer time was found to be 5 minutes by travellers. Both shorter and longer transfer times were perceived as less favorable in this context. Given that the Revealed Generalised method estimates only one linear coefficient, showing that a longer transfer time leads to a lower modal share, it cannot account for the possibility that this relationship may be the opposite between 2 and 5 minutes. Similar considerations apply to the linear correlation between TTF value and modal share. Previous research by Van den Heuvel (1997) has highlighted that for TTF values especially for ratios between 1 and 2, a notable decrease was observed, which could be better described using a curved rather than a linear relationship.

In future research, it would be beneficial to further investigate the Revealed Generalised approach, leveraging its strengths in assessing actual completed journeys and the decisions made by travellers between the car and train, thus enabling the capture of the actual impact on modal share. Overcoming the current limitations of estimating only one linear coefficient per component and overlooking characteristics such as the number of transfers and interchange types. This could involve the estimation of different types of relationships based on previous Stated Preference research, ensuring that the relationship type may differ for each travel time component and its segments. Potential additional factors for each train travel component can be explored, with potential factors that may be considered outlined in Table 30.

Train travel component	**Potential additional factors to include besides time**
Access/egress	Availability shared cars and bikes, availability BTM options, parking facilities
	Distribution housing and activities near train station
(Hidden) waiting	Station rating by travellers, station facilities
In-train	Sprinter or Intercity trains
Transfer	Number of transfers, type of interchange, possible extra waiting time

Table 30: Potential factors that could be included besides time for each D2D train travel component

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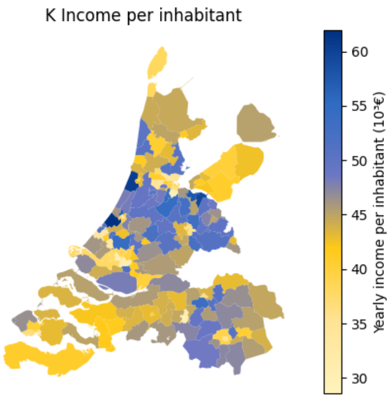
Appendix A Factoranalysis 2016

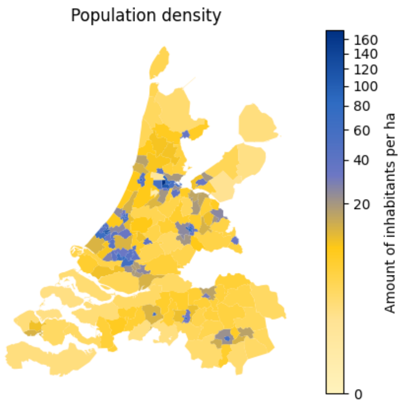
Factors	Statements	1	2	3	4
Car-minded	Driving a car offers many advantages compared to the use of other transport modes	0.714			
	The car gives me the freedom to go wherever I want	0.684			
	I cannot manage without a car	0.558			
	Driving a car is fun	0.551			
	If I have to go somewhere, I nearly always go by car	0.526			
Cost- conscious	Due to costs, it is difficult for me to own a car		0.789		
	My current financial situation is a reason to postpone the purchase of a (new) car		0.732		
	Due to high costs, I drive less with the car than I actually want to		0.64		
Status- sensitive	A car says a lot about a person's status in society			0.752	
	A car says a lot about someone's personal taste / sense of style			0.742	
Environmental aware	It is pointless to worry about the environment, because there is nothing you can do about it on your own				-0.760
	It does not make sense to not drive a car in order to benefit the environment, because other people continue to drive their cars				-0.674
	The environment will benefit if people drive cars less frequently				0.546
Cronbach's alpha		0.742	0.765	0.710	0.702

Table 31: Factor analysis 2016 with factor loadings and Cronbach's alpha

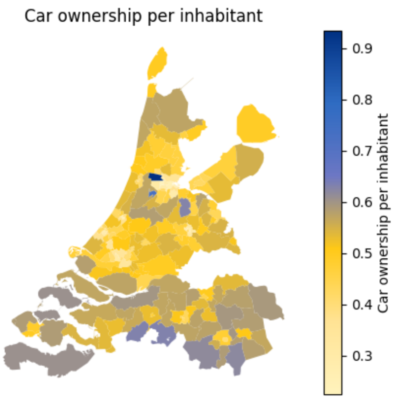
Appendix B   Zonal data



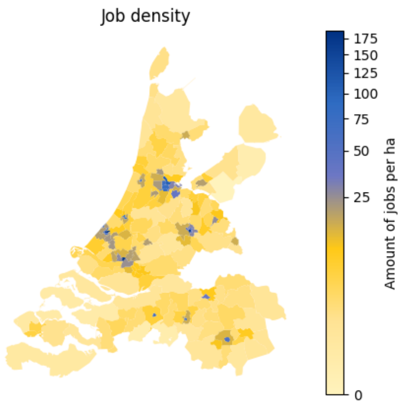
(a) Income per inhabitant per NS zone



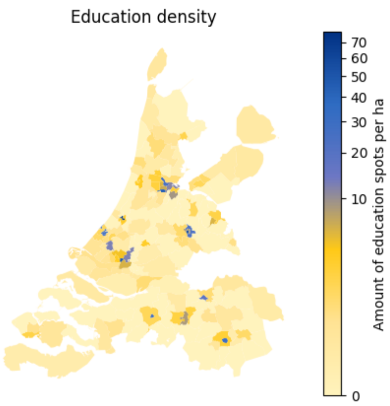
(b) Population density per NS zone



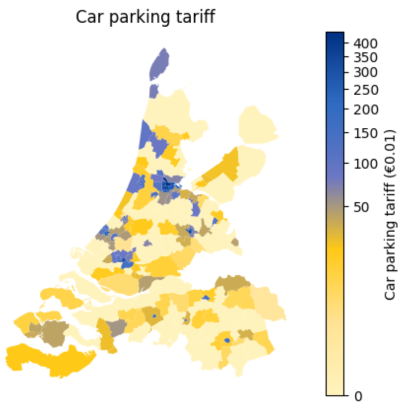
(c) Average car ownership per inhabitant per NS zone



(d) Job density per NS zone



(e) Education spots per NS zone



(f) Average car parking tariff per NS zone

Figure 24: Various NS zone data

Appendix C Piecewise linear function

This appendix further elaborates on the subprocess steps involved in establishing the conversion factor from straight-line distance to time. It also presents and evaluates the intermediate results.

In the process of establishing the conversion factor, data from the 'Rittenonderzoek' regarding the utilised access/egress mode of transportation and the straight-line distance between the origin postal code and the train station is utilized. Based on this data, the absolute numbers per mode of transportation are determined for each distance class of 0.5 in the 'Rittenonderzoek'. The findings from Figure 25 and Figure 26 indicate that generally, train travelers have their origin and destination located relatively close to the station, as reflected in the high volume of observations for the low straight-line distance classes. In the case of egress transport, the destination is often even closer than for access transport. Furthermore, the data illustrates that for shorter distances to the station, slower modes of transport are more commonly utilized. Specifically, within the 0 to 1 km straight-line distance range, walking is predominant, with bicycle usage becoming more prominent after 1 km of straight-line distance, while the number of pedestrians gradually diminishes. Additionally, there is a discernible difference in the modes of transportation used for access and egress, with walking being notably more prevalent for egress transport. This pattern is expected, considering that travelers often do not have access to their own bicycle at the activity end.

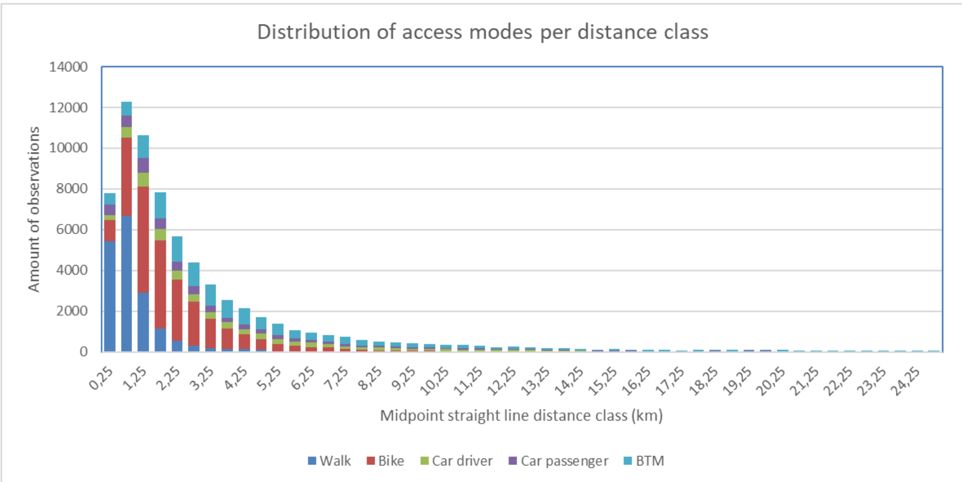


Figure 25: Distribution of access mode per distance class (n = 69892 trips)

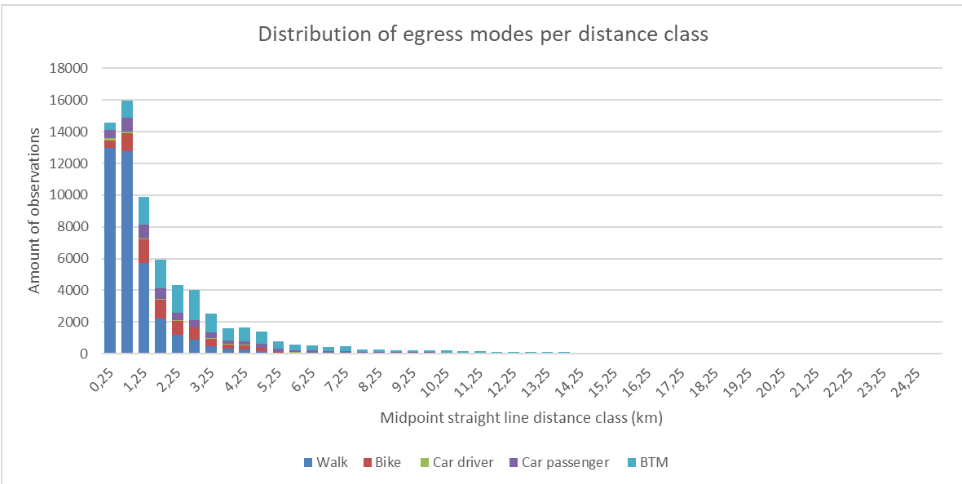


Figure 26: Distribution of egress modes per distance class (n = 67727 trips)

Ultimately, to convert the distance to time based on the mode of transportation used, specific assumptions need to be made regarding the walking and driving speed, parking time, and detour factor for each mode of transport. These assumptions are elaborated in detail in Table 32. With this information, the average time in minutes for each mode of transport for each midpoint of the distance class can be calculated by using Equation 18 representing the average time that travelers would spend using that mode of transport over that straight-line distance.

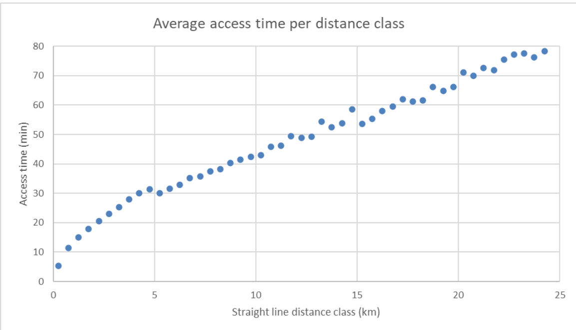
	Walk	Bike	Car driver	Car passenger	BTM
Retrieving (min)	0	1	1	1	10
Speed (km/h)	4,5[1]	12 [1]	40[1]	40[1]	28,4[4]
Detour factor	1.3[2]	1.37[3]	1.6[3]	1.6[3]	1.6[3]
Parking (min)	0	3	5	2	5

Sources: [1]Immers and J.E. (2011), [2]Linschoten and Snijders (2016), [3]Welles (2004), [4]Kennisplatform CROW (2020)

Table 32: Average retrieving, driving, detour factor and parking time for access and egress transport

$$Average\ access/egress\ time_{mode} = Grabbing_{mode} + (Midpoint\ distance\ class \cdot Detour\ factor_{mode})/Driving\ speed_{mode} \cdot 60 + Parking_{mode} \tag{18}$$

Given the average access and egress time per distance class per mode and the frequency of occurrence of those modes per distance class, as visualized in Figure 25 and Figure 26, the overall average access and egress time per distance class can be determined. The comprehensive average access and egress time per distance class is displayed in Figure 27.



(a) Average access time per distance class

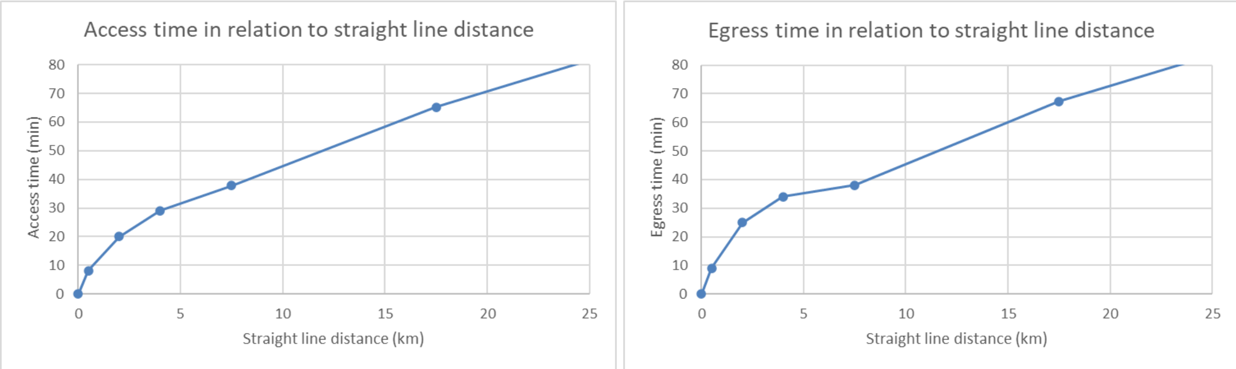
(b) Average egress time per distance class

Figure 27: Access and egress time per distance class

Figure 27 indicates that, on average, the access/egress time increases as the straight-line distance increases. This pattern is occasionally disrupted at higher distances due to lower observation counts. Since the speed over the straight-line distance segments is not constant, a piecewise linear function is utilized to approximate the conversion function. This approach involves approximating the access/egress time linearly for each distance segment, enabling a more accurate estimation of the total travel time while accounting for speed variations. Narrower straight-line distance segments have been chosen for shorter distances, where travel is more frequent and speed variations are more pronounced, necessitating a more precise determination. Ultimately, Figure 28 illustrates the approximation of the conversion using a piecewise linear function. The constants and coefficients for the use of these cumulative piecewise linear functions for both access and egress transport are detailed in Table 33. These values form the basis of the conversion detailed in Equation 6 and Equation 7.

Straight line distance category	Access transport		Egress transport	
	Constant	Speed coef.	Constant	Speed coef.
0-0.5		3.66		3.32
0.5-2	8.19	7.61	9.03	5.64
2-4	20.02	13.21	24.99	13.25
4-7.5	29.10	24.04	34.05	53.46
7.5-17.5	37.83	21.90	37.97	20.46
>17.5	65.23	27.59	67.30	27.70

Table 33: Constant and coefficients for piecewise linear function for access and egress transport



(a) Access transport

(b) Egress transport

Figure 28: Piecewise linear function for conversion straight line distance to time

Appendix D Example Amersfoort outside the city center to Municipality Stichtse Vecht (Breukelen)

In this appendix, an illustrative example showcases how the analyses can aid in elucidating the modal share for a specific OD pair and in formulating various measures based on this information. The example centers on the trip from Amersfoort outside the city center to the Municipality of Stichtse Vecht, chosen due to it being one of the OD pairs with an actual market share lower than expected based on the TTF value from the linear regression model.

The data relating to this OD pair indicates that on an average working day, between 7 and 9 o'clock in the morning, an estimated 580 car commuters and only 14 train travelers journey from Amersfoort outside the city center to the Municipality of Stichtse Vecht. Consequently, the train's market share stands at 2%. Based solely on the TTF value of 1.45, a significantly higher train market share would be expected. If the regression model with only the TTF value as the explanatory variable is used, a train market share of 27% would be anticipated.

Focusing more closely on the specific connection and zonal characteristics for this combination can help in explaining the market share train. Figure 29 illustrates the expected travel route for train passengers from Amersfoort outside the city center to the Municipality of Stichtse Vecht. Depending on the precise residential location in Amersfoort, the traveller will take the train from train station Amersfoort Vathorst, Amersfoort Schothorst, or Amersfoort Centraal, with an average access time of around 20 minutes. At Utrecht, a transfer to another train occurs, with an average transfer time of 11 minutes. Travellers will exit this train at train station Maarssen or Breukelen, with an average egress time of 14 minutes to reach the specific destination.

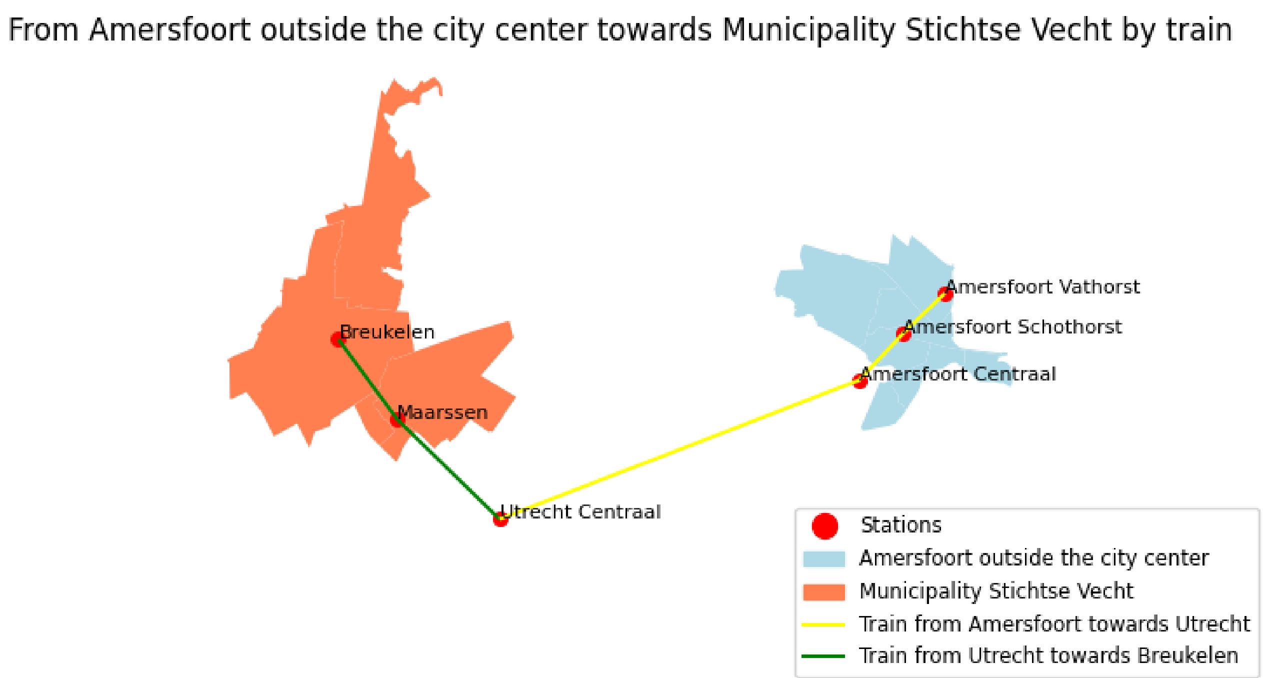


Figure 29: Travelling by train from Amersfoort outside the city centre to Gemeente Stichtse Vecht (Breukelen)

The detailed average times for this route can be found in Figure 29. Additionally, the table includes the travel time when the Revealed Generalized travel time is computed. Furthermore, it provides the car travel time, TTF value, and zonal characteristics of the origin (Amersfoort outside the city center) and the destination (Municipality Stichtse Vecht).

Category	Variable	Value for OD pair
TTF	TTF	1.45
Train time component	Train: Access time	20 min
	Train: (Hidden) waiting time	14 min
	Train: In-train time	27 min
	Train: Transfer time	11 min
	Train: Egress time	14 min
	Train: D2D TT	87 min
Car time component	Car: D2D TT	60 min
Zonal characteristics	Income Amersfoort outside the city center	46 thousand euros per household
	Population density Amersfoort outside the city center	26 inhabitants per ha
	Car ownership Amersfoort outside the city center	0.43 cars per inhabitant
	Job density Municipality Stichtse Vecht	2.2 jobs per ha
	Eduation density Municipality Stichtse Vecht	0 education spots per ha
	Car parking tariff Municipality Stichtse Vecht	0 eurocents

Table 34: Details for the route from Amersfoort outside the city center - Municipality Stichtse Vecht during the morning rush hour, for both train and car

In Table 35, the developed linear regression model with various included variables indicate the expected train market share for this specific OD pair. The observed trend reveals a slight decrease in the expected market share when considering car and train travel time as separate explanatory variables in the model. This stems from the realisation that representing two distinct regression coefficients, considering that travellers appraise a minute of travel time differently for car and train, inherently results in a lower expected market share for this connection. Upon comparing the market share difference between model B and C, it becomes evident that integrating train travel time valuation significantly reduces the expected market share. This is primarily due to the relatively long transfer time for this connection, heavily influencing travelers' choice between car and train owing to the diminished experienced value. Model D predicts an even lower expected market share. From the comparison of the zonal characteristics with the average values in Table 20, it becomes apparent that the predominant influence stems from the zonal characteristics at the destination. The Municipality of Stichtse Vecht exhibits relatively low job density, absence of educational facilities, and no set parking tariff for cars. In contrast, higher job and education density, along with a parking tariff, contribute to a greater market share for the train.

It is also evident that the variables included in model D still cannot fully explain why the market share from Amersfoort outside the city center to Municipality Stichtse Vecht is so low. This suggests that there are other characteristics not accounted for in the analysis that contribute to a reduced market share for this origin-destination pair. This could include factors such as the costs per train and car, or the proximity of workplaces and residential areas to the stations. In order to comprehend the market share for a specific origin-destination pair, it is necessary to have a better understanding of these areas and include characteristics that are not currently part of the analysis.

Linear regression model	Included variables	Expected market share train
Model A	TTF	27%
Model B	Car: D2D TT & Train: D2D TT	26%
Model C	Car: D2D TT & Train: D2D Revealed Generalised TT	18%
Model D	Car: D2D TT & Train: D2D Revealed Generalised TT & Zonal characteristics	14%

Table 35: Expected market share for the OD pair Amersfoort outside the city center towards Municipality Stichtse Vecht

If the objective is to increase the train's market share for this OD pair, the insights from these analyses could prompt an evaluation of the feasibility and effectiveness of altering the schedule to reduce transfer duration or exploring the potential to eliminate the need for a transfer. Furthermore, it may be worthwhile to assess the potential of relocating employment and educational opportunities to the Municipality of Stichtse Vecht, strategically positioned near the station to minimize access and egress times. Additionally, methods to make car travel less appealing to Stichtse Vecht could be considered. This might involve reducing parking facilities at companies for employees or implementing a car parking tariff.